A KD Framework in Football Data Analytics: A Value Co-creation Framework for the Use of Knowledge Discovery Technologies in the Football Industry

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ABSTRACT

Investment in sport technologies are expected to grow by 40.1% during 2016-2022 reaching approximately $3.97 billion by 2022. As well the recent changes in technology regulations by The Federation Internationale de Football Association (FIFA) since the 2018 World Cup created promising football technologies. This research questions addressing the issue of what is the value of such technologies for professional football teams? and what are the benefits of these technologies? This is achieved by developing a framework for understanding the value co-creation process from the knowledge discovery systems in the football industry. The framework aids in mapping the resources, pinpointing the outputs, identifying the competencies leading into capabilities, and finally in realisation of the value of the final outcomes in that journey. On another words, different teams have different resources that allow them to achieve certain outputs. These outputs enable the coaching team to achieve and maintain certain abilities. By changes in practice the will improve the team ability and enhance their analytical capabilities. Therefore, that will allow and aid the coaching team to gain new outcomes such as improving training strategies, transferring players, and informative match strategies. Additionally, improved understanding of the value co-creation process from the knowledge discovery systems in the football industry answering, why are some teams better able to gain value from investment in knowledge discovery technologies than other teams in the football industry. The framework has been developed in three phases in which semi-structured interviews where used in the first and second phases for developing and validating the framework respectively. The third and final phases is verifying the framework by developing a knowledge discovery maturity model as an online assessment's tool in operationalising the research findings. The main contributions of this research are the adaptation and customisation of Melville *et al.* (2004) to develop a value co-creation process form knowledge discovery resources. Moreover, applying Agile (APM, 2015) artefacts and techniques and tools in improving the value co-creation process between coaches and data analysts. That's aided in developing the value co-creation knowledge discovery framework in football analytics. Additionally, the development of a key performance indicators balanced scorecard and its adaptation as a in understanding the relationships between the key performance indicators (i.e. physical, psychological, technical and tactical performance indicators). Finally, the development

of the knowledge discovery maturity model in football analytics which was used in understanding and pinpointing areas of strength and weakness in the utilisation of the various football resources used in football analytics (human resources, technological resources, value co-creation resources and analytical models used).

GLOSSARY

Term	Details	Definition (*as defined by this research*)
KD	Knowledge Discovery	A systematic iterative procedure intended to enable the development of models and frameworks that can be used to study specific phenomena.
KDR	Knowledge Discovery Resources	KD resources used in the KD framework (i.e. technological resources, human resources, value co-creation resources and their sub-models.
KPI	Key Performance Indicators	Are used to measure players performance actions based on the related events or actions during a match or training.
MM	Maturity Model	A multi-phases assessment model to reflect on current practices.
KDMMFDA	Knowledge Discovery Maturity Model	The KDMMFDA developed in this research to assess the coaching team FDA strength and weakness.
CT	Case Team	-
FDA	Football Data Analytics	-
PA	Performance Analysis	-
KDV	Knowledge Discovery Value	-
User stores	-	are a technique for the development of the features required to meet the specific goals of users
Sprint	-	A method used to improve communication and gathering requirements.
Retrospective	-	It a technique for maintaining the iterative need between the questions, research and result so that level or collaboration is achieved as will leading enhancing maturity level in the collaboration process over time.
Transfer Strategy	-	The mechanisms that a team manager utilises to select and recruit players in fulfilment of the aim of achieving his overall objectives.
Match strategy	-	The process of using a match model to understand the strength, weaknesses, opportunities and threats (SWOT) of opponents in the match environment, in order to help the team winning the match.
Tactical KPIs	-	Are metrics that are intended to measure the ability of players to position themselves

		effectively in such a way the probability of passing, possessing, scoring and intercepting are improved.
Technical KPI	-	It is the ability to control the ball for the sake of accomplishing the required tasks effectively and efficiently.
Physical KPIs	-	Are those physiological and fitness measures for the players' abilities. Some of them are traits that cannot be changed, such as the height and ambidexterity while others can be improved by training such as speed, high/moderate intensity running and recovery rate.
Psychological KPIs	-	Referees to the ability to play in the standard performance under different psychological pressures, which can be called "resilience indicator".
Predictive models	-	Are equations or estimations used to estimate the probability of scoring in a variety of different situations.
Context-based modelling		Is defined in this research as the identification and measurement of the players' KPIs in different training and match context
Comparative modelling		Is a statistical method for the comparison between players or teams utilising different KPIs.
Synergetic modelling		Is a technique used to identify the correlation in a player performance with others in the team

Table of Case Studies

Wave One – Developing the framework

Code	Team / Bodies	Role
W1TD	Football National Teams	Technical Director & Expert (Coach, Player in Different Leagues)
W1FC2	Football Club - 1st Team	Coach
W1DA3	Football Club - 1st Team	Analysts
W1DA4	Football Club 1st Team	Analysts
W1FC5	Football Club - Olympic Team	Head Coach
W1DA6	Football Club - Olympic Team	Analyst
W1FC7	National Olympic Team	Coach
W1FC8	Football Club - 1st Team	Coach
W1FC9	Football National Teams	Assistant Coach
W1DA10	Football Club 1st Team UK	Analysts
W1BM11	Football Organisation - UK	Performance Analysis Team Member
W1BM12	Football Organisation - UK	Performance Analysis Team Member
W1BM13	Football Organisation - KSA	Technical Committee
W1RS14	Rugby Club	Director of Performance Analysis
W1PSC15	Sports Data Consultancy	Data/Video Analysts
W1BM16	Football Organisation - KSA	Technical Committee
W1PSC17	Sports Data Specialists - UK	Representative - Sports Data Specialist
W1PSC18	Sports Data Specialists - International	Representative - Sports Data Specialist
W1PSC19	Sports Consultancy - KSA	Manager – Football Data Specialist
W1PSC20	Sports Consultancy - KSA	Representative - Football Data Specialist
W1PSC21	Sports Data Specialists	Live Scouting Administration

Wave Two – Validating the framework

Code	Team / Bodies	Role
W2TD1	Football National Teams	Team Director – Former Player – Former Coach
W2EM2	Football Federation	Executive Manager of the Technical Committee
W2TCM3	Football Federation	Technical Committee Member – Professional coach
W2FC4	Football Federation - Football Club Academy	Professional Coach – Academy Director – Former National Team Coach
W2FC5	Football Federation - Football Club Academy	Professional Coach – Academy Director – National Youth Team Coach – Scouting & Talent Identification
W2FC6	Football Federation - Football Club Academy	Professional Coach – Professional Player Mentor
W2FC7	The UK Football Association	Professional Coach
W2FTM8	The UK Football Association	UK Team Manager
W2SC9	University	Principal Lecturer in Sports Coaching Science
W2TD10	Football Federation	Ethics Discipline Committee

Wave Three – Verifying the framework

Case	Code	Team	Role	Team / Bodies
Case 1	C1P1	CT1	Video Analyst	Football Club - 1st Team
Case 2	C2P1 C2P2	CT2	Assistant Coach Data Analyst	U19 National Team
Case 3	C3P1	CT3	Data Analyst	National Olympic Team
Case 4	C4P1	CT4	Assistant Coach	Football Club - 1st Team
Case 5	C5P1	CT5	Football Coach	Football Academy Club

KEYWORDS

Football data analysis, Performance analysis, value co-creation in football, competences and capabilities in football team, Resource basest view in football, football coaching, football data analysis, football data analytics, KPI Balanced scorecard.

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Chapter 1 Introduction, Research Question, Aim and Objectives

1.1 Introduction

Investments in sports technology exceeded $1 billion in 2015 (Magee, 2015). However, it is unclear whether football teams are able to realise the expected value from these technologies, or what reasons could explain some teams obtaining a greater benefit than their competitors. This chapter introduces the current research project into this issue. It begins by identifying the research problem, based on real life needs, then provides a brief outline of the key literature to identify what is known and the gaps in formal understanding of the variation in realising value from investment in technologies. Based on the knowledge gaps and the research problem, the following section the research question, aim and objectives are presented, and supplemented with an overview of the overall structure of this thesis.

