HOW CAN BIG DATA HELP FOOTBALL CLUBS ACHIEVE COMPETITIVE ADVANTAGE

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Abstract

Title: How Big Data can help football clubs achieve superior performance

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Integrated in a naturally competitive environment, football clubs will thrive based on the ability to generate competitive advantage. With the industry experiencing technological advancements that permit the dissection of athlete and team performances through modern tracking tools, the data inherent to the activity is increasingly relevant to model the approach towards competition. This thesis sets out to explore how Big Data can be advantageous for football clubs' performance, by extending the availability of the best talent in the team with enhanced injury preventive mechanisms. It also analyses how the decision-making process of the players can be bettered to extract the most value from every game situation. The connection of secondary data sources, both empirical and theoretical, hints on how football clubs can mobilize specialized resources to deliver a differentiating, performance-enhancing protocol. Despite denser competitive calendars, overall injury rates have declined in elite European football clubs between 2001 and 2017, suggesting that improved training methods helped control the occurrence of preventable injuries. In addition, an increasingly faster game promoted the need of having quick-thinking athletes, able to anticipate in-game scenarios and comply with the tactical demands of competition. With injury linked to poorer performance and decision-making associated with a player's ability to perform at high-level, the Big Data applications explored in this thesis are reinforced as they have the potential to promote the marginal gains that unbalance a low-scoring sport.

Keywords: Big Data, competitive advantage, football clubs, injury, prevention, noncontact, decision-making

Resumo

Título: Como a Big Data pode ajudar clubes de futebol a atingir uma vantagem competitiva

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Integrados num ambiente competitivo, o sucesso dos clubes de futebol assenta na sua capacidade de gerar vantagem competitiva. Com a evolução tecnológica na indústria, que permite dissecar o desempenho do atleta e da equipa com ferramentas de monitorização, os dados inerentes à atividade desportiva ganham preponderância na preparação para a competição. Esta tese explora formas de como a Big Data pode ser vantajosa para o desempenho dos clubes em campo, estendendo a disponibilidade física dos melhores talentos através de mecanismos inovadores na prevenção de lesões. Analisa, igualmente, o potencial formador da tomada de decisão dos atletas, para extrair o maior valor possível de todas as situações de jogo. A ligação de fontes secundárias, empíricas e teóricas, antevê a mobilização de recursos especializados para promover um protocolo diferenciador e potenciador. Apesar da existência de calendários competitivos densos, a taxa global de lesões diminuiu no período compreendido entre 2001 e 2017, sugerindo que a evolução dos métodos de treino contribuiu para controlar a ocorrência de lesões antecipáveis. Ainda, a crescente rapidez do jogo promoveu a necessidade de aliar velocidade à tomada de decisão, promovendo jogadores capazes de antecipar cenários de jogo e assim cumprir com as exigências táticas da competição. Com a ligação das lesões a um decréscimo do desempenho coletivo, e associando-se a tomada de decisão à capacidade do atleta competir a nível de elite, as aplicações de Big Data exploradas nesta tese apresentam o potencial de promover ganhos marginais que podem ser o fator desequilibrador num desporto de baixa pontuação.

Palavras-chave: Big Data, vantagem competitiva, clubes de futebol, lesões, prevenção, não-contacto, tomada de decisão

Contents

List of abbreviations

FC – Football Club

RBT – Resource-Based Theory

HR – Heart Rate

GPS – Global Positioning System

FIFA – Fédération Internationale de Football Association

UEFA – Union of European Football Associations

KPI – Key Performance Indicator

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1

Introduction

1.1 Topic presentation

With time, football (also known as soccer) evolved from a recreational activity performed and managed by amateur enthusiasts, to a high-profile business (Cross & Henderson, 2003), with Football Clubs (FCs) able to generate million-euro revenues (Appendix 1) and seeing part of those same entities become publicly listed (Appendix 2) (Grass, Holst & Jonsson, 2001). Having grown to this point, FCs are currently managed similarly to companies from diverse industries, facing equivalent strategical challenges and undergoing the same pressure to deliver profits for its shareholders (Grass et al., 2001; Rikardsson & Rikardsson, 2013).

Furthermore, competition grew to a degree that puts FCs on the lookout for strategies that allow them to achieve a superior performance relative to its opponents, be it on the field, in the form of victories and trophies, or off the field, with revenue and financial results (Kraaijenbrink, Spender & Groen, 2010).

Taking on that competitive landscape and linking it with technology, this thesis explores the application of Big Data as a source of superior performance on the field, via injury prevention and the enhancement of players' decision-making during match-play.

To secure a competitive advantage and foster a thriving organization, innovation is considered pivotal (Maggioni & Giudice, 2014). It implies that relying on the same methods over time, will see less innovative firms overtaken by those that show greater proactivity. To achieve superior performance, FCs are challenged to be innovative in the way they combine the available internal resources and capabilities, as to create a successful formula that is not easily imitable or understood by its opponents should the advantage be long-lived (Barney, 1991).

Thus, FCs are trying to detach from the competition by making use of information gathering and analysis techniques that can structure the data inherent to the game (Carling, Bloomfield, Nelsen & Reilly, 2008). Whilst Data Scientists have spent the past few years in efforts to further themselves in the learning curve regarding data collection, the current challenge is to find the best way to structure the overwhelming flow of information into crunched, real-time, actionable input that is relevant to the game.

Aided by technology, players and coaching staff (in other words, staff comprised by those who have influence in the preparation of the team, from the main coach to physiotherapists) can benefit from a decision-making support, to grant them the supplementary input that will inch the club closer to spearheading its competitive environment through enhanced training protocols that foster on-field value extraction.

1.2 Purpose

This thesis aims to deliver a comprehensive understanding on how a Big Data-driven approach can give FCs a competitive edge, whilst connecting existing literature in sports science with currently used, real-life applications of data analysis in football. Furthermore, this work assesses the competitive potential of improving the injury prevention protocol and enhancing the players' decision-making ability by incorporating Big Data analytics in the training methodology.

1.3 Problem Statement

The impact of Big Data on FCs' through injury prevention and player decision-making enhancement to boost sporting performance. This thesis strives to analyze whether Big Data applications can help FCs enhance their performance in competition. Specifically, this work focuses on the link between Big Data and injury prevention, as well as the athlete's gameplay decision-making, to promote better sporting results.

1.4 Research Questions

Gathering a range of Data that provides additional input to better prepare FCs for upcoming challenges was made possible with the integration of new technology in the form of sensors, high-definition cameras and GPS, to name a few (Cintia, Pappalardo, Pedreschi, Giannotti & Malvaldi, 2015).

With the achievement of technological maturity that satisfies scientific standards (Cintia et al., 2015; Rein & Memmert, 2016), the subsequent step is to comprehend how its integration in team preparation can optimize the performance of the team and its individuals.

Exploring the applications of Big Data will help understand how teams can leverage the internally generated resource that is the data collected from gameplay and training, to maximize each player's potential. As FCs are challenged to structure scattered data (Rein & Memmert, 2016), the first research question aims to uncover actionable data-driven strategies that promote the extended availability of the best talent in the team. In other words, a player's availability is measured according to the existence of technical, tactical, physical or psychological constraints.

Physical injuries being the most common cause for player absence in training and official matches in professional FCs (UEFA, 2016), an association was found between lower season injury rates and both domestic league and international European competition's increased performance (Hägglund et al., 2013). On that note, this thesis questions:

RQ1: Can Big Data help in injury prevention?

The second question addresses the potential impact of using Big Data analysis to enhance a player's decision-making ability on the field. Since the players' ability to implement the required technical and tactical actions is vital for the success of a tactic (Rein & Memmert, 2016), bumping up the rate of correct on-field decisions should allow FCs to extract the most value from the trained game tactics.

RQ2: Can Big Data improve a player's decision-making for match-play?

Finally, the third question attempts to couple the findings from the two previous research questions in order to evaluate if Big Data analysis will provide FCs with a competitive advantage.

RQ3: Does Big Data application promote better sporting results?

1.5 Academic and managerial relevance

A point of contact can be established between the football industry and the business world, as FCs have evolved from being underfinanced centres for leisure activities, to high-profile businesses (Cross & Henderson, 2003).

Linking it with Big Data takes a secular discipline like football and gives it a contemporary flair, as Big Data analysis has surfaced as one of the trendy sources of digital innovation for clubs to optimize performance (Chen & Lin, 2014). The increasing amount of Data available due to the technological progress in player tracking devices, like semi-automatic high definition cameras, GPS or sensors (Carling et al., 2008; D'Orazio & Leo, 2010), together with FIFA's permission to use wearable tracking devices in competition (Di Salvo, Tschan & Bachl 2007) suggests that Big Data analytics will shape the future of performance analytics in football (Rein & Memmert, 2016).

As a result, FCs that move ahead of the learning curve in integrating Big Data strategies to maximize performance may outpace the competition in achieving a superior performance.

1.6 Scope of analysis

Although many variables have the potential to affect the FC's on-field performance as well as the creation of a competitive advantage, this thesis focuses on associating Big Data to injury prevention and player's decision-making enhancement. Since these two themes have been related to the potential to perform, it is suspected that coupling Data-driven strategies can play a role in bettering the training protocol to achieve a competitive advantage.

Quantifiable data on injuries, performance and decision-making, that back the arguments in this thesis, referred to European FCs, ranging from youth to elite level. All the data derived from secondary sources, which were linked to provide a comprehensive understanding of how Big Data could influence the creation of a competitive advantage.

The real-life applications of Big Data in FCs, exemplified by SL Benfica's injury prevention protocol backed with Big Data, as well as German football club, TSG 1899 Hoffenheim's decision-making enhancing technology, represent evidence from the utility of Big Data in two European references in the sport's innovation for performance.

1.7 Organization

This thesis starts with an extensive literature review on competitive advantage, Big Data, injury and decision-making. It provides insight on economic and sports science theories that together, kickstart the inductive process on how Big Data can provide FCs with a competitive advantage. The theoretical backbone sets the ground to discuss if Big Data can improve the injury preventive models and enhance a player's decision-making ability, the two variables chosen for analysis.

It moves on to relate empirical data with the theoretical findings, establishing trends that hint at the utility of Big Data to improve injury preventive and decision-making models. Upon the assessment of utility, this thesis creates a framework that relates the two Big Data-driven strategies with enhanced performance on the field. To back up the inductive arguments, this thesis also addresses two real-life cases, showcasing how elite European FCs currently combine Big Data with injury prevention and decision-making improvement.

Concluding, this thesis connects the sports science with the economic theory, to provide a comprehensive understanding of the value underlying the innovative strategies regarding the competitive environment of the football industry. Lastly, a look at the present challenges in incorporating Big Data strategies in FCs, as well as a suggested path for the future is addressed.

2

Literature review

2.1 Competitive advantage

Sources of Competitive Advantage have been thoroughly discussed over the years in the field of Strategic Management (Barney, 1991). In this chapter, the two main trains of thought that tackle the origin of a firm's superior performance are scrutinized.

On one hand, for years Strategic Management focused on the link between strategy and the external environment to analyze a firm's opportunities and threats within its competitive environment (Amis, Pant & Slack, 1997). The environmental outlook pointed out the most favorable conditions that firms could explore to outperform the competition (Porter & Miller, 1985; Lado, Boyd, & Wright, 1992). Building on that, the context of industrial economics supported the development of research on industry attractiveness and competitive positioning within an industry (Gartner, 1985), the two determinants in the choice of competitive strategy to attain a competitive advantage over the industry's competitors (Porter, 1985).

On the other hand, a look into the individual firm's resources and capabilities redirected attention to internal strengths and weaknesses to estimate the sources of competitive advantage, forming the Resource-Based Theory (RBT) (Barney, 1986, 1991, 2011). Linking a firm's distinctive capabilities with its strategic choices emphasized the role of internal resources and capabilities as sources of superior performance (Amit & Schoemaker, 1993). Based on the assumptions of resource heterogeneity and immobility among firms (Barney & Hesterly, 2008), as well as larger differences found between firms intra-industry than across industries (Rumelt, 1991), the RBT suggested that the nature of the firm's internal resources and capabilities outweighed other determinants of competitive advantage (Amit & Schoemaker, 1993).

2.1.1 The firm and the external environment

Throughout the 80's, the major focus of strategic analysis lied upon the impact of the external environment on firms, to generate a competitive advantage within an industry (Lado et al., 1992).

In the path to developing a competitive advantage, in which the value a firm is able to create for its buyers exceeds the costs of creating it (Porter, 1980), firms need to deploy a competitive strategy to achieve it (Porter, 1985). Specifically, firms search for a competitive position, leveraging the industry's competitive pressures that allow them to reap profits (Porter, 1985; Grundy, 2006). Ultimately, firms choose their competitive strategy based on two central questions, industry attractiveness and market positioning (Porter, 1985).