1.2 Research Problem

Sports technology is believed to improve team performance by enabling superior measurement, monitoring and planning of performance. According to the Analytical Research Cognizance (Infoholic Research, 2016), the Worldwide Sports Analytics market is expected to grow by 40.1% during 2016–2022, reaching approximately $3.97 billion by 2022. Other studies have predicted that the sports analytic field will experience growth from $764.3 million in 2016 to $15.5 billion by 2023 (Infoholic Research, 2016), with wearable technologies predicted to grow annually by 20% to reach $29 billion market value by 2022 (CCS Insight, 2018). PlayerTek a company, recently acquired by Catapult, experienced a 365% increase in the market of amateur and semi-professional football clubs in Europe and Asia during 2017 (Lemire, 2018). Catapult estimates that 10,000 elite teams are being targeted by football wearables devices in 2018. Indeed, hundreds of start-up companies have been established to serve this market, including major players like Nike, Adidas, Amazon and Microsoft at the Hype Foundation event (BBC News, 2017). Although the producer side of these technologies has already demonstrated exceptional profitability, with many companies doubling their profits semi-annually, the value of such technologies is less clear from the consumer side. What is the value of such technologies for professional football teams? How can teams benefit from such technologies? Can all teams obtain the same value from investment in such technologies? This research seeks to provide new insights into these questions.

1.3 Research Motivations

In order to address the aforementioned questions, this research adopts a Knowledge Discovery (KD) approach, predicated upon the main argument that knowledge is a key power that could enable coaches to better understand the weaknesses and strengths of their teams, as well as those of their opponents. This kind of understanding would facilitate and support more effective planning for player transferring, training, and match strategies. These various insights may provide a way for teams to gain a competitive advantage. In other words, new knowledge may be crucial in optimising the performance of individual players and entire teams.

According to the information technology value framework, investment in technology only provides meaningful value to organisations when they have the suitable organisational resources, which are called organisational complementary resources (Melville and Kraemer, 2004). Accordingly, realising the expected value from the investment in technology requires two types of resources to be synchronised and orchestrated — technological and organisational resources (Piccoli and Ives, 2005; Badewi *et al.*, 2018). Technological resources are the hardware and software required to enable changes in the practices. In this study, KD resources can be defined as the hardware and software applications necessary to discover new knowledge that could help coaches to improve their team match strategies. The technologies primarily addressed in the literature are wearable sports devices (Dellaserra, Gao and Ransdell, 2014), cameras (Ding and Fan, 2006; Sugimoto *et al.*, 2012), GPS technologies (Rangsee, Suebsombat and Boonyanant, 2013), and body sensors (Marin-Perianu *et al.*, 2013). All of these technologies create a massive amount of data every day (Rein and Memmert, 2016). These technologies have been studied in terms of their usability (Marin-Perianu *et al.*, 2013), usefulness (Dellaserra, Gao and Ransdell, 2014), and effectiveness (Clemente *et al.*, 2013; Rein, Raabe and Memmert, 2017). The summary of such findings is that no one universally agreed upon answer why some teams are better in using these kinds of technological resources. Additionally, to date, no dedicated research has been undertaken to provide a detailed explanation of the different wearable technologies that could help in discovering knowledge.

Technology alone is not sufficient to create value without the support of human resources. Relative few studies have examined human resources (in terms of skills, competences, and knowledge) as the main producer of such knowledge (i.e. the data analyst) (Wright *et al.*, 2013; O'Donoghue and Holmes, 2014; Wright, Carling and Collins, 2014; Scheider, Ostermann and Adams, 2017). Limited papers have focused on the resources required by the consumer of the knowledge (e.g. the coach). Clarification is also required about the relationship between the producer and consumer of this knowledge. Is it a 'give-and-take' selling process (i.e. data analyst produces the knowledge based on specifications and sell it to the coach)? Or it is a value co-creation process (i.e. data analyst shall work closely with the coach to develop new knowledge)? If it is a value co-creation process, what are the tools and methodology that could frame such process? The previous literature has not dealt with these issues.

Although KD relies on human and technological resources to create value to the coach by increasing the probability of winning matches, the mechanisms connecting resources and value are unclear. One way in which to connect the relationship between resources and benefits is through the use of benefits map frameworks (Ward and Daniel, 2012; Jenner and APMG International., 2014; Serra and Kunc, 2015; Badewi, 2016). However, benefits maps have not been used in sports analytics studies to explain the relationship between resources, mechanisms to deliver benefits, the required changes in practices, and the potential benefits of investment in such technologies.

This research aims to use software engineering tools in KD, as a knowledge gap also exists in maturity models for data analytics in football information systems. One of the first maturity models developed in information systems literature was by Churchill *et al.* (1969), which was subsequently improved by Nolan (1975) and McFarlan *et al.* (1983) to explain the ability of organisations to effectively adopt the applications of different information systems. Maturity models were then used in more than 150 information systems sub-domains (Chen and Nath, 2018), ranging from classic fields, like software development (CMMI), to contemporary areas, such as e-business (Pranicevic, Alfirevic and Stemberger, 2011), business analytics and KD (El-Gayar *et al.*, 2011). However, these studies focus on business applications, rather than on sports knowledge discovery applications and technologies. This contribution to knowledge could help technologists in sports science to develop tailored roadmaps for teams to improve their abilities to compete through KD resources. Accordingly, this research aims to utilise the knowledge maturity model to assess the ability of teams to realise value from KD systems.

1.4 Research Question

Why are some teams better able to gain value from investment in knowledge discovery technologies than other teams in the football industry?

1.5 Research Aim

To develop a framework for understanding the value co-creation process from the knowledge discovery systems in the football industry.

1.6 Research Objectives

1- To operationalise the expected value of KD to the coaching team.

2- To identify and taxonomise the KD resources and design a model to understand the role of each class of football technologies in improving coaching performance.

3- To identify and frame the role of different knowledge, skills and competences required from the producer (i.e. data analyst) and consumer of the knowledge (i.e. coach) to enable the expected value from the KD to be realised.

4- To frame the value co-creation process and augment it with different tools to improve its value.

5- To develop resource-based maturity model to identify the weaknesses and strengths in the augmentation of the resources to get value from knowledge discovery activities.

1.7 Research Main Contributions

This section presents the two major contributions of the research which are, the Knowledge Discovery Value Co-Creation Framework for Football Data Analytics (KDVCCFFDA) and the Knowledge Discovery Maturity Model for Football Data Analytics (KDMMFDA). The detail of the initial development of the proposed KDMMFDA were introduced and discussed in Chapter 2 , section 2.5. Then, the proposed KDVCCFFDA is improved and enhanced after interviewing experts in the sports industry as discussed in Chapter 4 and Chapter 5 . The KDMMFDA then developed to operationalise the research findings in aiding and pinpointing areas of strength and weakness for teams or players in improving football data analytics. The following sections is to present the main contributions of the research to aid in navigating to related materials within the thesis.

1.7.1 Knowledge Discovery Value Co-Creation Framework for Football Data Analytics - KDVCCFFDA

The first contribution of the research is in the development of the KDVCCFFDA which consists of 4 main models; the technological resources model, the human resources model, the value co-creation model, and the key performance indicators model. The framework was developed in three phases. The framework development phases are discussed in detail in sections 3.3. First, the initial framework which was developed from literature (see section 2.5). Then, the improvement and enhancement of the framework is discussed in Chapter 4 and Chapter 5 A compacted version of the final framework - KDVCCFFDA is presented as hyperlinked diagram for easily presentation and navigation to the related sections within the thesis as shown in **Error! Reference source not found.**.

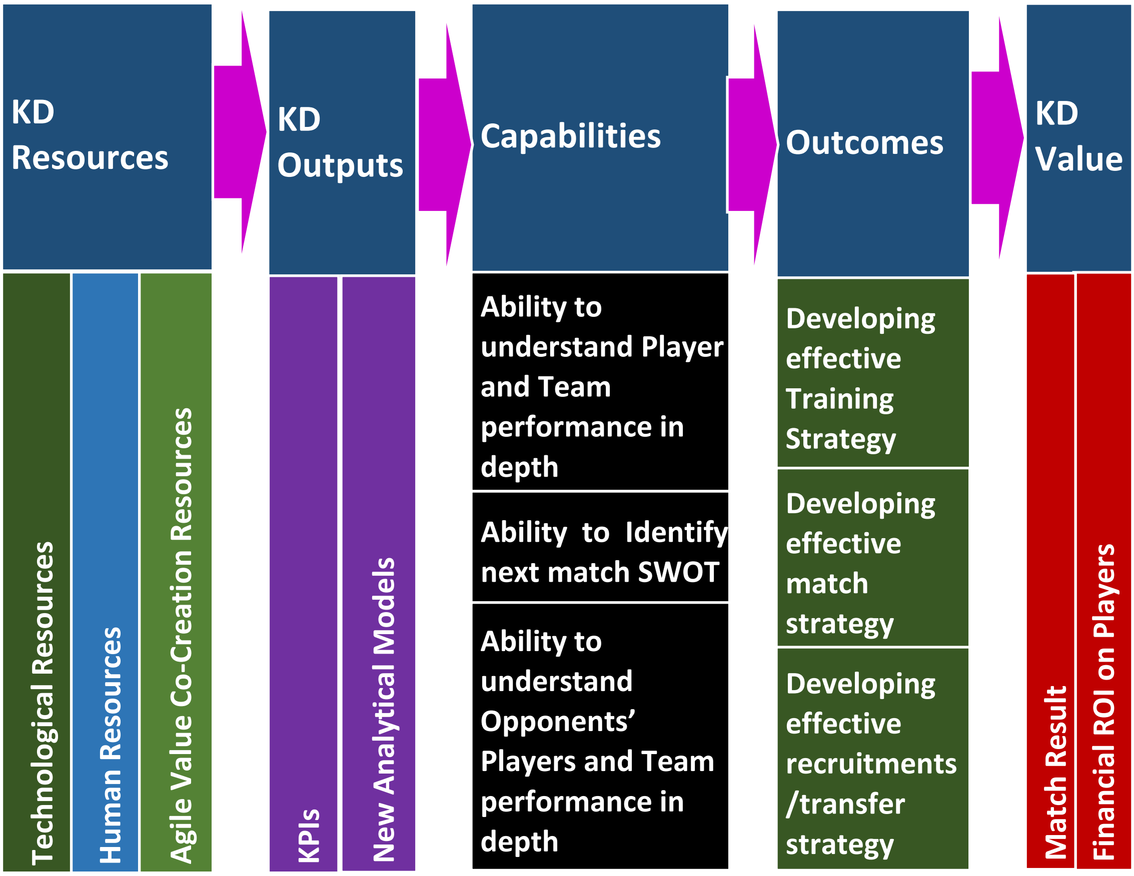

Figure 1-1: Hyperlinked Figure of the Framework - © by the researcher

The figures highlight the main models of the framework and the shows the transformation of utilising the KD resources, leading to outputs, aiding in improving the capabilities, to outcomes that enable the realisation KD value. The detailed framework is presented here in Figure 1-2, as well to show an in-depth view of the models and sub models within framework.

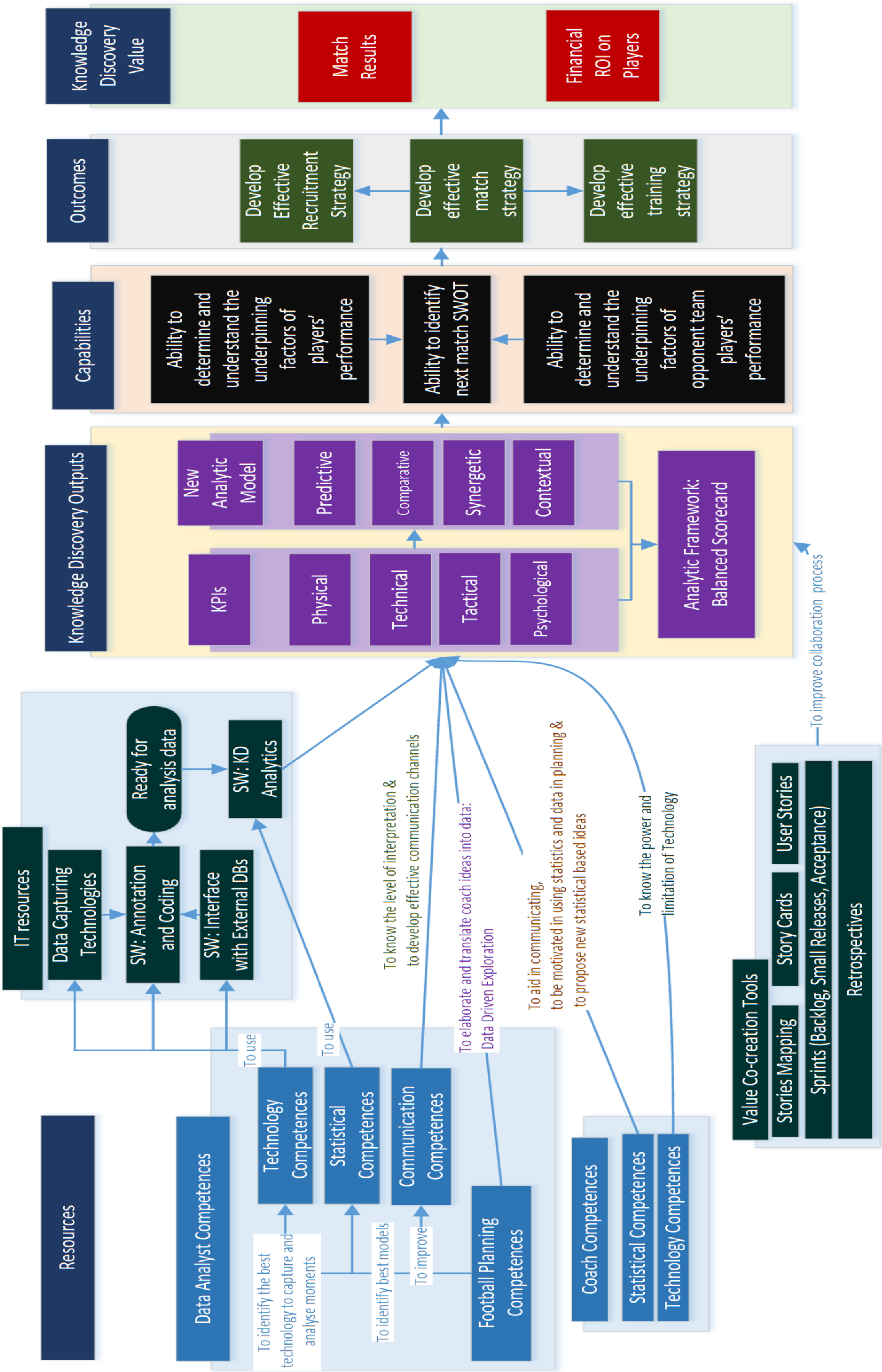

Figure 1-2: Detailed KDVCCFFDA - © by the researcher

1.7.2 Knowledge Discovery Maturity Model for Football Data Analytics - KDMMFDA

The next contribution of this research in the development of the KDMMFDA in which aided in operationalising the research findings as well in assessing teams football data analysis. The KDMMFDA were proposed in Chapter 2 in section 5.7. it is based on 4 maturity levels (i.e. Ad-hoc, Defined, Managed and Optimised. It aids in understanding areas of improvements in human resources, technological resources, knowledge discovery co-creation and analytical models developed. An overview of the final Model can be seen in Chapter 5 section 5.7.

1.8 Thesis Structure

This thesis is organised into seven chapters. After introducing the research question, aim, and objectives in chapter 1, chapter 2 reviews the relevant literature and sets the theoretical foundations of this research. Chapter 3 presents the research methodological approach, strategy, and tools that this research uses to answer the research question and fulfil the research objectives. The analysis and findings are presented in three chapters. Two chapters outline the development and final versions of the chosen analytic approaches (knowledge discovery framework and its subset models and the maturity model) using data obtained from interviews with representatives of 7 teams in Saudi Arabia (13 coaches, team managers, and data analysts). Chapter 4 focuses on the identification and role modelling the technological and human resources required in delivering value. Then, chapter 5 operationalises the definition of KD value in the football sector. The main practical output of chapter 4 and 5 is the proposal of a knowledge discovery maturity model, which is validated using findings from 14 data analysts, team managers, and coaches from 5 teams. In fulfilment of this aim, chapter 6 discusses the application and validation of the KD maturity model. Finally, chapter 7 summarises and consolidates the research findings.