2.1.1.1 Industry attractiveness

Firms assess the attractiveness of an industry regarding its long-term profitability potential (Porter, 1985). That assessment is based on an external examination of the industry's opportunities and threats, whilst complemented with the industry's structural parameters (Lado et al., 1992). In this case, the structural parameters represent the industry's attributes that determine profitability: threat of new entrants, threat of substitutes, bargaining power of buyers and suppliers and intensity of rivalry (Porter, 1980). Additionally, the external examination arises from the premise that superior performance results from the response of a firm to selective industry pressures (Lado et al., 1992).

Since not all parameters exert equal influence on the profitability of a company, studying them allows firms to pinpoint the forces that ought to be explored to enhance industry attractiveness (Porter, 1985; Amit & Schoemaker, 1993). Accounting for the external factors that make for an attractive industry allows firms to decide strategically, knowing that opportunities will outnumber and outweigh the threats in the industry (Porter & Miller, 1985). Ultimately, the external analysis highlights the average industry profitability and provides a foresight of how it could evolve in the future (Porter, 2001).

Notwithstanding, the long-term strategic choice of a firm, balancing the industry pressures, will not suffice to establish a company's competitive strategy, leading to the second central question of this theory (Porter, 1985).

2.1.1.2 Market positioning of a firm

To complement the choice of competitive strategy, the drivers of industry profitability are associated with the market positioning of the firm, a set of generic strategies from which firms attempt to generate a competitive advantage over the rivals in the industry (Porter, 1980, 1985).

Altogether, firms target above-average profitability in the industry, in other words competitive advantage, either by achieving operational effectiveness that allows to lower the cost position below its competitors (Porter, 2001; Banker, Mashruwala & Tripathy, 2015), or by differentiating in a way that the firm is able to increase the customer's willingness to pay for a product or service (Porter & Miller, 1985; Lado et al., 1992; Banker et al., 2015).

Alternatively, firms can choose to change its competitive scope and focus, adapting its business model to a distinct, selective segment of the market in which firms with a broader scope underperform (Porter & Miller, 1985).

Nevertheless, the position of the firm is established as a response to the imposed industry pressures (Lado et al., 1992; Bar-Eli, Galily & Israeli, 2008).

2.1.1.3 Critical assumptions

The influence of industrial organization led to a focus on the external environment to justify the emergence of competitive advantages (Lado et al., 1992; Grundy, 2006). That focus is reinforced by the underlying assumption that an industry, as in a group of firms producing products that are close substitutes of each other (Porter, 1980, 1985), experiences resource homogeneity among firms (Porter, 1981). Moreover, resource homogeneity is protected by the high mobility of the resources used to implement a strategy (Porter, 1981). Thus, the impact of firm management decisions regarding performance is reduced compared to the influence of industry's forces (Bar-Eli et al., 2008).

That way, analyzing these strategic questions per se does not guarantee an appropriate choice of competitive strategy (Porter, 1985). Whilst firms may fail to achieve a privileged competitive position in an attractive industry, others that are well positioned may be in a less attractive industry, enhancing the importance of balancing the industry's structural parameters that influence profitability (Lado et al., 1992; Porter, 2001).

2.1.2 Resource-Based Theory

Regarding business management, the goal of a firm is set in creating value (Conner, 1991). To better understand its creation, strategic management research was redirected from the external outlook of the firm to internal sources of competitive advantage (Wernerfelt, 1984). The RBT grew to link a company's distinctive competencies with the ability to outperform the competition or pioneer a value-creating strategy (Reed & Defillippi, 1990).

In doing so, the RBT recognized the idiosyncratic relevance of the firms' resources and capabilities as generators of competitive advantage (Lado et al., 1992; Amit & Schoemaker, 1993). The bundle of assets, tangible or intangible, used in the implementation of a competitive strategy represents the resources that back the firm's strategic choices (Daft & Lengel, 1983; Barney & Hesterly, 2008). Nevertheless, it is with the ability to leverage those resources within a competitive strategy that firms can step towards achieving superior performance (Amit & Schoemaker, 1993; Barney & Hesterly, 2008).

The mere mention of distinctive competencies led to an assumption that different potential generators of competitive advantage exist across firms, making for resource heterogeneity (Reed & Defillippi, 1990). Building on this, the combination of the firm's knowledge with the untapped potential of its strengths and weaknesses consolidates an idiosyncratic outlook towards strategy (Kogut & Zander, 1992).

On another note, diverse insights arose on how resources, organization and causal ambiguity, as in the uncertainty about what factor combination led to a certain result, contributed for the establishment of superior performance. Consequently, these insights helped build the assumption that industries face resource immobility, further consolidating the strategic shift towards looking inwards (Barney, 1986, 2001, 2011).

All in all, the RBT suggests that firm performance is a product of the interaction between the different bundles of resources and capabilities, addressing the internal strategies and *modus operandi* of a firm as potential creators of a competitive advantage (Barney, 1986; Lado et al., 1992).

2.1.3 Choosing the RBT

This work focuses on the football industry and the application of the game's Big Data to enhance performance in FCs. Therefore, the fit between different strategic management theories and the thesis had to be analyzed.

Taking that into consideration, the theory that links the external environment with competitive advantage is challenged for a few reasons.

Firstly, assuming a cost leadership strategy hardly applies to FCs, since the best talent and infrastructures that often translate into wins are directly related to larger expenditure (Grass et al., 2001).

In addition, the differentiation strategy established by firms is oriented towards external stakeholders (Lado et al., 2001; Grundy, 2006), limiting the gameplay applications and its impact on sporting results. Also, the inability to legally protect tactical innovations that differentiate the FC's take on the game, leads to rapid appropriation by other FCs (Trequattrini, Giudice, Cuozzo & Palmaccio, 2016).

Regarding the key assumptions that support this theory, although FCs share the ultimate goal of winning, they possess heterogeneous resources for gameplay, as in players and coaches, agents that cooperate to express a team's singularity (Duarte et al., 2013). Furthermore, these agents, protected by contracts (Grass et al., 2001), cannot be easily transferred between FCs, thus challenging the mobility of resources (Porter, 1981). Reinforcing the idea of imperfect resource mobility, some firm-specific agents may be unable to maintain a high level of performance under a different tactical or environmental context (different team, different country), thus losing part of its value (Glazier, 2015; Trequattrini et al., 2016).

The challenges faced in connecting the theory with the football industry led this thesis to address the RBT instead, as it discusses the idiosyncratic competencies of a firm as potential generators of competitive advantage (Amis et al., 1997). Similarly, FCs are looking at internally generated data to adapt and optimize the training sessions in an attempt to fulfill the true potential of the players (Castellano, Alvarez-Pastor & Bradley, 2014; Owen, Djaoui, Malone & Mendes, 2017). With that goal in mind, FCs expect that distinctive competencies in mobilizing specialized resources, in the secrecy of football training sessions, can determine an advantage over the adversaries (Lado et al., 1992; Rein & Memmert, 2016).

Considering the heterogeneity of resources across FCs, the ability to better estimate the current and future value of the resources and capabilities allows the creation of unique strategies that create a potential edge in the path towards competitive advantage (Barney, 1986; Lado et al., 1992). For that, detailed monitorization of training and competitive behavior of the team can provide FCs the opportunity to extract value from its assets to achieve marginal gains that coupled together, can make the difference in a predominantly low-scoring sport (Appendix 3) (Hughes & Bartlett, 2002; Nevill, Atkinson & Hughes, 2008).

2.2 Big Data

Despite not having a universally accepted definition, Big Data is characterized by 1)Volume, for the sheer size of the data, 2)Variety, regarding the heterogeneity of the data collected and 3)Velocity, concerning the speed at which information is gathered (Chen & Lin, 2014).

Whilst Data Scientists have spent the past few years developing efforts to learn the most efficient and accurate ways to gather it (Castellano et al., 2014), the current challenge is to find the best way to turn the overwhelming flow of information into crunched, real-time, actionable input that is relevant to provide an advantage in the game (Dutt-mazumder, Button, Robins, & Bartlett, 2011; Leser, Baca & Orgis, 2011; Rein & Memmert, 2016).

2.2.1 From notational analysis to Big Data

Traditional notational analysis aimed to provide a statistical description of what happened during one event or a series of events (James, 2006). Over time, it evolved to become the norm in assessing tactical behaviour and player performance through match-play observation (Dutt-Mazumder et al., 2011). Nevertheless, increased robustness in the analysis of the game resulted that observational methods, although considered the best available alternative, became time-consuming (Carling et al., 2008). On top of this, tactical analysis from observational methods relied on average statistics which still discarded most of the contextual information, limiting its explanatory power (James, 2006; Carling et al., 2008; Glazier, 2015).

Facing constraints in the analysis of individual and collective tactics, FCs have turned to novel methods of gathering training and gameplay data to level up their performance (Leser et al., 2011; Rein & Memmert, 2016). High-precision microwave technology that enabled computer systems to simultaneously track the position of the players and the ball throughout the game, led to the development of advanced tracking tools (Beetz et al., 2005; Leser et al., 2011). As a result, FCs recognized the performance-enhancing potential of technology so that it has become common practice to monitor tactical and physiological aspects of the team (Gonçalves, Figueira, Maçãs & Sampaio, 2013; Bush, Barnes, Archer, Hogg & Bradley, 2015; Ehrmann, Duncan, Sindhusake, Franzsen & Greene, 2016). Tactically, the ability to monitor actions in space and time led to the development of spatio-temporal tools that can perform an analysis of football performance, for example, passing analysis or clustering player movements, (Gudmundsson & Wolle, 2013). Furthermore, the use of GPS surfaced as the go-to technology that allowed for control in ensuring optimal workloads that maximize physical performance whilst reducing the occurrence of injury or illness (Leser et al., 2011; Owen et al., 2017). With access to detailed information, coaches can adjust the training methods to the team's daily needs whilst leveraging visual, quantitative information to share and debate with their coaching staff or players (Buchheit, 2014; Rein & Memmert, 2016).

To better understand the link between gameplay and Big Data, technology like the high-definition cameras that are scattered around the fields, can track any object from the game 10-25 times per second, amounting to 135.000 data points in a typical soccer game (Grunz, Memmert, & Perl, 2012; Gudmundsson & Wolle, 2013). Unaided by digital and specialized human resources, it becomes very difficult for FCs to structure and extract value from the data (Gudmundsson & Wolle, 2013; Rein & Memmert, 2016). This suggests that clubs are paving a way in which they will become more dependent on a multi-disciplinary approach, with the likes of sport scientists and performance analysts gaining relevance in the decisions made by the head coach regarding the preparation of the team (Glazier, 2015; Carpita, Sandri, Simonetto & Zuccolotto, 2016; Rein & Memmert, 2016).

2.2.2 The rise of Big Data in FCs

Sports science has reinforced the impact of performance analysis by reaching a general agreement that the most effective method for preparing athletes for the competition is the one that replicates the competitive performance conditions more accurately (Di Salvo et al., 2007; Carling et al., 2008).

Consequently, the analysis of performance during training and competition has become the norm amongst professional FCs, elevating the relevance of data collection (Carling et al., 2008; Buchheit, 2014; Ehrmann et al., 2016). Supporting the shift to a technology-backed methodology in preparation for the game, four aspects arise.

Firstly, technological evolution of computer-aided tracking technology, in the form of downsized radio-wave sensors, GPS and high-resolution cameras, allowed access to a stream of precise information on the performance of the players (Buchheit, 2014; Cintia et al., 2015). Consequently, analysts can now, more than ever, perform valid, robust statistical descriptions of what happened during one event or a series of events (James, 2006; Castellano et al., 2014). For instance, data records from a single season of the Bundesliga (Germany's top division) can amount to 400 gigabytes of player tracking data alone (Rein & Memmert, 2016). In short, Video and Computer Science advancements made possible not only gathering a plethora of data-points with little effort but also extracting value from it by shaping the training protocol (Carling et al., 2008; Grunz et al., 2012; Castellano et al., 2014).

Additionally, advancements in technology uncovered and reinforced the usefulness of training and match-play analysis, opening doors for biomechanical studies and sport medicine investigations (Di Salvo et al., 2007; Carling et al., 2008).

The second aspect that arose, biomechanical studies, benefited from enhanced tracking systems to comprise the analysis of motion characteristics according to the different roles within a team's organization (Di Salvo et al., 2007; Carling et al., 2008). Based on those, the coaching staff of FCs started manipulating the time, space and number of athletes in an exercise, to comply with the different performance profiles among roles on the field (Carling et al., 2008; Gonçalves et al., 2013; Bush et al., 2015).

Thirdly, sport medicine investigations on heart rate monitorization, hormone level variations or the impact of injuries in the performance of teams were made possible (Buchheit, 2014; Ehrmann et al., 2016; Jaspers et al., 2016). Findings from those studies permitted the evolution of practice sessions, bringing them closer to recreating multidirectional physical requirements that are integrated with a variety of technical skills in the game (Bush et al., 2015; Owen et al., 2017). Such studies have experienced growing acceptance in the sports environment due to the accuracy of the data gathered and the potential to enhance the performance of the clubs that seek a competitive advantage (Carling et al., 2008).