Chapter 2 Literature Review

2.1 Introduction

This chapter seeks to develop the theoretical basis for the current research through a comprehensive review of salient literature. The aim of this chapter is to provide a coherent and active review that not only engages with the relevant papers to illustrate the knowledge gap and the potential contribution of this study, as well as to critically engage with the literature to enable the construction of a new analytic framework and its concepts. In this way, the chapter provides a sound basis with which to inform data collection, particularly in terms of creating interview and codes for data analysis, and the discussion of findings. The literature approach tends to be a mixture of qualitative systematic review/qualitative evidence synthesis (Grant, M. J. and Booth, A. 2009) in which to understand and enrich and meet the scope and depth of the research.

In the following sections (sections 2.2 and 2.3), this literature review defines the concept of 'knowledge' within the context of the current research, enabling the discussion of Knowledge Discovery (KD) to be well-articulated and framed. This is followed, in section 2.4, by an overview of the main theories underpinning KD and its value in the context of modern sport. Based on these theoretical foundations, section 2.4 provides a focused review of the use of KD in the football industry, in order to clearly illustrate the knowledge gap and importance of the current research. As the literature does not agree on one specific framework with which to investigate the value realisation from KD in the football industry, a critical discussion is provided of the three analytic frameworks proposed for data collection and analysis: the value framework, which is adopted from IT Business literature (Melville and Kraemer, 2004); the value co-creation framework, from IT marketing literature; and the Agile framework, adapted from software engineering literature. Section 2.5 examines the value framework for KD in the specific football context, then outline the applicability and theoretical underpinnings of value-creation and Agile methods for KD in this context. Finally, the chapter (section 2.6) reviews the literature on the use of maturity models in software engineering and data analytics in order to inform the design of the model used in this research. Section 0 concludes the chapter with a summary of findings that outlines the critical review of literature in the context of the current study.

2.2 Definition of Knowledge

Comprehensive engagement with the process of "Knowledge Discovery" (KD) requires a thorough understanding of the hierarchy of knowledge. This concept refers to a means of conceptualising and defining the relationships between information. One such approach to categorising and analysing information in a hierarchical system is the DIKW (Data, Information, Knowledge, and Wisdom) pyramid (Rowley, 2007, p. 163). Data are objective, discrete, facts and consequently have no intrinsic meaning without being processed or organised (Awad and Ghaziri, 2004; Baškarada and Koronios, 2013; PhridviRaj and GuruRao, 2014). They are simple records of observations, events, things or actions (Boddy, Boonstra and Kennedy, 2005; Turban, Rainer and Potter, 2005; Laudon and Laudon, 2006), meaning that they require interpretation in order to gain meaning or applicability (Baškarada and Koronios, 2013).

Broadly speaking, many published sources agree that information is distinct from data. Essentially, data that has been aggregated and processed to offer insights and understanding of a particular topic can be thought of as information (Bocij *et al.*, 2015). In addition to inherent advantage of being synthesised and consolidated, information is valuable for comparison and prediction (Laudon and Laudon, 2006), as well as facilitating decision making (Awad and Ghaziri, 2004). As a specific example of this, information can be a useful tool to predict behaviour in a given context (Laudon and Laudon, 2006), or making data retrieval and processing simpler or more effective (Hevner and Chatterjee, 2010). The conversion of data into useful information is most often achieved through statistical, arithmetic, or algorithmic models (Laudon and Laudon, 2017), which produce information that is structurally different and is therefore useful in different kinds of applications.

Knowledge enables experts to understand and interpret information, thereby enabling them to give more accurate and meaningful opinions (Turban, Rainer and Potter, 2005; Bocij *et al.*, 2015). Unlike data, which is a property of things, knowledge is a property of people, and therefore leads to certain behaviour (Boddy, Boonstra and Kennedy, 2005, p. 9), which means that the development of knowledge is invariably closely related to the interpretation of people and information. The construction of knowledge from information therefore requires some degree of subjective interpretation of background and communication (Chi, Slotta and De Leeuw, 1994). Data can be conceptualised using information theory reasoning (Shannon, 1948; Mishra, Akman and Mishra, 2014). In effect, data can be thought of as patterns that have no meaning, while information is data that has been consolidated to give it meaning, and knowledge refers to “information incorporated in an agent's reasoning resources“ (Aamodt and Nygård, 1995, p. 197). Finally, wisdom describes accumulated knowledge, which has changed behaviour, capabilities and practices of an individual, group or population (Jessup and Valacich, 2003). In other words, wisdom is the manifested capacity to utilise knowledge (Jashapara, 2011, pp. 17–18), realising the translation of knowledge into new practice. This is an abstract level that gives foresight (Awad and Ghaziri, 2004, p. 40).

2.3 Knowledge Discovery (KD) Definition

The current research defines the process of KD as a systematic iterative procedure intended to enable the development of models and frameworks that can be used to study specific phenomena. The KD process involves exploration, observation, description, analysis, synthesis and testing (Fayyad, Piatetsky-Shapiro and Smyth, 1996; Kwasnik, 1999). There are three principle approaches to KD: descriptive statistics, which are utilised to quantify facts; visual data mining, which enables relationships to be explored in depth; and machine learning, which aims to create the conditions, predictions and rules for given contexts, enabling specific scenarios to be simulated and tested (Bandaru, Ng and Deb, 2017).

In essence, KD describes the results obtained from extracting useful information from large quantities of data (Agrawal and Shafer, 1996). This has resulted in KD being perceived as an approach (Mariscal, Marbán and Fernández, 2010), a methodology (Alsultanny, 2011), and a technique (Hegland, 2001). However, KD differs from other approaches, including performance analysis (PA) (Garganta, 2009b), data mining (Chen and Liu, 2009), and big data (Kalambe, Pratiba and Shah, 2015; Rein and Memmert, 2016). KD seeks to discover and investigate knowledge (Bandaru, Ng and Deb, 2017), usually in general terms rather than in a single dataset. In contrast, data mining is concerned with investigating specific databases (Bramer, 1999; Larose and Larose, 2014), while big data focuses on the speed and volume of the data extracted from diverse sources (Sagiroglu and Sinanc, 2013). Therefore, KD can be understood as a higher level than big data, data mining and performance analysis, as it seeks to unearth knowledge about the adoption of technological platforms and systems (Wu *et al.*, 2014), in addition to the creation or development of new models for defining, testing or understanding concepts or phenomena (Larose and Larose, 2014). In this sense, KD is a way for organisations to find ways to outperform their competitors (Manco *et al.*, 2016). In summary, KD describes a process for using tools and instruments to find knowledge and, in this sense, has a broader concept and function than data mining, performance analysis, or big data analysis.

2.4 KD in the Football Industry

The KD approach has had a profound impact on the performance of sports teams in numerous fields (Ofoghi *et al.*, 2013), through the use of a range of algorithms, including neural network, genetic algorithm, machine learning, and heuristic analysis (Rein and Memmert, 2016; Constantinou and Fenton, 2017; Hoch *et al.*, 2017). However, it is important to note that the current research is predicated upon a different understanding of KD than the majority of extant football literature, which principally focus only on the use of data mining tools, rather than specifically examining KD as a tool to inform data analysis and the improvement of coaching practices. This approach can be seen in a recent study that utilised a hierarchical KD approach to compute and measure key team performance indicators at the individual, group, tactical and team level (Hoch *et al.*, 2017). This enabled the development of a human-like approach to improve individual and team performance. However, the development of a single unified analytic model may be more relevant in the field of data mining than KD, as the latter requires a focus on both qualitative and quantitative data, as well the process by which data and information are utilised.