Finally, the fourth aspect tying it all together, the release of FIFA's legislation allowing the use of wireless tracking devices in competition reinforces the contemporality of data collection for analysis and performance maximization (Buchheit, 2014; Rein & Memmert, 2016).

2.3 Injuries in football

In football, an athlete's aptitude to play is determined by the combination of four drivers, technical ability, tactical knowledge, psychological condition and physical availability, in no order of importance (Carling et al., 2008; Bush et al., 2015; Glazier, 2015). This thesis revolves around the impact of Big Data on the latter to provide FCs with a competitive advantage. In fact, physical limitations, in other words, injuries, represent the main cause for player absence from training or a competitive match (Hägglund et al., 2013; UEFA, 2016).

Player absence due to injury is usually determined by one of two, traumatic injuries, any from concussion to broken bones, or noncontact injuries, for example, muscle/tendon sprains (Hägglund et al., 2013; Ehrmann et al., 2016). Traumatic injuries result from physical contact that cannot be avoided or anticipated, leaving little space for improvement in the prevention of such misfortune (Anthony, 2017). On the other hand, noncontact injuries may occur due to accumulated fatigue or unpreparedness to cope with the explosive accelerations and decelerations, as well as changes of direction that are required in a high-intensity context like the game (Nevill et al., 2008; Bush et al., 2015; Owen et al., 2017). While the definition of high-intensity activity can vary dependent on the study in question, we will take it as any activity in which athletes perform efforts between 85% to 89% of their maximal Heart Rate (HR) or cover distances at more than 19.8 km/h (Bush et al., 2015; Jaspers, Brink, Probst, Frencken & Helsen, 2016).

Particularly, muscle injuries (noncontact) can amount to nearly one-third of all injuries that required recovery time in professional FCs (Jaspers et al., 2016). When the scope of analysis broadens to encompass all noncontact injuries reported by the elite FCs present in the UEFA Champions League for the season 2016/2017, they represent 69.9% (518) of all the injuries (UEFA, 2017).

Since noncontact injuries result mostly from a build-up of physical stress over a muscle, tendon or ligament, there is a window of opportunity to predict and prevent its occurrence through monitorization, thus diminishing the injury burden and incidence in FCs (Hägglund et al., 2013; Gabbett, 2015; Ehrmann et al., 2016). Specifically, injury burden represents the number of injury days lost per 1000h of practice, factoring the number of injuries incurred with the average absence of the athletes. Also, the rate of injury incidence is explained by the number of injuries sustained per 1000h of activity (Hägglund et al., 2013; UEFA, 2016).

As lower injury incidence and a higher player's match availability were related to better national league position and international cup performance, the effort to reduce these figures became more relevant (Hägglund et al., 2013).

By neglecting the prevention of noncontact injuries, FCs are subject to being deprived of its athletes for longer periods of time, when compared with traumatic injuries (Hägglund et al., 2013). Considering the association between injuries and performance, the importance of continuous improvements in medical services and training monitorization is reinforced to better manage a player's condition throughout the season (Hägglund et al., 2013; Owen et al., 2017).

2.3.1 Importance of monitorization

For a long time, the coaching staff relied solely on a player's external indicators of effort such as heavy breathing or resting with the hands above the knees, to grasp the intensity of an exercise, or overall session, making for a subjective analysis at best (Leser et al., 2011). The development of tracking technology, along with FIFA's regulation that embraced the integration of tracking devices during competition, impacted the approach of FCs to player monitorization (Castellano et al., 2014; Rein & Memmert, 2016).

That impact influenced FCs to use varied methodologies to assess a player's readiness to train or play, with the most common being the use of individualized questionnaires, hormonal markers, HR variability or sleep control (Ehrmann et al., 2016; Buchheit, 2014). Nonetheless, FCs have turned to GPS technology to control the players' effort during their activity (Ehrmann et al., 2016; Jaspers, et al., 2016; Owen et al., 2017).

With the acknowledgment of GPS's reliability in tracking the workload of team sports, professional FCs have integrated it in training, with both players and coaching staff fully aware of its presence and goal behind it (Buchheit, 2014; Cintia et al., 2015; Ehrmann et al., 2016). The assessment of the workload performed by athletes is therefore paramount in ensuring the optimal training load that will maximize physical conditions whilst minimizing the occurrence of noncontact injury (Jaspers, et al., 2016; Owen et al., 2017).

Increasingly dense competitive calendars, with players subject to club and national team competitions, pose a threat to an athlete's fitness (UEFA, 2016). Since accumulated fatigue can impact the risk of sustaining an injury, the need for monitorization increases along the modern exigencies of the game (Nevill et al., 2008; Bush et al., 2015; Ehrmann et al., 2016).

Ultimately, the monitorization becomes paramount for an individualized evaluation of the response to training, fatigue levels and/or recovery status of a player, in the pursuit of maximized availability of the FCs' most valuable resources, the players (Buchheit, 2014; Jaspers et al., 2016).

2.4. Data-driven decisions on the field

In a game where each player averages 98.9% of the time performing off-the-ball duties (defending or moving to be a valid passing option, among others), positioning and decision-making arose as the two variables that best predicted future performance for individual players (Di Salvo et al., 2007; Carling et al., 2008; Kannekens et al., 2010; Gonçalves et al., 2013).

Moreover, facing an increasingly faster game, the player's decisions ought to be anticipatory, thus reducing the time taken to identify a problem and deploy the technical skills to overcome it (Araujo, D., & Hristovski, R., 2006; Bush, M. et al 2015). This connection is intimately related to the athlete's perceptive skills and procedural knowledge, in other words, knowing how to proceed in a match situation, characteristics that expert players have been found to score highly in, especially those playing in midfield positions (Kannekens, R., Elferink-Gemser, M., & Visscher, C., 2010; Sampaio, J., & Maçãs, V., 2012).

In professional football, the coaching staff can help improve the decision-making speed by narrowing the variability of actions to achieve a goal (Araujo & Hristovski, 2006). As it can be done by showcasing practical examples from relevant sources of information, FCs are turning to data analytics and technologically advanced methods to improve the player's speed of action (McKenna, 2017).

Ultimately, Big Data has the potential to improve the efficiency of a player's decision-making by providing detailed feedback either on the athlete's performance or about the opponent's patterns, creating a symbiosis between the perception of key information sources and the external environment faced in competition that will aid the player in having a clearer idea of what to do on the field (Nevill et al., 2008; Araujo & Hristovski, 2006).

3

Methodology

As seen in the introductory chapter of this thesis, the problem statement revolved around the impact of Big Data on FCs, through injury prevention and player decision-making enhancement to boost sporting performance. Taking that into consideration, two research methods, quantitative and qualitative, were analyzed to point out the most suitable approach to delve into the subject under scrutiny.

Although Big Data is used to retrieve quantitative results on performance, the aim of this study was to assess the applications of those data points as a structured tool to generate a competitive advantage. Thus, the emphasis lied on the quality and feasibility of the process that is and will be applied by FCs to differentiate from the competitors (Denzin, K., & Lincoln, S., 1994).

In addition, the use of secondary data unveiled different perspectives on the following subjects that were of interest to the study:

- Competitive Advantage
- Big Data
- Injury in football
- Athlete's decision-making

Most of the relevant concepts for the work, apart from Competitive Advantage, have only been addressed in further detail in recent years. In fact, many of the findings from research on the link between technology and sports performance are a consequence of evolving tracking devices (Castellano, J., Alvarez-Pastor, D., & Bradley, P., 2014; Dutt-Mazumder, A., 2011; Cintia, P., et al, 2015). Taking that into consideration, the inductive approach allowed for flexibility in the data collected, as well as further interpretation of the information gathered from articles, reports and journals.

The inductive process derived from the analysis of sport science studies that provided empirical evidence on matters like injury, physiological performance or decision-making speed and ability. That quantification was used to reinforce the interpretation of the concepts explored in different, secondary data sources. Thus, the conclusions in this thesis result from the link between empirical evidence and theoretical analysis, connecting the relevant concepts that justify the impact of Big Data in FCs.

Altogether, the choice to proceed with this method provided a more robust answer to the research questions which could not be reduced to meaningful models with quantifiable variables.

4

Discussion

4.1 The need for Big Data in injury prevention

For many years, coaches made decisions disregarding the unobservable metrics of physiological performance, trusting only their intuition, recollection of events and observation of external signs of fatigue, apparent when a player rests with the hands on the knees or breathes heavily (James, 2006). However, the context has evolved to a point where elite FCs are equipped with reliable technology that can control, in detail, the exertion of effort from the players.

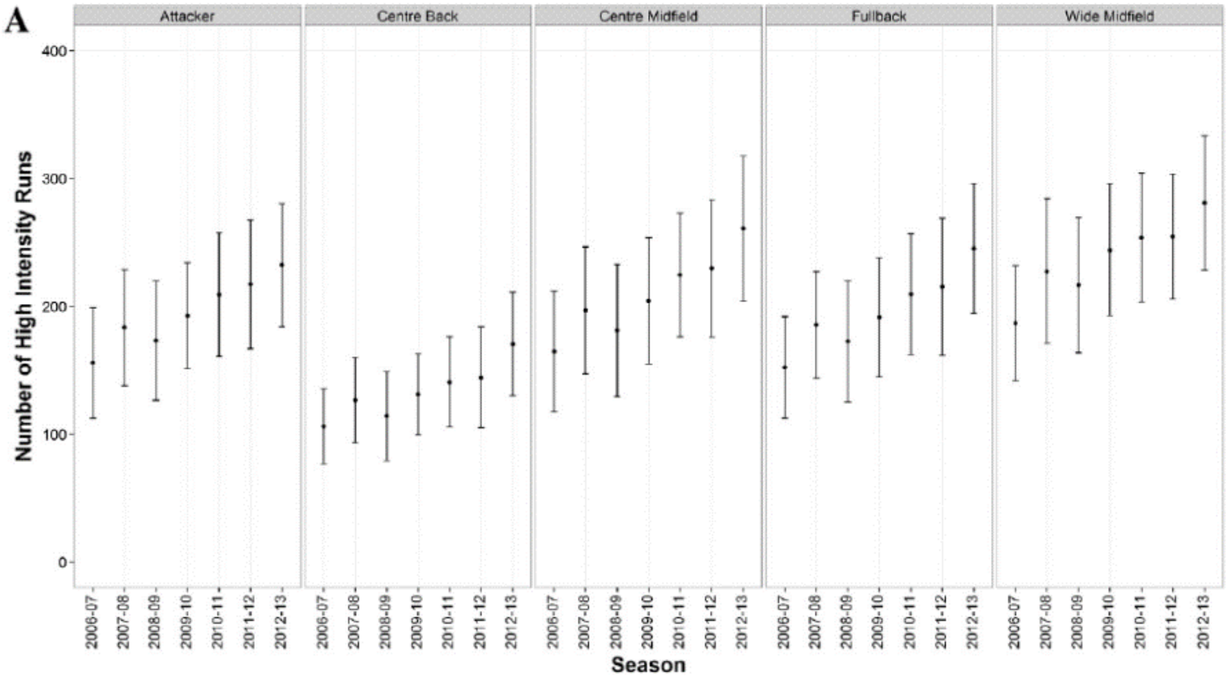
This evolution allows FCs to better prepare for the physiological demands of increased match and training density, which divided between FCs and National Team appearances, results in a strenuous effort for the players over the season.

In a 5-year analysis of elite European FCs, the number of yearly training sessions went from averaging 199 in the season 2012/2013, to 232 training sessions in 2016/2017. Similarly, whilst in 2012/2013 the FCs performed an average of 57 competitive matches, that number climbed to 60 competitive matches in 2016/2017 (UEFA, 2017).

In fact, not only has the match and training density increased, but also have the intensity levels of effort during competition. Despite the aerobic nature of football, in which a mere ~7-12% of the distance covered by players is performed in high-intensity efforts (19.8-25.1km/h) and 1-4% sprinting (>25.1 km/h), the frequency of intermittent efforts in the running categories of high-intensity running and sprinting has increased across every playing position, as seen in Figure 1 and 2 (Bush et al., 2015).