2.4.1 Objectives of KD in Football

The literature on football coaching has examined the value of KD from a host of different perspectives. Analysis of team performance has been shown to a competitive advantage to the participating team (Kuper and Szymanski, 2018), resulting in higher win ratios (Wooster, 2013) due to the ability of informed coaches to make superior decisions (Groom, Cushion and Nelson, 2011; Wright, Atkins and Jones, 2012; Wright *et al.*, 2013). This section seeks to synthesise the literature and obtain a holistic view of the potential objectives of the KD approach. KD can support the effective storage and retrieval of historical data, granting the head coach access to new KPIs and even creating opportunities for additional, previously unknown, performance indicators to be uncovered. These outcomes can enable the development of more effective, tailored coaching practices and strategies, improving team capacity and ultimately offering competitive advantage to the team.

2.4.1.1 To develop decisions based on Objectives and Evidence-based

KD can offer a systematic, objective documentation of data, which is essential to help coaches make better decisions, by removing individual bias, perception errors and subjectivity. Without this systematic documentation, analysing and documenting the data, coaches will use their own experience, which is called the critical incident technique because coaches remember only critical events not objectively all events (Flanagan, 1954).

The integration of technology into the coaching process is recognised as one way in which to foster objectivity and encourage fact-based decision-making. Proponents of this approach cite the fallibility of human memory, with some studies suggesting that most coaches can only accurately recall 30-50% of the events in the most recent games that they have watched (Franks and Miller, 1986, 1991; Laird and Waters, 2008). This limited recollection illustrates the inherent value of having a system like KD, which includes data collection and database technology, meaning that it is able to gather and store data about key events that occur throughout specific matches (Nicholls and Worsfold, 2016). Access to this kind of data can increase the effective memory of coaches to incorporate all KD-captured events in the team history. This can potentially encapsulate long periods of time (Franks and Miller, 1986, 1991), reducing subjectivity (Horton *et al.*, 2014) and the selective interpretation and perception of past events (Hughes and Franks, 2004), thereby enabling more accurate, effective decisions to be made.

2.4.1.2 To Create Change in Practices, and Match Strategies

The integration of the discipline of KD through data analysis into football has led to numerous examples of positive changes to the philosophies, approaches, and practices of coaches (Reep and Benjamin, 1968), with studies of statistical analysis showing measurable improvements in coaching practices and capabilities (Pollard, 2002; Doyle, 2007). An example of the positive impact of data analysis can be seen in the rejection of ‘possession football’, with analysis leading teams to adopt more direct strategies that involve fewer passes per team possession (Bate, 1988). This is evidenced in the new approaches used by professional and national teams, as illustrated by Olsen and Larsen

(1997), who studied the playing style of the Norwegian national team. They found that performance analysis had drastically changed the playing style of the team. This importance has been recognised by new research, such as the studies by the Carling research group, which documented the emergence of approaches and practices among professional clubs (Carling and Dupont, 2011a; Collet, 2013a; Carling *et al.*, 2014). For instance, the knowledge that players should maintain a minimum constant speed of 24 km/h during a game has made speed a preliminary selection criteria during recruitment (Carling and Dupont, 2011b).

2.4.1.3 To develop new KPIs and New Coaching Perspectives

KD resources track and measure a wide range of events and contexts, opening new opportunities for analysis. This has led to the design of new key performance indicators, which offer coaches deeper, more accurate insights into match performance dynamics (Hughes *et al.*, 2012; Mackenzie and Cushion, 2013; Wright, Carling and Collins, 2014; McLean *et al.*, 2017). New data models can also grant access to new coaching perspectives, potentially uncovering correlations between superficially unrelated factors and a better understanding of their influence at an individual and group level, leading to the effective development and improvement of overall team performance (Bampouras *et al.*, 2012; Sarmento, Pereira, *et al.*, 2014; Wright, Carling and Collins, 2014).

In essence, KD provides enhanced performance analysis to coaching teams, enabling new perspectives into match events to be captured and analysed, then processed in terms of different scenarios and contexts. This approach is based upon the notion that better understanding of player performance and the performance of their competitors, the more effective plans that can be developed, leading to improved results at a match level. Given this perspective, the following section will review the literature on performance analysis, after which a discussion will be provided of the kinds of strategic improvement that football teams might be possible to achieve through KD performance analysis.

2.4.2 Performance Analysis in Football

KD resources improve the effective use of Performance Analysis (PA) to improve coaching practices and obtain better match results. The inception of PA can be traced to the 1960s, with the analysis of team performance in American football and basketball, albeit through annotation and coding notes rather than technological approaches (Carling *et al.*, 2005; Hughes and Franks, 2007). However, PA has evolved from a simple, linear process utilising descriptive schemas and flow charts (Cushion, Armour and Jones, 2006) to an advanced science that represents a complex, complementary interdisciplinary approach involving the use of sport, behavioural and data sciences are to obtain detailed insight into sport performance (Stein *et al.*, 2017a).

PA is a well-established tool in the world of elite sport (Wright *et al.*, 2013) and has become integral to modern football coaching approaches (Hodges and Franks, 2002; Stratton *et al.*, 2004; Carling, Williams and Reilly, 2005; Groom, Cushion and Nelson, 2011; Cushion and Lyle, 2016). This has led to substantial growth in research in this discipline (Lago-Ballesteros and Lago-Peñas, 2010). The majority of extant research in this discipline is focused on analysis methods (e.g. Lorains et al. 2013) or outputs (e.g. Liu et al. 2016), with PA becoming increasingly sophisticated and complex (Groom, Cushion and Nelson, 2011). Research trends are increasingly focused on modelling the interactions between specific KPIs, which will be discussed in more detail in the following section (Cushion, Armour and Jones, 2006). The complexity of these parameters and needs necessitate the use of KD, as a systematic analytical approach with which to explore interactions between known (in databases) and unknown variables (derived through special sensors or through deriving the current database). The next sections discuss and expound upon these known variables, that is the KPIs, and introduce the analytical models that are currently used.

2.4.2.1 Key Performance Indicators (KPIs)

Each key moment or action in a game that can be numerically documented is referred to as an event. Events record the action, location and time of each event, in addition to any other information deemed important. As an example of this, a football pass would be recorded as the action (passes), the location in the field (X, Y coordinates) and the time that the pass was made, as well as potentially any relation or effect of the pass on the game. Researchers refer to each of these events as a Key Performance Indicator (KPI). These parameters enable individual or team attributes to be described and evaluated (O’Donoghue, 2008; Parmar *et al.*, 2017), and are most commonly used to compare players or teams (Hughes and Bartlett, 2002; Collet, 2013b; Liu, M. A. Gómez, *et al.*, 2016). In some scenarios, KPIs can also predict the outcomes of matches (Min *et al.*, 2008; Huang and Chang, 2010), with the difference between teams that win and lose being visible in terms of differences in certain game-related KPIs (e.g. quality of opposition, total number of shots on goal, or quantity of ball possession) (Hughes and Franks, 2005a; Collet, 2013c; Winter and Pfeiffer, 2016; Tenga, Mortensholm and O'Donoghue, 2017; Fernandez-Navarro *et al.*, 2018a). There is a close relationship between KPIs and KD, with KD being used to analyse, understand and control phenomena identified from new attributes, and KPI informing the performance and behaviour of players during a given match. The identification of these KPI provides a better understanding and therefore improvement of individual and team performance, including valuable insights into opponents. It has been claimed that more sophisticated, customised KPI can also grant insights into the behaviour and performance of players, leading to more effective match planning and performance. Synthesis of literature indicates that KPIs are typically classified as being physical, technical, tactical or psychological indicators, all of which can help a coach to better understand a team and their needs (Parmar *et al.*, 2017).

2.4.2.1.1 Physical KPIs

Traditionally, physical attributes and fitness are the main indicators in the analysis of sports performance (Bloomfield, Polman and O'Donoghue, 2004; Woods *et al.*, 2016; Yang *et al.*, 2018). In terms of football match results, high intensity running with the ball is a critical factor (Randers *et al.*, 2010), although it should be noted that different positions have specific bioenergetics, physical, physiological requirements (Di Salvo *et al.*, 2010; John Moores and Reilly Building, 2010). As an example of this, match performance is influenced by the ability of the midfield players to run quickly over long distances, because of their vital link role between attackers and defenders (Hughes *et al.*, 2012; Vilar *et al.*, 2013). This difference can be seen in terms of the distance covered by elite midfield players (11.5km) in comparison to elite attackers and defenders (10-10.5 km) (Mohr, KRUSTRUP and BANGSBO, 2003).

Physical KPIs are concerned with profiling and understanding players in terms of a wide range of factors. These include, but are not limited to: maximum speed and recovery time (Carling, Le Gall and Dupont, 2012; Ndlec *et al.*, 2012; Collet, 2013c); and low speed, medium speed, or high speed running (Di Salvo *et al.*, 2009; Gregson *et al.*, 2010). Studies have examined player behaviour under fatigue, in order to examine whether, and to what extent, speed and reaction time are affected (Lyons, Al-Nakeeb and Nevill, 2006; Min *et al.*, 2008; Rampinini *et al.*, 2009; Ndlec *et al.*, 2012), including examination of factors that include fatigue from overfilled calendars (Bradley *et al.*, 2014), from fasting during Ramadan for Muslim football players (Zerguini *et al.*, 2007), and the effects of fatigue among substitutes and replaced players (Carling *et al.*, 2014). Analysis suggests that the performance of football players is affected by a number of factors including short recovery periods between matches and even the playing formation, which had a larger effect on results than the impact of fatigue (Bradley *et al.*, 2011; Carling and Dupont, 2011b).

2.4.2.1.2 Technical KPIs

Technical capabilities describe the ability of players to control the ball (Hoernig *et al.*, 2016). Extensive investigations have been conducted into the relationship between this factor and physical KPIs (Kempton *et al.*, 2015), with studies identifying a positive correlation between technical KPI and physical KPIs in the prediction of match performance (Gibson Moreira *et al.*, 2015). Consistent with this logic, technical performance tends to significantly decline during the second half of a match (Rampinini *et al.*, 2009; Carling and Dupont, 2011b), with the last five minutes of games seeing the largest fall in technical skills due to the impact of fatigue on physical performance (Sarmento, Marcelino, M. Teresa Anguera, *et al.*, 2014).

Annotations capabilities are essential in understanding this relationship between physical KPIs and technical KPIs. This approach enables considerations like different dribbling styles to be annotated and analysed in terms of the success ratios of each KPI per player or per team. Another factor, which is one of most important technical KPI in football, is the ability to control the ball. Analysis shows that higher levels of control yield significant gains in the space and time available to perform a given action with the ball (Tenga, 2010; Hoernig *et al.*, 2016).

2.4.2.1.3 Tactical KPIs

In studies of sport, tactical KPIs are those indicators focused on match tactics and the successful implementation of planning (Tenga, 2010), including such considerations as successful constructive passes, team possession, ability to regain possession, and conversion rate (e.g. shots on goal to scoring a goal). There is a high correlations between the tactical KPIs and other KPIs. Hughes and Franks explained the relationship between the tactical KPIs and other KPIs in their book as follow:

"Tactical performance indicators seek to reflect the relative importance of the use of pace, space, fitness and movement, and how players use these aspects of performance, of themselves and their opponents, targeting the technical strengths and weaknesses of the respective performers" (Hughes and Franks, 2004, p. 175).

Tactical KPIs such as ball possession, (Collet, 2013c; Barreira, J. J. Garganta, *et al.*, 2014), crosses (De Baranda and Lopez-Riquelme, 2012), or interceptions and clearance (Lago-Peñas, Lago-Ballesteros and Rey, 2011; Barreira, J. Garganta, *et al.*, 2014; Woods *et al.*, 2016) can potentially be strong predictors for match results (Clemente *et al.*, 2014; Kempton *et al.*, 2015; Winter and Pfeiffer, 2016). For example, a study of the Norwegian professional football league found that tactical KPIs relating to possession, including such considerations as directness of offence or ability to penetrate opposite defence, were an effective way to distinguish teams (Tenga *et al.*, 2010b). These insights also provided meaningful strategic insights, such as the relative strength of counter-attacks versus complex attacking patterns when playing against an imbalanced defence. Meaningful gains in understanding can also be obtained from the use of KPIs to study certain actions in the context of success, like quantitative KPIs that study the importance of ball possession by examining the relative probabilities of goals being scored or conceded (Pollard and Reep, 1997).

Perhaps the most important tactical KPI in analysis of football is the passing accuracy and success (Hughes and Franks, 2005b; Tucker *et al.*, 2005; Taylor *et al.*, 2008a; Gyarmati, 2016; Rein, Raabe and Memmert, 2017). This is particularly important in the context of fatigue, with studies showing poorer tactical performance of Italian league players, as measured by differences between first and second half performance in terms of involvement with the ball, number of short passes and number of successful passes (Rampinini *et al.*, 2009), which negatively affected the amount of time that players spent in defence, midfield or attack (Lago, 2009; Ndlec *et al.*, 2012; Sarmento *et al.*, 2017).

2.4.2.1.4 Psychological KPIs

Physical, technical or tactical performance can vary widely depending on context and the mental pressure on players. These factors KPIs are known as psychological KPIs. As an example of this, game location has been shown to have a profound impact on technical, tactical and physical performance (Carling and Dupont, 2011b; Hughes *et al.*, 2012; Gibson Moreira *et al.*, 2015). Psychological KPIs can be used to explain why players demonstrate significantly higher performance levels when playing at home, due to the ‘home advantage’ (Jacklin, 2005; Hughes *et al.*, 2012; Škegro, Milanović and Sporiš, 2012; Collet, 2013b; Liu, M. A. Gómez, *et al.*, 2016; Den Hartigh *et al.*, 2018; Fernandez-Navarro *et al.*, 2018a). The reduced stress involved in playing at home can be reflected through higher numbers of goals scored (Poulter, 2009; Armatas and Pollard, 2014; Bialkowski *et al.*, 2014); more shots being taken on goal (Taylor *et al.*, 2008b; Lago-Peñas, Lago-Ballesteros and Rey, 2011; Sampaio *et al.*, 2012); more crosses (Lago-Peñas, Lago-Ballesteros and Rey, 2011; Sampaio *et al.*, 2012), more successful passes, more successful dribbles and more corners (Lago and Martín, 2007; Poulter, 2009; Collet, 2013b), as well as improved discipline, in terms of fewer fouls (Poulter, 2009) and fewer yellow cards (Lago-Ballesteros and Lago-Peñas, 2010; Liu *et al.*, 2015)..

2.4.2.2 Analytics Models

Analytic models are algorithms that can describe or explain, certain solutions or behaviours (Hazır, 2015) . The three main type of analytic models are: descriptive analytics, which focuses exclusively on frequency and ratios; context analytics, which measures sensitivity to different contexts; and predictive analysis, which utilises the other approaches to simulate likely match outcomes in particular scenarios (Sarmento, Marcelino, M Teresa Anguera, *et al.*, 2014). A brief discussion of these models is given below.

2.4.2.2.1 Descriptive Analytics

Event data is the lowest level of analysis in football performance management. This kind of data focuses on those actions that are “match-relevant and happening during the match” (Stein *et al.*, 2017b). From a technical perspective, events are timestamped occurrences of known and defined categories that are deemed important in that context. They may also be annotated with spatial coordinates or additional information, such as the players involved in the event. These data are then saved in semi-automatic coding video analysis applications (Tovinkere and Qian, 2001; Xie *et al.*, 2002; Assfalg *et al.*, 2003a; Ekin, Tekalp and Mehrotra, 2003; Xu *et al.*, 2008). A popular system for the classification of events is in terms of actions taken on the ball and those that occur off the ball (Maksai, Wang and Fua, 2015; Kamble, Keskar and Bhurchandi, 2017). Another approach is to classify events in terms of time, such as the start and ends of a given period, or in terms of the ball, such as the occurrence of a foul situation during a free kick (Liu, M.-A.

Gómez, *et al.*, 2016; Stein *et al.*, 2017a; McKenna *et al.*, 2018a). Event data is typically compiled by counting the frequency of each event in a particular match or tournament (Stein *et al.*, 2017a). A descriptive summary of events in a football game are listed below (see Table 2-1: Sample of events).