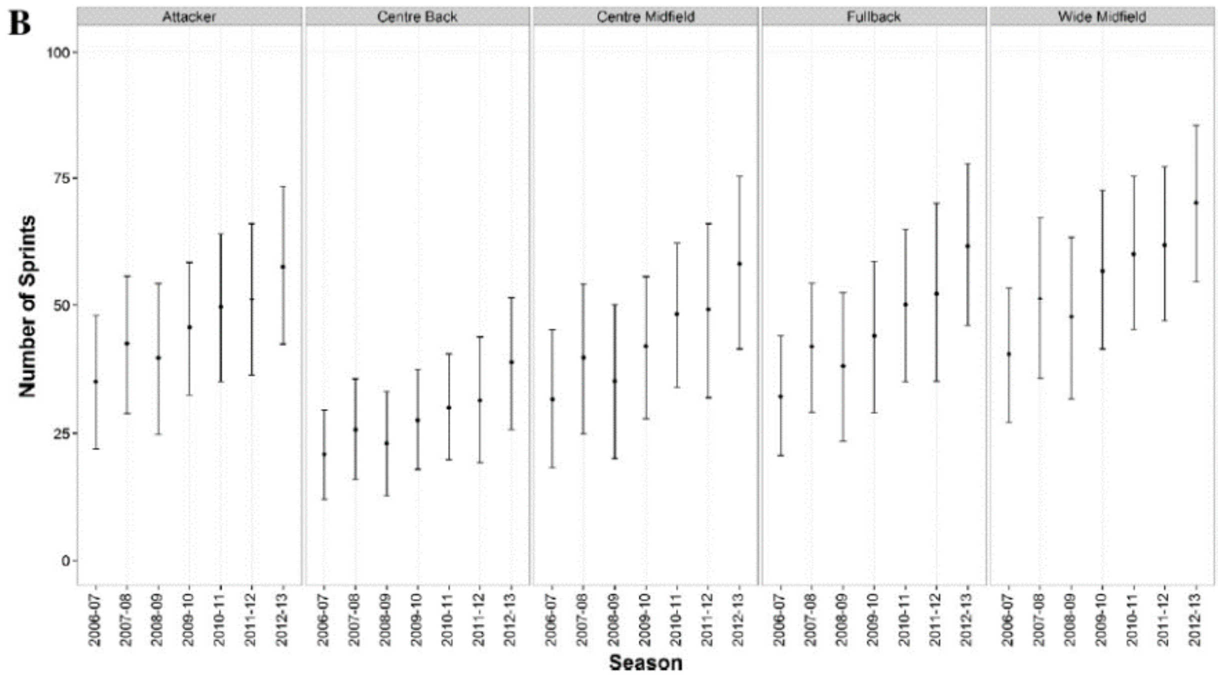
This represents a higher number of sporadic accelerations and decelerations, which coupled with changes of direction contribute for increased energy expenditure (Bush et al., 2015; Carling et al., 2008). As an example, the evolution of match performance indicators in the English Premier League over the years, show that over a span of 6 seasons, between the season 2007/2008 and 2012/2013, the average number of high-intensity running by attacking players increased from an average of 150 to over 200 high-intensity runs per season (Bush et al., 2015). As for sprints by attacking players, there was an increase from an average of around 30, to over 50 sprints per season (Bush et al., 2015). In addition, all other positions revealed a similar growth trend.

Figure 1
Number of high intensity runs per playing position between 2006 and 2013



Source: Bush et al. (2015)

Figure 2
Number of sprints per playing position between 2006 and 2013



Source: Bush et al. (2015)

Although successful teams were found capable of performing high-intensity efforts more frequently than less successful teams (Carling et al., 2008), high, uncontrolled efforts were also linked with higher injury rate, particularly concerning strains, a noncontact, preventable injury (Nevill et al., 2008; Gabbett, 2015; Bush et al., 2015).

As the exertion of effort became quantifiable and accessible to FCs, its analysis confirmed that players have different physiological needs according to positional and tactical context (Carling et al., 2008, Castellano et al., 2014, Bush et al., 2015). These differences are corroborated by the differences in values of maximal oxygen uptake (i.e. VO2max) or distance covered for specific playing positions, suggesting that personalized training can optimize the player's preparation for the competitive moment (Di Salvo et al., 2007; Gonçalves et al., 2013; Bush et al., 2015).

On top of it, player fatigue is the physiological constraint that most affects performance (Glazier, 2015). For example, players can perform 35-45% fewer high-intensity runs in the last 15 minutes of play. Alternatively, substitute players were found to cover greater distances in the same time frame, indicating that depleted energy levels will influence the ability of the team to perform the high-intensity efforts that inch the teams closer to success (Carling et al., 2008; Leser et al., 2011). Tying it with the increased density of training and games, residual fatigue can play an important role in the appearance of injuries (Carling et al., 2008), particularly if the recovery time between competitive matches is less than 4 days (Ehrmann et al., 2016).

Ultimately, considering that the most reliable and acclaimed method of training manipulates the energy use through the variation of space, number of athletes and duration of the exercises, controlling the training loads becomes paramount to match the levels of the competitive environment whilst preventing the occurrence of fatigue-related injuries (Di Salvo et al., 2007; Carling et al., 2008).

4.1.1 Big Data improving injury prevention through personalized control

The possibility to analyze the data regarding a player's physiological performance provides an information platform for the coaches to carry out well-structured decisions that optimize the conditioning elements of training and match-play (Carling et al., 2008).

The quantification of pre-established parameters using a combination of video and tracking technology can grant an individualized perception of a player's physiological condition. Thus, it leads to better preparation and management of both training sessions and competitive matches as it provides insight on a player's response to effort and cumulative fatigue (Jaspers et al., 2016). In addition, it permits the creation of a training protocol that respects the physiological differences across playing position, making for a closer representation of the energy expenditure in a match.

For example, the application of Heart Rate (HR) measurement during activity, allows to understand the level of commitment of a player, working as an internal training load indicator that measures the impact of the training load on the athlete's body (Gabbett, 2015). In addition, monitoring the HR shows how players adapt to different phases of the training sessions or matches (Buccheit, 2014). Based on those data points, managers can make informed decisions on the adjustments that need to be made by changing drill or manipulating it to achieve the intended physiological response (Buccheit, 2014). In case a drill has the purpose of having the athletes not exceed an HR of 140bpm, but the data shows that some players are regularly at 160bpm, it gives the coaching staff the opportunity to adapt the exercise or advise the players to adjust their performance avoiding higher workloads that can lead to overtraining, increasing the likelihood of injury.

Even though the HR metric alone does not provide an overview of a player's wellness, it is vital when integrated with other metrics to evaluate the player's response to training (Buccheit, 2014).

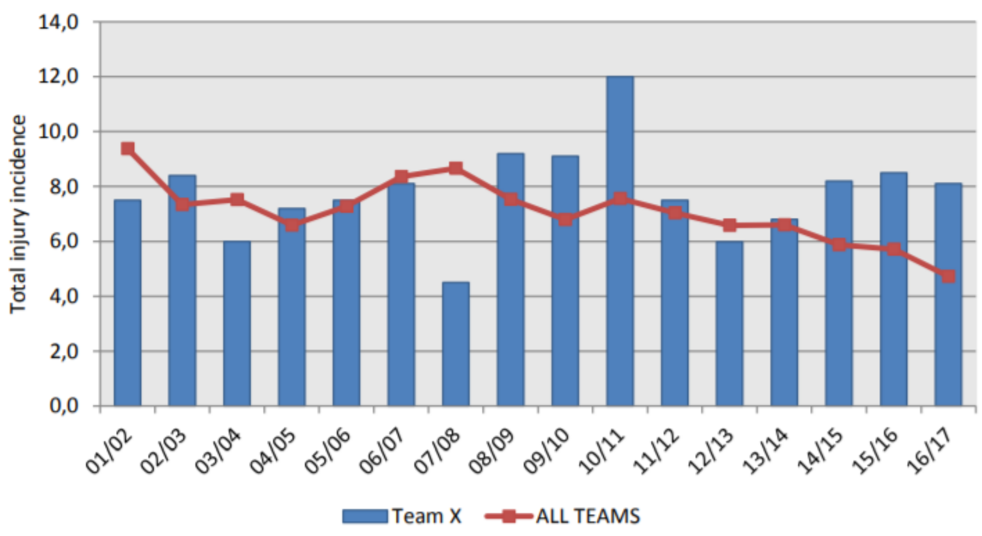
That takes us to recognize the importance of the GPS in the external training load (total distance covered, intensity of sprints, to name a couple) monitorization and prevention of injuries (Gabbett, 2015). Whilst analyzing the distance covered per se may not be very insightful, the ability to examine it together with the different movement intensities will provide an objective picture of performance during the drills or match-play (Di Salvo et al., 2007). On that note, monitoring the players' average meters covered per minute can help prevent noncontact injuries as it has been proven that player's present higher values in this variable right before an injury (Ehrmann et al., 2016). This suggests that prolonged time at high intensity increases the injury risk. Also, sudden increases in the body load sustained by a player are related to the appearance of injuries (Ehrmann et al., 2016; Gabbett, 2015). In that case, a player that may have been holding back in training is likely to be unprepared to cope with the intermittent efforts of the match that are so demanding on muscles, tendons and ligaments, the body parts most affected in noncontact injuries (UEFA, 2017). Therefore, with the help of GPS technology, injury can be prevented by adjusting the training protocol or leaving the athlete out of competition until the physiological standards are met.

Altogether, the ability to control and adapt the training protocol to respect the levels of optimal workload of each player can reduce the likelihood of suffering noncontact injuries in the team. Knowing that noncontact injuries are responsible for high injury burden (Hägglund et al., 2013), its prevention may result in having more player availability throughout the competition.

4.1.2 A 16-year analysis of injury for elite European football clubs

An analysis of the 16 seasons comprehended between 2001 and 2017, comprising data from a total of over 50 elite FCs that participated in the UEFA Champions League across that period, showcases a declining tendency regarding the total injury incidence across clubs. Despite registering occasional spikes, Figure 3 demonstrates that the total average injury incidence rate dropped from almost 10 injuries sustained per 1000h of sport practice in the season 2000/2001, to an average rate of fewer than 5 injuries in the season 2016/2017. These values follow a continuous decrease in the average injury incidence rate since 2010/2011, to register the lowest value of the last 16 years.

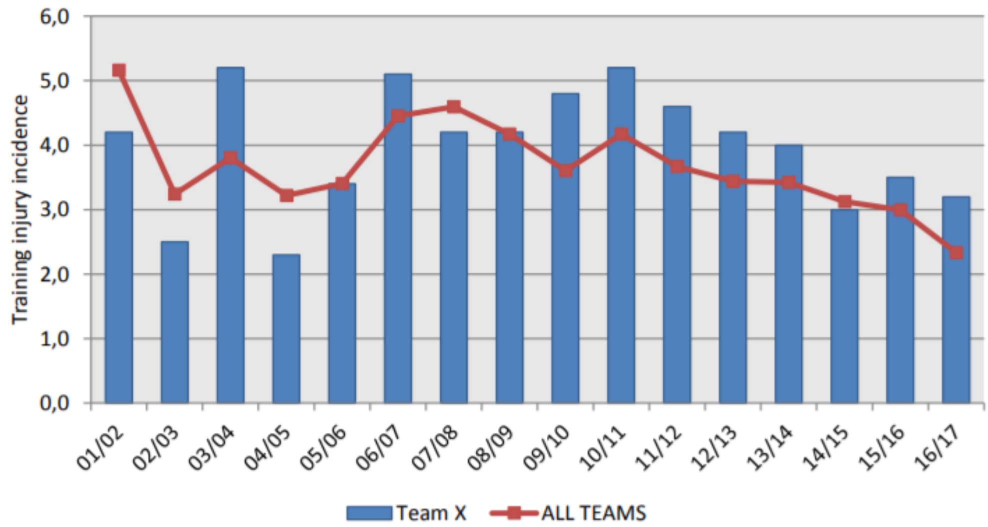
Figure 3
Total injury incidence rate



Source: UEFA (2017)

Following this trend, in Figure 4, the average training injury incidence rate, in other words, the average number of injuries that occur, for every 1000h of training, recorded the lowest value of this 16 year-period, dropping from a rate of over 5 training injuries per 1000h in 2001/2002, to an average value below 3 injuries, continuing a declining trend that has prevailed since 2010/2011.

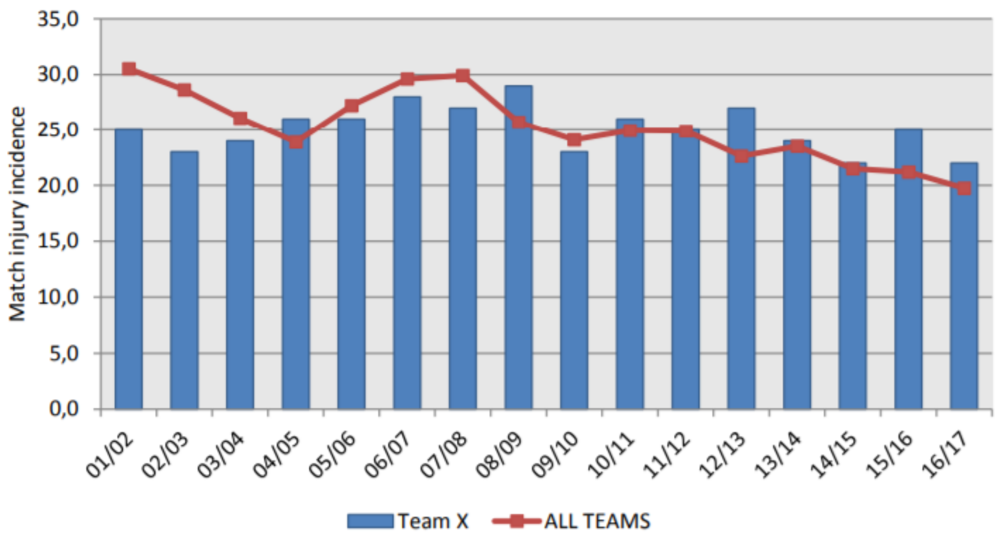
Figure 4
Training injury incidence rate



Source: UEFA (2017)

On a similar note, as can be seen in Figure 5, the average match injury rate registered a 16 year-low in 2016/2017, dropping below the 20 injuries per 1000h of activity, for the first time in the analyzed period.