Table 2-1: Sample of events from (Stein et al., 2017c)

Event	Description
Foul Penalty	Free kick on the goal defended only by the goalkeeper
Foul direct free kick	Free kick that is allowed to be directly shot into the goal
Foul indirect free kick	Free kick that is not allowed to be directly shot into the goal
Foul throw in	Throw in that is not correctly executed
Halftime Start	First or second half starts
Offside	Player is in an offside position
Out for goal kick	Ball passes the end line after an opponent touched it
Out for corner	Ball passes the endline after a player from the own team
Out for throw in	Ball passes the sideline of the soccer pitch
Goal	Awarded when the whole of the ball crosses the whole of the
Shot on target	Any shot attempt that would or does not enter the goal if left
Shot not on target	Any shot attempt that would or does enter the goal if left
Pass	Ball touch from one player with direction towards a team
Reception	Ball touch made by the player after receiving it from another
Clearance	Hard ball touch where the player tries get the ball away from
Hold of ball	Play action when the keeper takes the ball with his hands
Running with ball	Used by the player to move the ball around without passing
Cross	Hard ball touch where the executing player is positioned in
Neutral contact	Characterized by ball touch which is difficult to control
Pass assist	The last pass to a teammate in a way that leads to a goal
Cross assist	The last cross to a teammate in a way that leads to a goal
Catch	Keeper catches the ball and hold it in his hands on a
Catch drop	Keeper does not manage to hold the ball but lets it bounce
Drop of ball	Keeper drops the ball after having caught it or holds it in
Punch	Keeper punches the ball with his hand away
Diving save	Keeper jumps to a side to catch the ball
Drop kick	Kicking a ball that is dropping to the ground as it starts to
Yellow card	Displayed by referee to indicate that a player has been
Red card	Displayed by referee to indicate that a player has been

Halftime Ends	First or second half ends
Substitution	Replacing one player with another during a match.

2.4.2.2.2 Context Analytics

As discussed above, in the overview of psychological KPIs, the factors influencing player and team performance are neither fixed nor constant. In addition to being influenced by psychological factors, there are a number of important non-psychological considerations that should also be integrated into analysis. One such factor is the impact of weather, including humidity, temperature and wetness, with some players being more vulnerable to climatic factors than others (Lago, 2009; Lago-Peñas, Lago-Ballesteros and Rey, 2011; Castellano, Casamichana and Lago, 2012; Collet, 2013b). Another important non-psychological issue for a player is the reaction, behaviour, and performance of their opponents (Tenga *et al.*, 2010a; Sarmento, Marcelino, M. Teresa Anguera, *et al.*, 2014), with logistic regression analysis of tactical KPIs demonstrating that opponent strength is associated positively with passes, but negatively with ball possession (Tenga *et al.*, 2010a; Vilar *et al.*, 2013; Sarmento *et al.*, 2017). Other studies have supported this assertion that opponent strength influences technical skills, with dribbles being affected (Taylor *et al.*, 2008b), and physical indicators, with players tending to run for shorter distances with the ball (Carling and Dupont, 2011b; Orth *et al.*, 2014).

Recent research supports the idea that indicators are context based, meaning that analysts should situate KPIs in specific contexts (Hodges and Franks, 2002; Williams and Hodges, 2005; Koehn and Morris, 2012; Mackenzie and Cushion, 2013; Fernandez-Echeverria *et al.*, 2017). For instance, player-opponent interaction results in players adjusting their performance to reflect the capacity of opponents (Moll, Jordet and Pepping, 2010; Vilar *et al.*, 2013; Sarmento *et al.*, 2017). This observation is not completely new, with older studies suggesting that chance is not an important determinant in match outcome (Reep and Benjamin, 1968, p. 585).

2.4.2.2.3 Predictive analysis

The effective integration of multiple KPIs can produce models capable of predicting match outcomes in specific scenarios (Min *et al.*, 2008; Haghighat, Rastegari and Nourafza, 2013). However, this remains a relatively unexplored area in the literature, although certain recent studies have sought to map out likely probabilities for winning or scoring for specific teams in different match scenarios (Huang and Chang, 2010; De

Baranda and Lopez-Riquelme, 2012; Mahony, Wheeler and Lyons, 2012; Ruiz-Ruiz *et al.*, 2013; Machado, Barreira and Garganta, 2014; Ibáñez *et al.*, 2018). Perhaps the most promising avenue of predictive analysis is sensitivity analysis, which entails the construction of models with parameters that can be altered to measure different outcomes (O'Donoghue and Cullinane, 2011; Collet, 2013b). Predictive systems adopt a dynamic approach to the consideration of contextual factors (e.g. goal scoring during the first 5 minutes and last 5 minutes of the match) (De Oliveira Bueno *et al.*, 2014) and factors during the match (e.g. fatigue level and stress) (Rampinini *et al.*, 2009; Redwood-Brown *et al.*, 2012; Sarmento *et al.*, 2017). The development of such models is potentially challenging and requires in-depth investigation, as well the implementation of accurate KD models by the teams involved, resulting in relatively few papers having been published in this area.

2.5 Theoretical Development: Resource-Based View

The effective creation and application of knowledge requires a number of considerations. In the modern global context, a key issue is the investment and design of technologies that are able to obtain, process and disseminate data (Gullo, 2015). There can be a diverse range of factors to explain why certain organisations use such technologies more effectively than their competitors, enabling them to gain a competitive advantage. In the context of football clubs, it remains unclear how clubs' benefit from these technologies, as these factors influencing Return On Investment (ROI) in KD are multivariate and complex. This issue of ambiguity has also been recognised in IT literature (Chae, Koh and Park, 2018), with the result that there has been extensive investment into IT business value research (Schryen, 2013). These studies suggest that beneficial outcomes are more closely related to implementation of strategies than utilisation of key technologies (Badewi *et al.*, 2018). In other words, the success of IT-enabled business transformation is primarily attributable to issues relating to 'people' (Kotter, 1995).

This kind of question can be answered through the theoretical lens of the resource-based view, which argues that performance variation primarily occurs as a result of resources (Barney, 1991), which can be financial, human, organisational or technological (Melville and Kraemer, 2004). This approach specifically attributes variation in performance to the heterogeneous distribution of available resources between organisations (Peteraf and

Barney, 2003). Resources are technological and organizational complementary resources (Melville and Kraemer, 2004).

There are wide ranges of technological resources and approaches that can assist organisations in augmenting or leveraging data. Examples of these resources include collaboration (Serrador and Pinto, 2015), distributed learning (Lara *et al.*, 2014; Khajah, Lindsey and Mozer, 2016), KD (Mariscal, Marbán and Fernández, 2010), knowledge mapping (García-peñalvo and Conde-gonzález, 2017) or intelligence (Brooks, El-Gayar and Sarnikar, 2015). Collaboration and distributed learning technologies foster more effective and constructive collaboration between individuals in a given organisation (Duffield and Whitty, 2015). KD technologies enable the exploration of internal and external knowledge, whereas organisations can use knowledge mapping technologies to track and catalogue internal data and knowledge application technologies enable existing knowledge to be utilised in more effective ways. Finally. intelligence technologies enable performance tracking and the analysis of competitors (Sun, Sun and Strang, 2018). The current research is focused on KD technology, because of its close relationship with all other knowledge related technologies.

But technological resources alone are not sufficient to realise the promised value. In this context, value is found in the effective integration of technological resources with other complementary resources (Melville and Kraemer, 2004), using both in tandem to effectively and efficiently realise value (Nevo and Wade, 2010). This has been observed in IT-enabled customer service departments, where investment in technology yields measurable benefits to the business when IT resources complement organisational complementary resources (Nevo and Wade, 2011). Research suggests that differentiated performance and competitive advantage are largely attributable to human and organisational complementary resources (Bendoly, Rosenzweig and Stratman, 2007). In a study of 13 companies that had adopted Enterprise Resource Planning Systems, Badewi (2018) found that each technological resource required certain complementary resources for optimal functioning. In the same vein, According to a study by Stratman and Roth (2002), human resources are a differentiating factor in successfully achieving sustainable competitive advantage from Enterprise Resource Planning (ERP) systems.