Figure 5
Match injury incidence rate

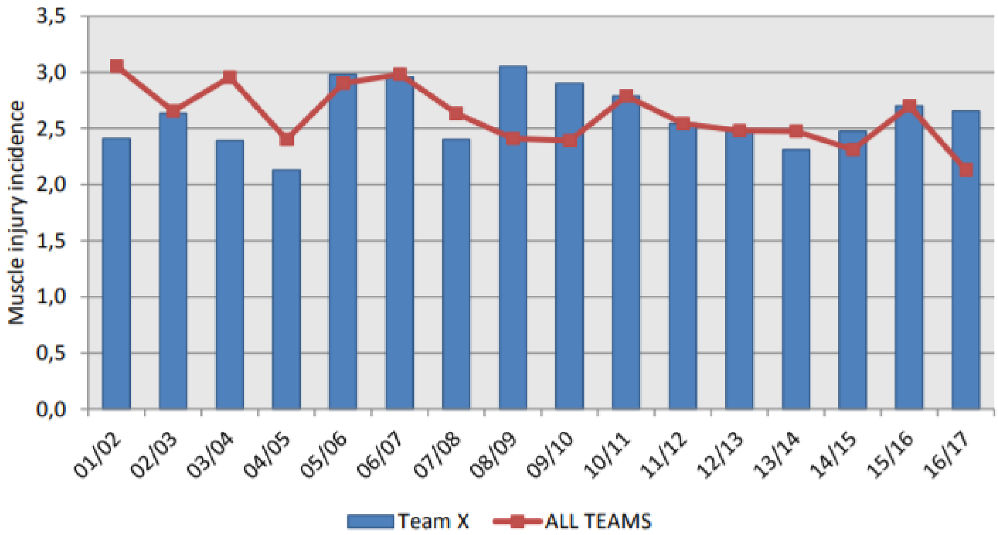


Source: UEFA (2017)

When analyzing muscle and ligament injuries, two body components that are commonly affected by non-contact injuries (Hägglund et al., 2013), a similar tendency was found.

In Figure 6, muscle injury incidence dropped from averaging an injury rate of 3 injuries to a rate of nearly 2 injuries. Although the injury rate in the season 2015/2016 increased in relation to the preceding season for the first time since 2010/2011, the overall declining tendency achieved a 16 year-low in 2016/2017.

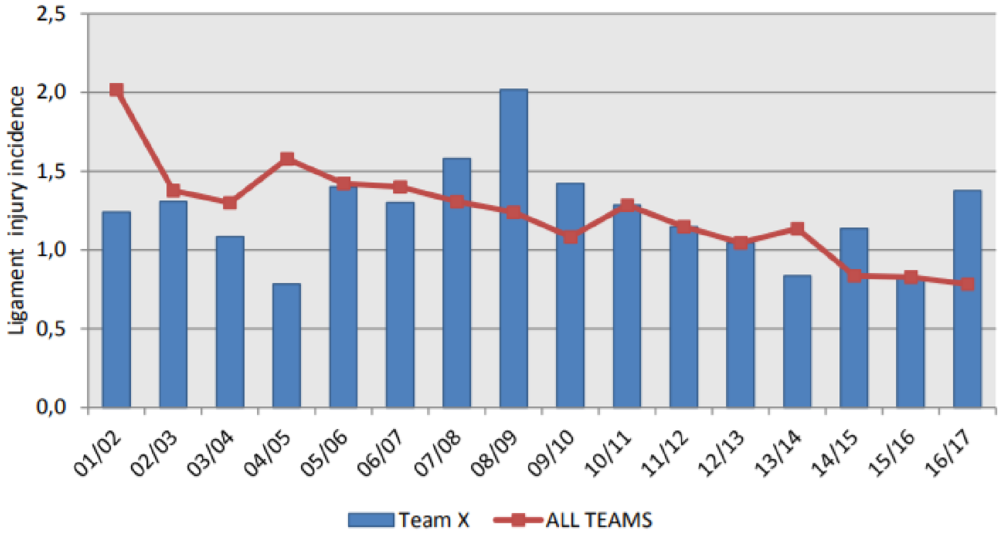
Figure 6
Muscle injury incidence



Source: UEFA (2017)

As for the ligament injuries, in Figure 7, 2016/2017 registered the lowest injury rate since 2001/2002, the first year of the analysis. The average ligament injury incidence across the FCs dropped from 2 injuries to less than 1 injury sustained per 1000h of practice over the period of 16 years.

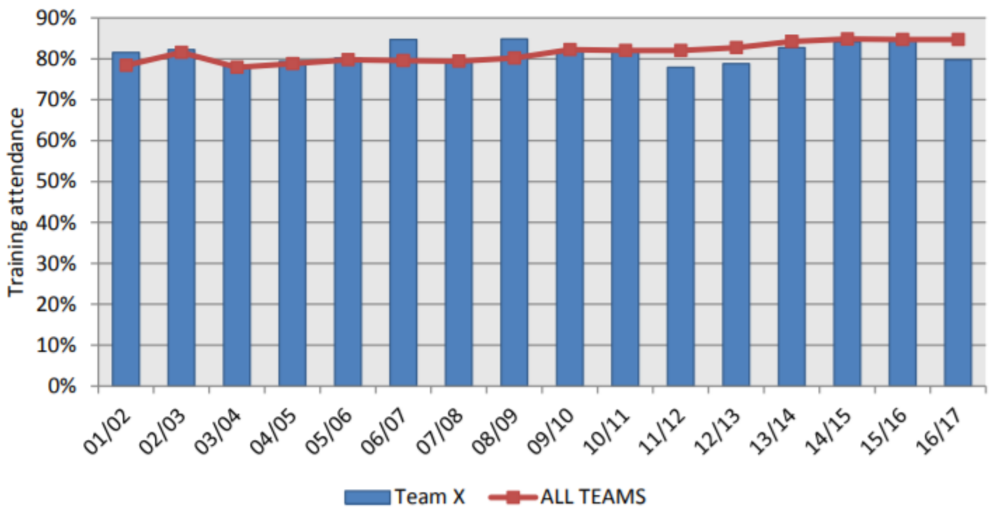
Figure 7
Ligament injury incidence



Source: UEFA (2017)

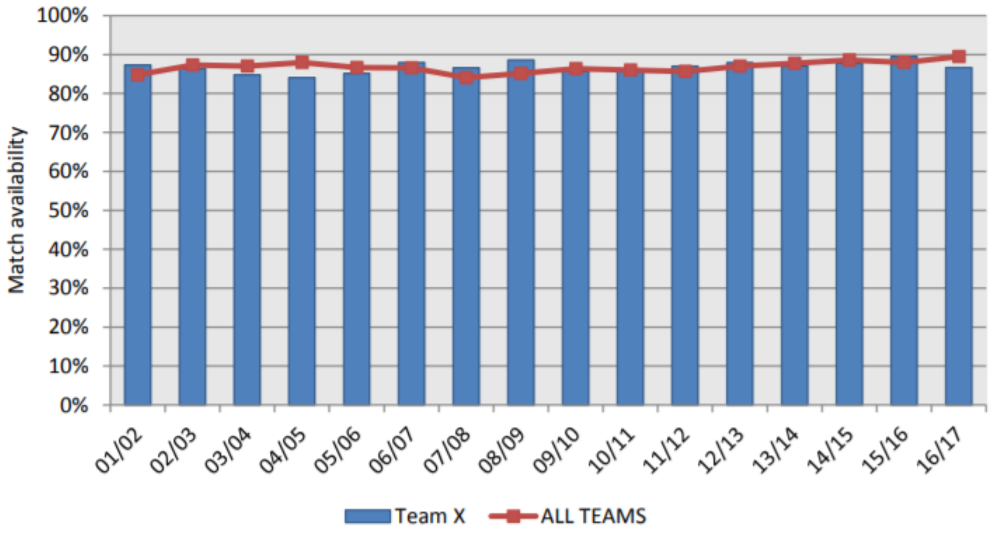
As a consequence of the declining injury incidence tendency, higher training and match availability are observed in Figure 8 and 9, with squad training availability, the percentage of players in the team that are available to perform, averaging a 16-year high, well above the 80% availability. As for match availability, FCs are finally very close to achieving a squad availability of 90% for the first time.

Figure 8
Squad training availability



Source: UEFA (2017)

Figure 9
Squad match availability



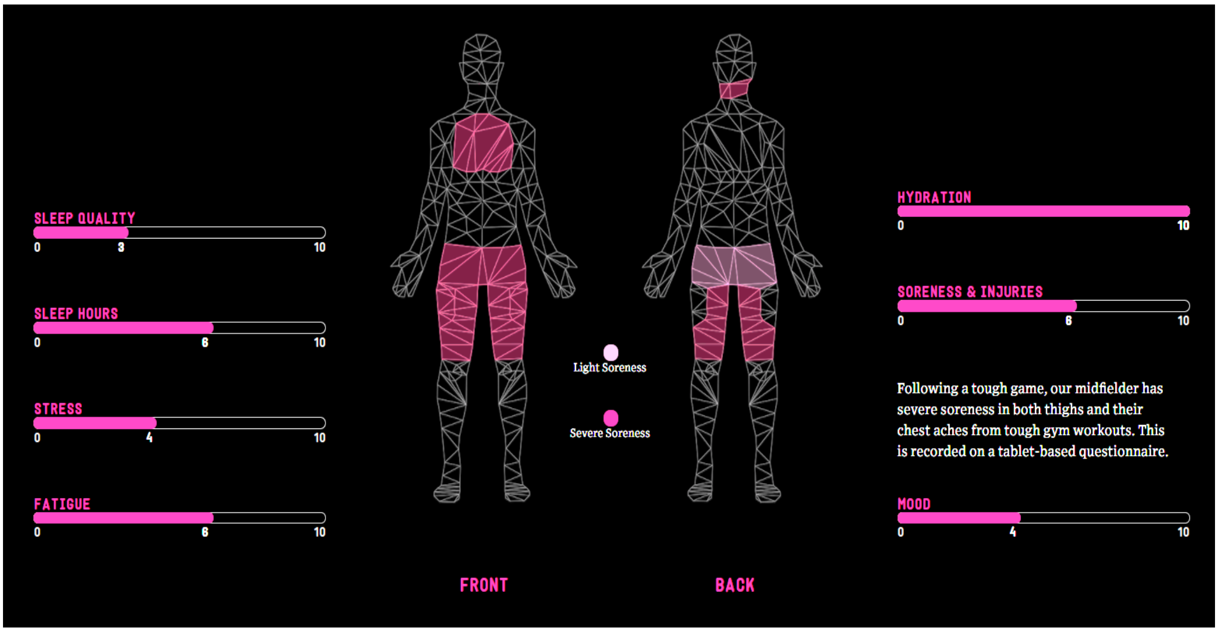
Source: UEFA (2017)

Whilst the overall decline in the number of injuries is not justified, there is reason to believe that the evolution of the tracking technologies, that allowed for diverse breakthroughs in sports science, influenced this tendency. With enhanced training methodologies based on specialized knowledge and the ability to control and adapt the training loads according to specific needs, FCs have been able to perform higher intensity displays whilst reducing the occurrence of injuries, thus optimizing the player availability. These tendencies also set the ground for corroborating the usefulness of Big Data applications in injury prevention.

4.1.3 The case of SL Benfica

Whilst very little can be done to prevent injuries that result from contact, in other words, traumatic injuries (Anthony, 2017), with the help of Big Data, the coaching staff can predict and prevent the appearance of non-traumatic soft-tissue injuries, specifically muscle and ligament injuries. Taking the special example of SL Benfica, the club, within its science department, BenficaLAB, is striving to create an accurate, predictive injury-model that can assist the coaching staff in analyzing the physical strain on athletes. The goal is to understand how far a player can be pushed before an injury is sustained and identify the kind of injury at risk, along with its recovery time. Big Data plays a big role in this strategy since Benfica has been tracking players for over 10 years for stress and fatigue over training and competitive matches.

Figure 10
Player profile with use of Big Data



Source: Anthony (2017)

Moving forward, with the aid of Microsoft's Azure Machine Learning, SL Benfica is turning to new tools that can create and validate their injury models, that have been tested over the years in the search for the best Key Performance Indicators (KPIs) and measurements to help correlate the data gathered from their athletes.

4.2 Big Data and player's decision-making

In a game of football, players need to adapt to an ever-changing context, having to make decisions based on the location of the ball on the field, position of the colleagues, adversaries and distance to both goals. This variability allows for each player to interpret different game situations according to his/her own experience and preparation for that moment, enhancing the role of the player's decision-making. Additionally, the decision-making ability is relevant for both on-the-ball and off-the-ball moments, as the objective of the game is to score goals and avoid conceding.

Emphasizing the importance of effective decision-making, tactical skill has been indicated as a precondition for expert players in football. Specifically, it refers to the ability to correctly decide which action to perform in any given moment of the game, having surpassed the influence of the player's physical characteristics as performance differentiator (Kannekens et al., 2010).

As important as deciding correctly, the speed of the decision-making process should be at par with the increased speed of the modern game (Kannekens et al., 2010; Bush et al., 2015). The analysis of the differences between the 1966 World Cup and the 2014 World Cup reported that players in 2014 were 35% better at targeted passes and quickness, in comparison with players in the 1966 World Cup. Moreover, a player's ball-contact time in the German National side saw a decrease from 2.9 seconds in the 2006 World Cup, to 0.9 seconds in the 2014 World Cup (McKenna, 2017). Consolidating the idea of an increasingly faster game, high-intensity running increased in the English Premier League, for the period between 2006 and 2013, as seen in Figure 1, which coupled with higher work rates from the players, enhances the importance of allying speed to the procedural knowledge of the athletes (Carling et al., 2008; Bush et al., 2015).

A player will, therefore, have an advantage provided he is able to ally speed to his procedural knowledge. The speed of action does not mean that the player needs to run faster than the opponents. Instead, it means that deciding faster will increase the probability of being well positioned or perform better passes, thus conditioning the adversary's game.

To achieve that, considering the complexity of the sport, it is important that the coaching staff can reduce the game's unpredictability for the players, providing clearer expectations of the situations that they will be confronted with, making for a clearer decision-making process (Di Salvo et al., 2007). Moreover, exposure to structured environments in training will create patterns of behavior that also increase the speed and quality of the decision-making process (Araujo & Hristovski, 2006).

While doing so, FCs can turn to Big Data to potentially enhance a player's decision-making ability.

4.2.1 Clustering movements

To better prepare players for the competitive moment, specific knowledge of both the opponents and the team's tactical patterns is important. Knowing beforehand the most common actions performed by the adversary will not only help the coaching staff in the preparation of the game but also help structure the player's response to the external environment based on key information sources (Araujo & Hristovski, 2006).

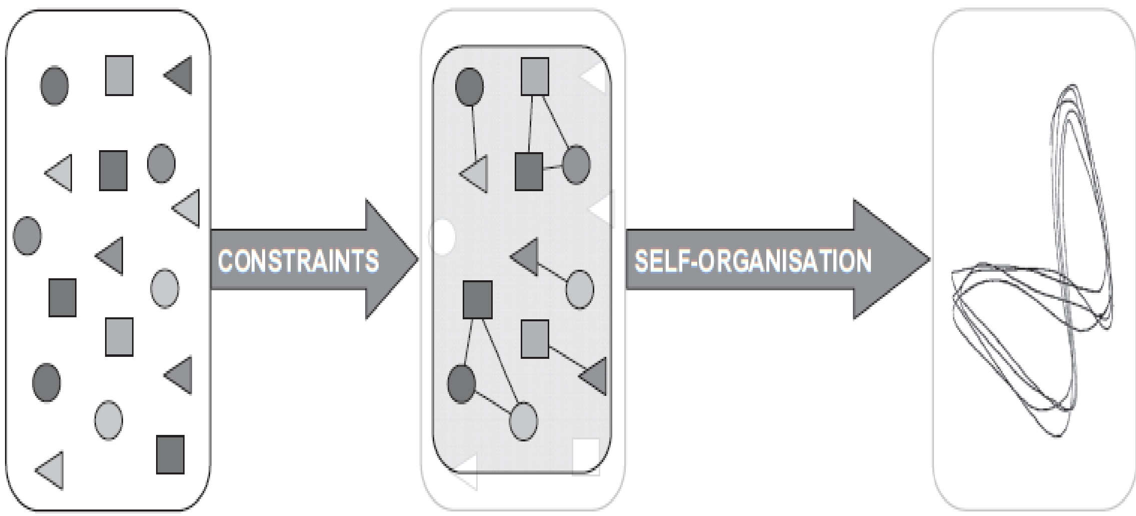
The impact of Data on technical-tactical analysis regards, among others, the benefit of identifying opponent's patterns in different phases of the game. For example, using spatio-temporal tools to cluster the movements that characterize the collective pressing made by the opposing team (Appendix 4), will uncover their pressing strategy (Leser et al., 2011; Gudmundsson & Wolle, 2013). With this information, the athletes are given more specific and reliable directions on how to overcome the opponent's pressing since it allows to identify the pockets of space available to play in, according to the opponent's formation.

As seen before, narrowing the variability of action by identifying movement patterns can enhance a player's decision-making ability (Araujo & Hristovski, 2006), inching the FC closer to gaining a competitive edge.

4.2.2 Improving feedback for better decision-making

Feedback from the coaching staff to the players is one of the most important performance improvement processes in training (Nevill et al., 2008, Hodges & Franks, 2002). Used during training drills, it is based on task-related constraints that intend to create coordinative structures in the player's behaviour regarding the team's principles of play, as demonstrated in Figure 11 (Araujo & Hristovski, 2006; Gonçalves et al., 2013; Glazier, 2015).

Figure 11
Creating coordinative structures for better decision-making



Source: Glazier (2015)

From that process, most of the feedback is related to the tactical component of the game, more specifically the player's positioning, movement and decision-making. To guarantee the quality of the feedback, the coaching staff should be backed with tools that guarantee the robustness and precision of the information passed to the player (Nevill et al., 2008).

Figure 12 demonstrates how a software can combine video and tracking technology to provide the coaching staff with information such as a player's dead angles, as in the parts of the field that the player is not aware of, due to its body position, represented by the highlighted orange triangle, number of players within a 5-meter radius from a selected position, among other relevant statistics about player and overall team performance.

Figure 12
Demonstration of video-tracking software

Source: SAP TV (2014)

For that reason, the data gathered from the combination of tracking devices and video cameras provides the opportunity for the coaching staff to assess visual information that is straight-forward, thus removing subjectivity from the coach's perception in the analysis of the player and team's performance, leading to clearer, more robust decisions with less margin of error. In this specific case, the coaching staff could suggest a different body positioning for any player or analyze the distances between players and compare it with the pre-established measures from training.

Concerning the decisions for off-the-ball moments, using tracking systems to control for distances between players allows for precise coordination of the different lines within the defensive organization of a team. The distance between the lines and between players in the same line gains relevance as they represent the space that the opponent tries to explore. Therefore, input on inter-player distances will improve the team's positioning and most likely, its performance. Also, it allows for constructive debate with the players, giving them the opportunity to understand their positioning and compare it with their on-field perceptions.

Again, Big Data is impacting the decision-making ability of the player by guaranteeing that the athlete is following structural patterns that are part of the club's strategy to win the game.

On another note, performing a passing analysis with spatio-temporal tools can uncover the passing patterns that represent the most relevant links between players. If used on the opponent, the incremental knowledge on the opponent will facilitate the neutralization of the most used connections. Used upon the own team, will show how the team feels more comfortable playing, allowing the coaching staff to adjust the game-plan to the characteristics of the players (Gudmundsson & Wolle, 2013).

The passing analysis can also rate the difficulty of a player's passing options or assess the decision to perform a certain pass by scrutinizing other player's positioning as valid passing alternatives (Appendix 5) (Gudmundsson & Wolle, 2013).

Altogether, analyzing data on the game and the decisions made by the players provides the coaching staff the legitimacy to give objective feedback that can potentially improve their decision-making ability within the team's proposed strategy.

4.2.3 The case of Hoffenheim

TSG 1899 Hoffenheim, a German club that managed to make their way from Germany's 5th division to playing in European competitions in the season 2017/2018 has had the financial backing of Dietmar Hopp, co-founder of SAP, the multinational software corporation.

On the back of the ascent to the professional divisions is the attention paid to data analytics. Nowadays, Hoffenheim is working to develop the players' logical, conscious thinking with the help of video games (for example, using a software by the name of Helix-180), specifically adapted to the football reality. With them, players are faced with virtual reality situations against avatars that represent both teams in the field. With this technology, Hoffenheim expects to better their athletes' positional awareness, as well as the peripheral vision, according to Jan Mayer, one of the club's sport psychologists. Another advantage of this software is that the exercises can be tailored to fit the positional demands of different players and adapted to different age brackets.

For the intuitive, fast-thinking aspects that players perform automatically, Hoffenheim relies on technologically backed fields (like the Footbonaut) that aim to test the player's response to unpredictable technical contexts. In these fields, the club can customize individual training drills according to a player's technical ability. In the end, response times or technical accuracy are registered to create the player's profile and monitor evolution.

Tying it all together, combining the approach to conscious thinking, related to tactical aspects, with the fast-thinking training protocol, related to technical aspects, will potentially improve the player's decision-making as it challenges the ability to perceive the situations and execute accordingly.

4.3 Big Data promoting better sporting results through injury prevention and decision-making enhancement

As seen before, finding applications for Big Data has the upside of equipping the FCs with full control of training metrics, fomenting educated decisions that allow for the improvement of the training protocol and team management actions.

Injury-wise, the ability to structure the Data regarding the internal and external loads that each player is subject to throughout the season (Gabbett, 2015), presents the opportunity to critically analyze and adjust the training for optimal performance.

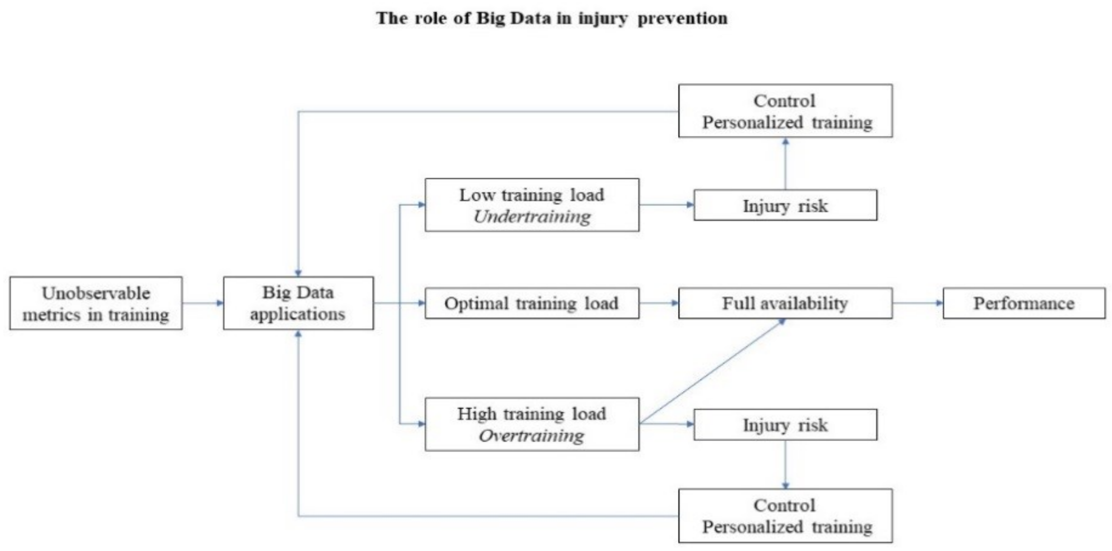
With this, FCs can improve their preventive approach towards injuries through tailored protocols that meet the needs of the athletes (Buccheit, 2014), thus reducing the likelihood of sustaining noncontact injuries. Prevention of such injuries, that have been proven to represent higher injury burden for FCs compared to the unpredictable traumatic injuries, will increase player availability in training and competitive matches (UEFA, 2017).

Another approach contemplates the enhancement of a player's decision-making, by facilitating the comprehension and analysis of game-related actions. Associating Big Data to decision-making, not only aims to develop the procedural knowledge of the players, but also to increase the speed at which good decisions are made. With decision-making related to the ability to perform, FCs can make the most of data inherent to the game, modelling the decision-making process of its athletes.

4.3.1 Creating a framework to leverage injury preventive methods with Big Data

Looking at the framework in Figure 13, using Big Data to analyze what previously were unobservable metrics of performance, the coaching staff can assess the training load that a player is being subject to.

Figure 13
The role of Big Data in injury prevention



Adapted from Gabbett (2015)

- Low training load

In case the player's data signals a low training load, otherwise known as undertraining, the injury risk is present since the athlete is not ready to face the intermittent, high-intensity bursts of the competitive moment. As sudden increases in a player's body load increase the probability of injury, the coaching staff is advised to control the situation through, for example, personalized training that can restore the desired physiological and fitness levels to satisfy the demands of the competitive moment.

- High training load

On another level, if the player's data suggests training loads beyond pre-established metrics, in other words, close to overtraining, although the athlete is fit to play, the non-contact injury risk is also present on account of overuse and accumulated fatigue. For this reason, the coaching staff can adjust the training sessions to provide the athlete with an adequate recovery process from previous efforts, stabilizing the training load indicators around the optimal levels that maximize performance.

- Optimal training load

This control leads players to optimal levels of training load, represented by the point of fitness right before fatigue starts to affect negatively the performance of the athletes (Appendix 6).

With optimized physiological and fitness conditions, FCs can enjoy fully available players to partake in the preparatory sessions, as well as in the competitive matches.

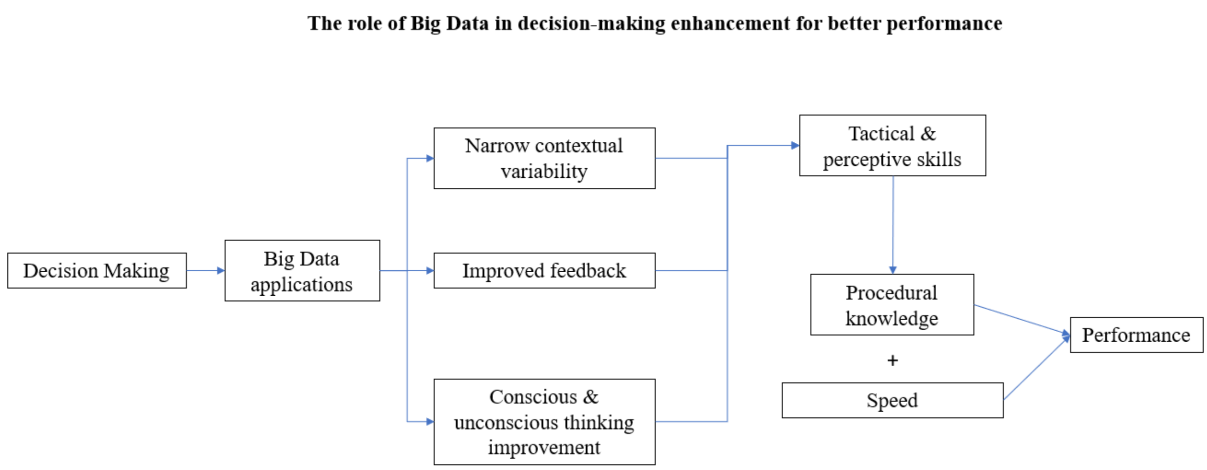
- Injury prevention as performance enhancer

Therefore, having the best talent in the squad available and fit to play, improves the chances of a FC achieving sporting success (Owen et al., 2017). As players are available, they can participate in the team's preparation, reinforcing its dynamics and increasing the chances that the strategical take on the game is carried out more effectively, moving closer to fulfilling its competitive potential. This reinforces the role that Big Data can have within FCs, since lower season injury rates are associated with both domestic league and international European competition's increased performance (Hagglund et al., 2013). Also, the existence of long-term injuries like tendon or ligament injuries, which are mostly classified as noncontact, also increases the likelihood of the FC underperforming (Hagglund et al., 2013).

4.3.2 Creating a framework to leverage the player's decision-making with Big Data

Big Data can also work as a vehicle to impact a player's decision-making ability and improve performance, combining 3 different methods (Figure 14).

Figure 14
The role of Big Data in decision-making enhancement for better performance



- Narrow contextual variability

Firstly, considering that Big Data can help anticipate game patterns through video-tracking devices (Gudmundsson & Wolle, 2014), players are given clearer expectations about the situations they will face during the game, thus narrowing the possibility that a player will be surprised with unexpected contexts. In the end, preparation and management of the expectations through structuring the information from gathered Data will improve the speed and quality of the decision-making process by reducing the exposure to unknown contexts.

- Improved feedback

Secondly, another Big Data application to impact the player's decision-making process, spatio-temporal tools, can aid the coaching staff in visualizing the passing options that players had in the game and evaluate them against the option taken (Gudmundsson & Wolle, 2014), facilitating the creation of clear, task-related, precise feedback that will educate the players on making better decisions to inch the team closer to better performance overall (Nevill et al., 2008, Hughes & Franks, 2002). Further feedback improvement can be achieved with video-tracking software (Figure 12) that allows the players and coaching staff to analyse specific situations in the game, creating a demonstrative, visual platform for players to learn from and improve their procedural knowledge.

- Conscious and unconscious thinking improvement

Thirdly, FCs have started to explore software that can test and improve the player's conscious thinking and perceptive skills, closely linked to the procedural knowledge that is paramount in identifying the best action to take under any game circumstance (McKenna, 2017). Other technologically-backed fields tackle the development of fast, subconscious thinking, which linked with technical improvement, will equip the players with the tools to identify and solve the most diverse challenges in the game (McKenna, 2017).

- Decision-making as performance enhancer

Altogether, as FCs turn to Big Data to carry out decision-making enhancement strategies, their players become better prepared to perform at the elite level. This is due to the anticipatory, tactical and perceptive skills that are developed, helping the athlete's cope with the intermittent, fast-moving blocks of the game. As players become more efficient in solving technical and tactical problems during the game, through enhanced procedural knowledge, the likelihood that the team's tactics are performed satisfyingly increases.

Ultimately, should players be able to perform increasingly faster and better technical and tactical decisions, FCs will be given the ability to deploy skilled resources, as in players, to extract the most value of every game situation, increasing its competitiveness and fulfilling the team's potential, promoting the probability of sporting success.

5

Conclusion

This work aimed to assess the impact of Big Data on the FCs' strategies to enhance performance, through injury prevention and player decision-making enhancement, in order to guarantee a competitive advantage on the field.

Going back to the first research question, on the utility of Big Data in injury prevention, we conclude that the capability to tightly control and manage the load that each player faces throughout the season allows for better injury prevention, thus increasing the availability of the FC's most important resources. Looking at the declining trend in injury incidence in elite European FCs, and the data's potential to shape training protocols to improve performance and prevent injury, it is apparent that Big Data can help better the FCs' injury prevention strategies.

Regarding the second research question, on the utility of Big Data for the enhancement of a player's decision-making ability, we conclude that FCs can leverage the capability to improve a player's decision-making process with the use of Big Data applications. Accessing data on pre-established moments of the game or performance indicators, allows to simplify, accelerate and critically evaluate the players' decision-making ability. Also, sport-specific software to train the conscious and unconscious thinking of the players is being used to improve perceptive skills. This takes us to conclude that Big Data has the potential to improve a player's decision-making in the game, through demonstration and practice.

The third research question explored if Big Data applications on injury prevention and decision-making enhancement could promote better sporting results.

On one hand, FCs were found to achieve better performance in seasons with lower injury incidence (Hagglund et al., 2013). Furthermore, injuries that impact FCs with high burden were found to affect the final standing at the end of the season (Hagglund et al., 2013). The reinforcement of these associations with the developed framework on the ways Big Data could control the training loads for optimal fitness, led us to conclude that having Big Data improve the injury preventive protocols, will result in higher player availability, thus increasing the chances of promoting better sporting results.

On the other hand, decision-making was associated with the ability to perform at the elite level. On top of that, we created a framework to connect the use of Big Data with decision-making enhancement strategies. Thus, as players become better at making good tactical and technical decisions, their in-game performance increases, furthering the team's chances of outperforming the opponent, leading us to the conclusion that Big Data applications dedicated to improving a player's decision-making, have the potential to improve sporting results.

Generally, considering the heterogeneity of resources across FCs, as in athletes and coaching staff, the development of unique and detailed training protocols became paramount. Based on quantifiable performance indicators scrutinized through advanced tracking tools, FCs set out in the pursuit of optimal training load and maximized performance for their athletes.

Building on this RBT assumption, FCs are faced with the opportunity to leverage their internal resources and capabilities to gain an advantage over their adversaries. With Big Data, FCs can better estimate the value of their resources, fostering the ability to deploy adequate strategies, based on interdisciplinary synergies that maximize the value extraction from both players' and coaching staff's potential.

Nevertheless, the final result will always be dependent on more than one variable, like the talent of a player, motivation or even luck. Even though Big Data applications cannot guarantee success, on account of football's low-scoring nature, the capability of extracting more value than the opponent to achieve gains, even if marginal, has the potential to be the differentiator that promotes a competitive advantage.

5.1 Challenges for Big Data strategies

Despite the upside of incorporating Big Data in FCs' process towards superior performance, FCs still face some challenges in executing these value-adding strategies. FCs are past the data gathering struggle as they are now able to extract countless data-points per second using the aforementioned tracking technologies. For now, the challenge lies in finding and securing the specialized professionals who can treat manipulate data into actionable material. In addition, FCs still need to adapt and organize its processes, policies and strategies to make the most of the information that is captured. Since combining Big Data with performance is a novelty for FCs, early adopters might develop an advantage by staying ahead of the learning curve.

Further challenges lie in making the input from Big Data actionable in real time. With the present solutions requiring human input to provide the coaching staff with advice, part of the potential of impacting match decisions is still untapped. This suggests that coaches will be increasingly dependent on the data scientists' work to make their decisions concerning the team's strategies.

Still, FCs have yet to identify with certainty which KPI's are more relevant in constructing injury predictive models or guaranteeing enhanced sporting performance. Whilst some studies correlate variables with success or injury incidence, there are still many unforeseeable variables that can influence the end-result, one of them being luck. Despite working to reduce the unpredictability of a chaotic game, FCs can still be outperformed by opponents that strike lucky.

In the end, although there are good conditions for the proliferation and impact of Big Data in FCs, the strategy is still undergoing an evolutive process.

5.2 Future

The response to the challenges that arise from integrating Big Data in the training protocol and competitive moment shape the future for research in this field.

The integration of Artificial Intelligence and Machine Learning systems to come up with pre-determined models that can send customized suggestions to the coaching staff represent the subsequent step towards achieving a competitive advantage on the field. For example, alerts on player fatigue or intra-team distances, regarding predetermined values, can represent the way forward in assuring tactic efficacy in real time.

This tendency brings FCs closer to a dependency on multidisciplinary synergies to maximize the performance, thus increasing the chances of the FC being successful.

For future studies, it would be interesting to collect concrete data from FCs, to measure the impact of Big Data on performance, providing a more robust view of the influence of this technology-based strategy

5.3 Limitations

As this thesis develops a recent issue, it was common that papers and articles would not reach a finite conclusion, but rather recommend further study thematic to deepen the knowledge on the applications of data by FCs. On this note, whilst it confirmed the relevance of this study, it introduced another limitation for the secondary data, openness to interpretation. Having followed the inductive approach, it is possible that the interpretations made on the information gathered would differ depending on the reader's background and context.

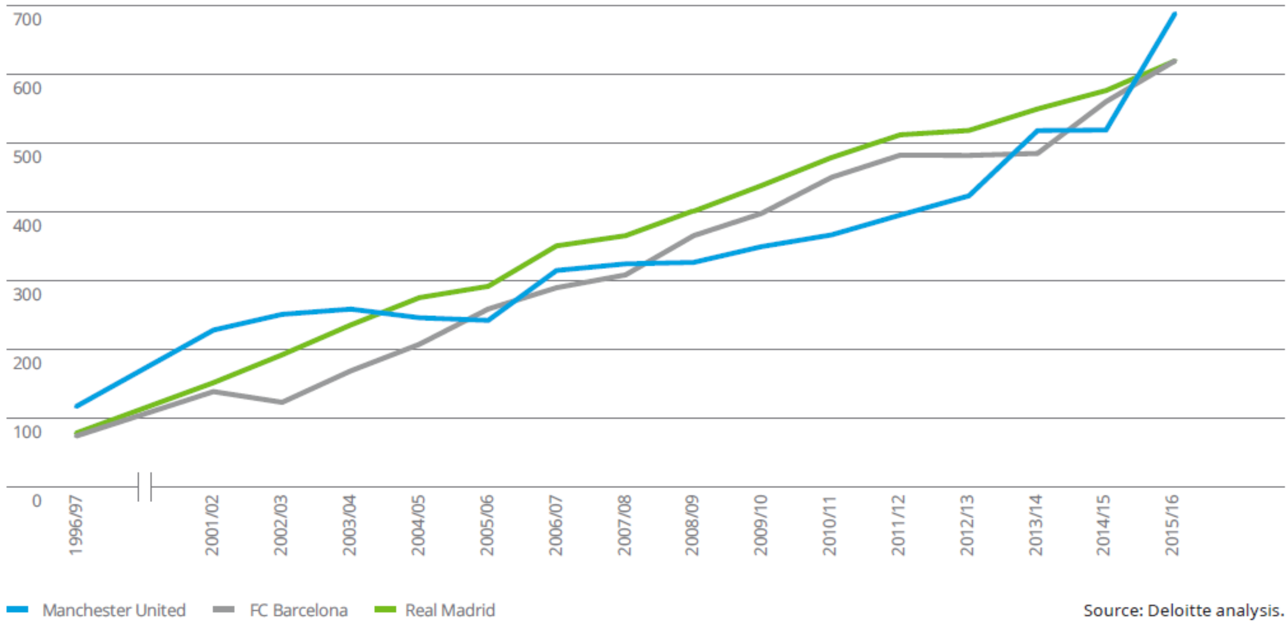
Another limitation was the source's mutual dependency. Since the scrutinized theme was recent, each source would be partially dependent on each other. While facilitating research through web referencing, it could form a bias. This work compiled only the theories that promoted a clear, flowing logic, making for an easier understanding of the advantages of incorporating Big Data to enhance football performance through injury management and decision-making development.

In the end, obtaining primary data information from specialized personnel in sports science turned out unattainable, since FCs rely on the secrecy of data management processes to try to achieve a singular advantage over their opponents.

Appendix

Appendix 1

Football Clubs’ revenue (€m)



2015/16 Revenue (€m)

DFML position	Change on previous year	Number of positions changed	Club	Revenue
1	↑	2	Manchester United	689
2	↔	0	FC Barcelona	620.2
3	↓	(2)	Real Madrid	620.1
4	↑	1	Bayern Munich	592
5	↑	1	Manchester City	524.9
6	↓	(2)	Paris Saint-Germain	520.9
7	↔	0	Arsenal	468.5
8	↔	0	Chelsea	447.4
9	↔	0	Liverpool	403.8
10	↔	0	Juventus	341.1

2014/15 Revenue (€m)

DFML position	Change on previous year	Number of positions changed	Club	Revenue
1	↔	0	Real Madrid	577
2	↑	2	FC Barcelona	560.8
3	↓	(1)	Manchester United	519.5
4	↑	1	Paris Saint-Germain	480.8
5	↓	(2)	Bayern Munich	474
6	↔	0	Manchester City	463.5
7	↑	1	Arsenal	435.5
8	↓	(1)	Chelsea	420
9	↔	0	Liverpool	391.8
10	↔	0	Juventus	323.9

DFML position Change on previous year Number of positions changed

Source: Deloitte, Football Money League (2017)

Appendix 2

Football Clubs in the stock market

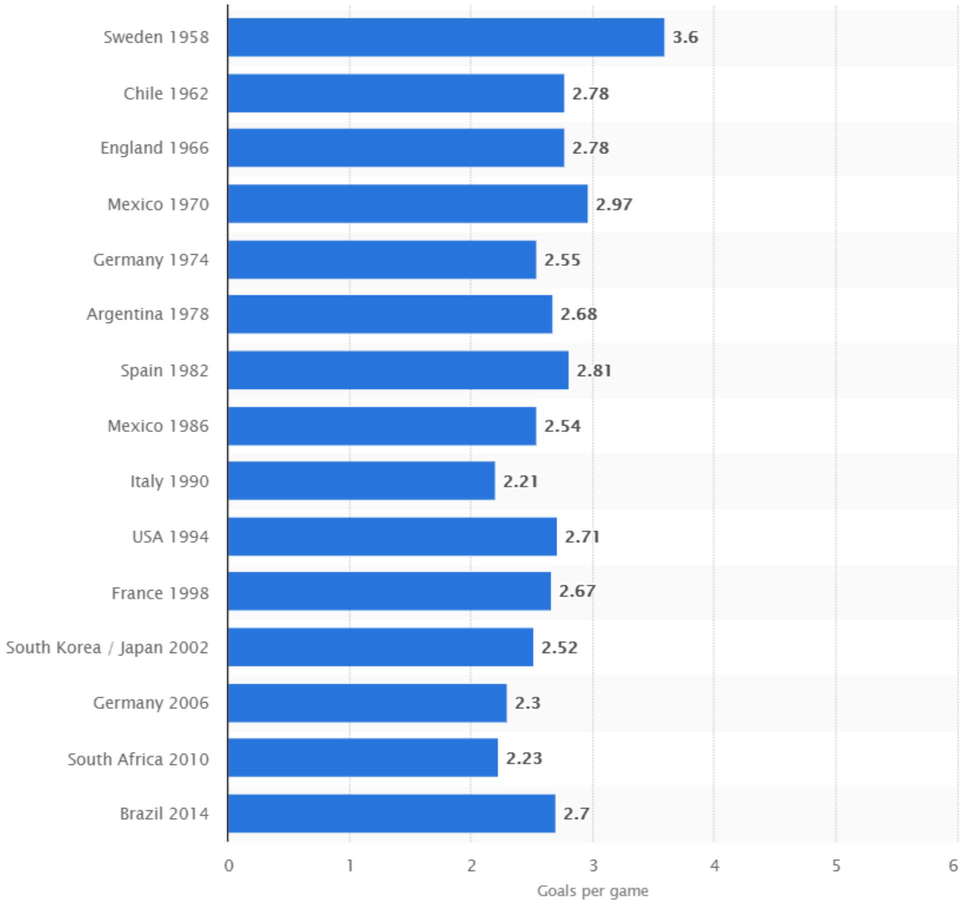
Club		Currency	Price close (as of 30 December 2015)	Price close (as of 30 December 2016)	Annual change (%)
Trabzonspor		TRY	1.27*	2.84	123,6%
Beşiktaş JK		TRY	2.16*	4.00	85,2%
Galatasaray SK		TRY	17.67*	32.30	82,8%
Olympique Lyonnais		EUR	2.03*	2.94	44,8%
Borussia Dortmund		EUR	4.01	5.26	31,1%
Juventus FC		EUR	0.26	0.30	15,8%
SS Lazio		EUR	0.52	0.58	11,8%
Arsenal FC		GBP	15,670.00*	16,510.00	5,4%
Fenerbahçe SK		TRY	37.20*	39.00	4,8%
AFC Ajax		EUR	8.50*	8.75	2,9%
FC Porto		EUR	0.70*	0.69**	-1,4%
Celtic FC		GBP	0.74*	0.71	-3,4%
SL Benfica		EUR	1.04*	0.98	-5,8%
AS Roma		EUR	0.49	0.41	-15,1%
Manchester United FC		USD	17.81*	14.25	-20,0%
Sporting CP		EUR	1.10	0.62	-43,6%

Notes:
**As of 31 December 2015*
***As of 29 December 2016*
Source: KPMG Football Benchmark research; Thomson Reuters

Source: KPMG Football Benchmark research (2016)

Appendix 3

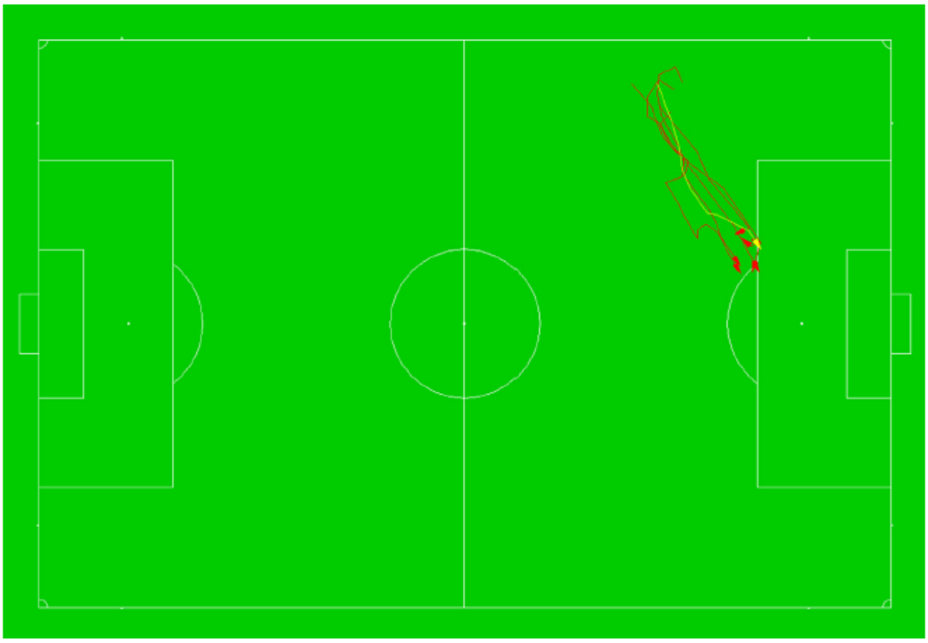
Average number of goals scored at the FIFA World Cup since 1958



Retrieved from: https://www.statista.com/

Appendix 4

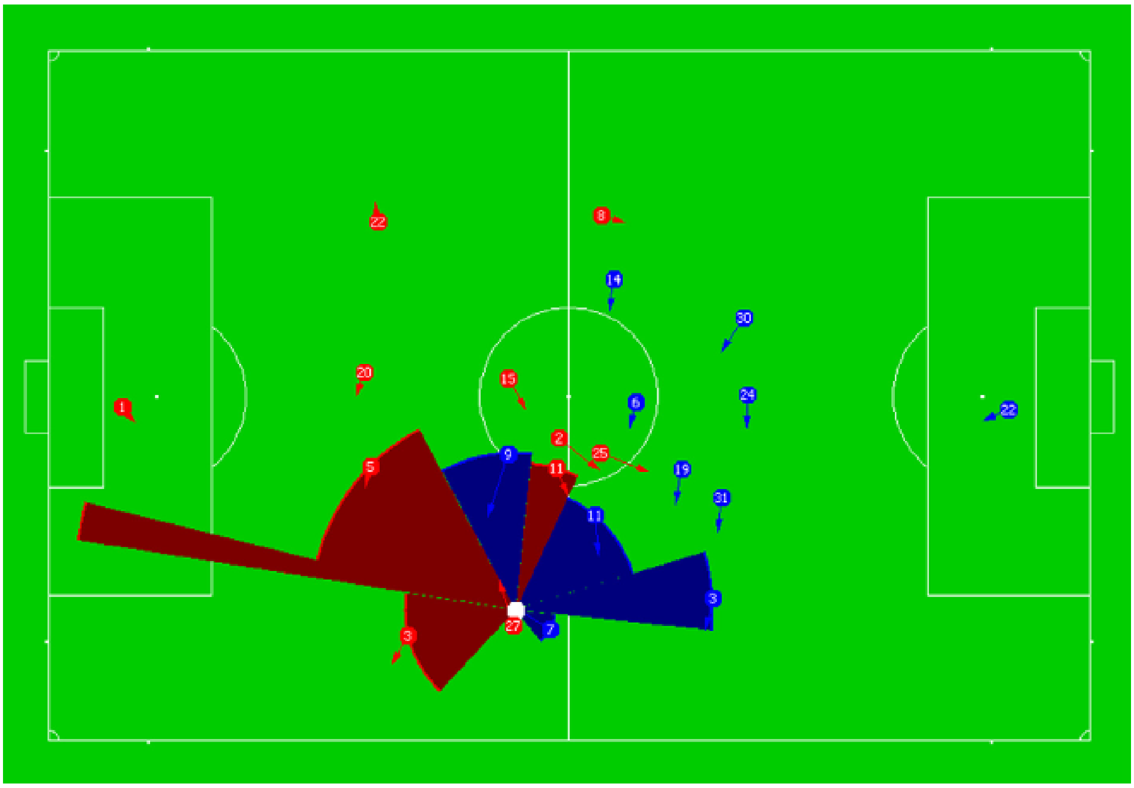
Clustering movements with spatio-temporal tools



Source: Gudmundsson & Wolle (2013)

Appendix 5

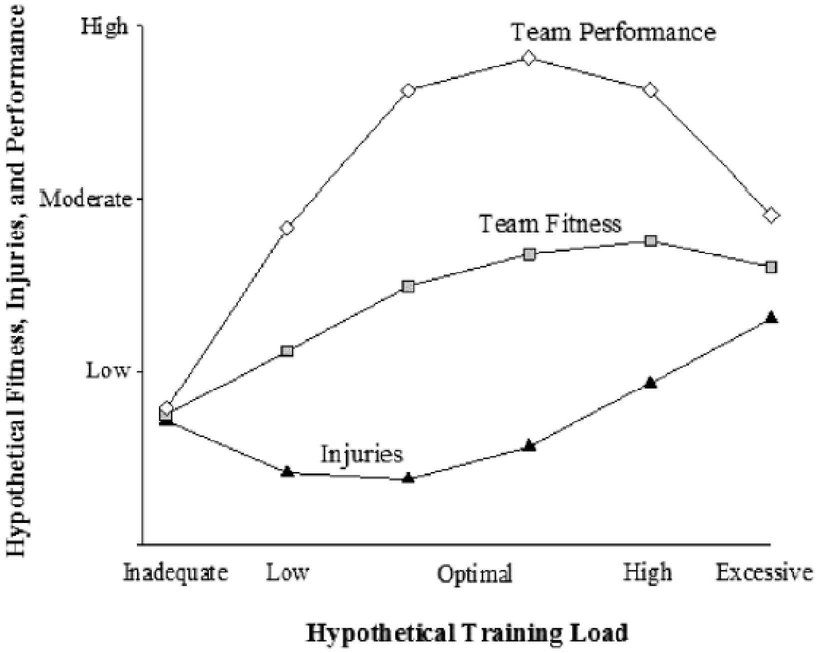
Passing analysis tool with spatio-temporal technology



Source: Gudmundsson & Wolle (2013)

Appendix 6

Hypothetical relationship between Performance and Training Load



Source: Gabbett (2015)

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