Human resources are referred to as 'human capital' in sports literature (Felin and Hesterly, 2007) and are acknowledged as crucial to team performance (Dawson and

Dobson, 2002). The quality (i.e. skills, knowledge and abilities) of sportspeople and coaches is a key differentiating factor in team performance (Smart and Wolfe, 2003; Holcomb, Holmes Jr. and Connelly, 2009; Jones, Harris and Miles, 2009). However, irrespective of their value, certain human resources (e.g. knowledge or competencies) are difficult to imitate because they arise from extensive training, experience or specific contexts (Wright, McMahan and McWilliams, 1994). Other organisational resources are also difficult to imitate and cannot be transferred, such as culture (Wright, McMahan and McWilliams, 1994), or communication and collaboration (Kerr and Jackofsky, 1989). Similarly, routines in coordination and collaboration to develop strategies are organisational capabilities difficult to imitate (Grant, 1991; Winter and Szulanski, 2002; Helfat and Peteraf, 2003). Basketball studies have shown that these routines can be a differentiating factor in team performance (Berman, Down and Hill, 2002).

2.5.1 Proposed KD Value Framework in Football Data Analytics

The creation of value through investment in technology can be understood from reactive or proactive perspectives. Reactive theories primarily deal with perceptions of IT and the effect that this has on behaviour (DeLone and McLean, 1992; Petter, DeLone and McLean, 2008; Venkatesh and Bala, 2008; Venkatesh, Thong and Xu, 2012). In contrast, proactive approaches focus on the ways in which technological investment tends to shape the process of value creation (Peppard, Ward and Daniel, 2007; Venkatesh and Bala, 2008; Venkatesh, Thong and Xu, 2012; Ward and Daniel, 2012). Examples of proactive theories include value management and benefits management. A hybrid stream also exists, which seeks to better understand value creation in this context by categorising factors as organisational complementary resources and technological resources (Melville and Kraemer, 2004). In the context of this study, technological resources describes the key features, ancillary systems, technological artefacts, and characteristics of a given technology (Badewi *et al.*, 2018). Effective integration of these technologies requires the presence of the correct organisational complementary resources, which are referred to as KD human resources in the current research. These include attitudes, perception, alignment, culture, norms, competences, skills, and organisational structure. The current research is adopting the framework proposed by Melville (Melville and Kraemer, 2004) to investigate and understand how teams can create value from KD. However, while coherent, the Melville framework can be criticised as being too generic to operate as the sole form of analysis for technological value creation. Therefore, this study will also utilise map framework as an analytic framework to better investigate the process of converting resources into outcomes, leading to changes being implemented to ultimately realise value or benefits.

The diagram below illustrates the discussion that will follow. It begins by underlining the value of the KD approach. As KD is a system, a review will then be provided of the technological platform, its technical requirements, and salient software applications. Finally, the last section discusses key human resources in terms of the various KD stakeholders and the value co-creation process as a whole.

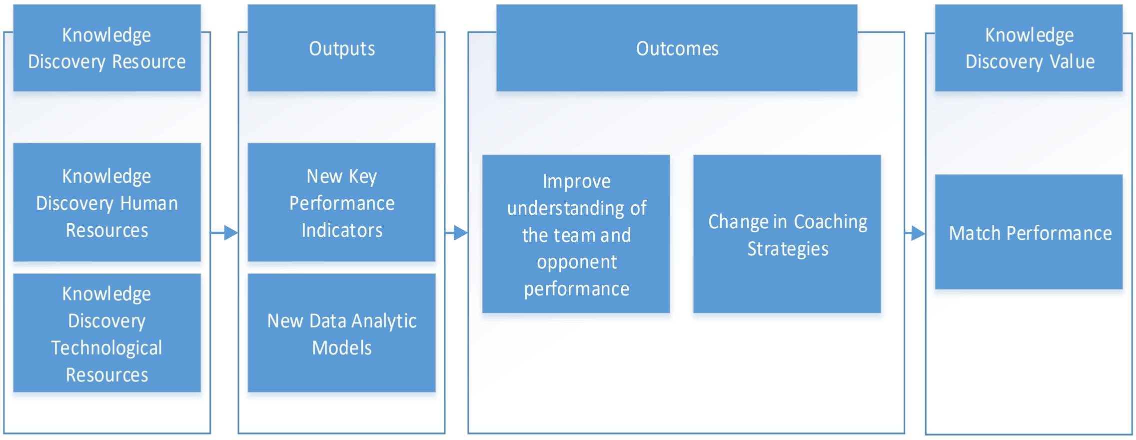

Figure 2-1: Proposed KD Value Framework in Football – © by the researcher

2.5.1.1 KD Technological Resources in football

KD systems require the integration of technology to gather accurate, meaningful data, which can then be analysed and reported, in order to provide usable insights to coaching teams (Maren *et al.*, 2005; Mooney *et al.*, 2011). In order to establish an effective KD system, it is most important for the technological infrastructure to be able to capture and analyse. Event capture technologies seek to identify, measure, track and report changes in the subject matter under analysis (Fuss, Düking and Weizman, 2018). These include wearable technologies that track the movements of players (Li *et al.*, 2016; Mara *et al.*, 2017), those that quantify patterns of motion (Stein *et al.*, 2015), and those that chart internal body behaviour in different scenarios (Moll, Jordet and Pepping, 2010; Humana, 2011; Düking, Holmberg and Sperlich, 2017; Hoch *et al.*, 2017). In contrast, data analysis technologies identify, codify, correlate, and group data in order to process it into new and usable forms of information, which can then be converted into knowledge (Seshadri *et al.*, 2017).

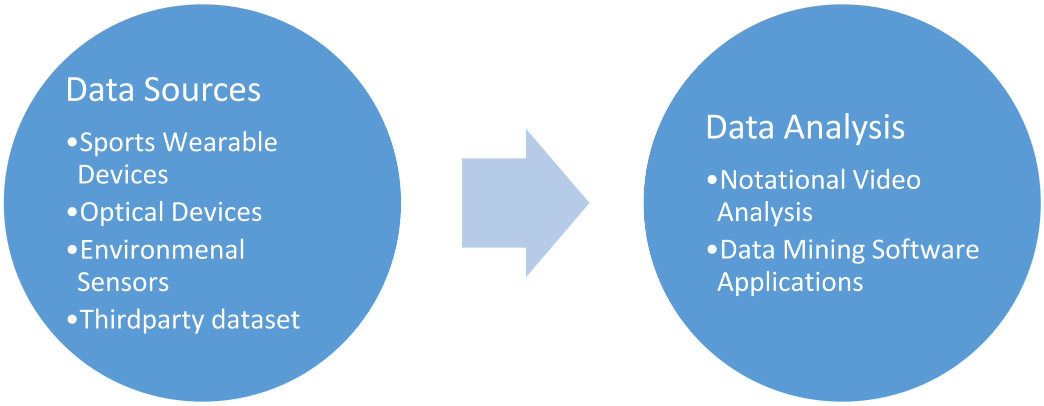

Figure 2-2: KD Technological Resources – © by the researcher

2.5.1.1.1 Data Sources Technology

In this research, data sources technologies serve to measure, track, and report issues that have the potential to improve team performance. In broad terms, these technologies can be classified into third party datasets (InStat, 2018; OPTA, 2018; STATS, 2018; STATSports, 2018); optical devices (Farin, 2005; Ronkainen and Harland, 2010; Trewin *et al.*, 2017); environmental sensors (Leser, Baca and Ogris, 2011; Rein and Memmert, 2016); and wearable sports devices (Li *et al.*, 2016; Lemire, 2018).

The third-party databases function as the source of the data. This is a comparatively cost-effective stage of the process as there are many such databases available on the market, such as InStat Opta, STATSports and Stats (formerly ProZone). The main units of third-party databases are generally teams and the players metrics (Tunaru and Viney, 2010; Liu *et al.*, 2013). These details can then be extracted, analysed and evaluated using customised tools or applications to develop understanding about the various outcomes of a game (Cobb, Unnithan and McRobert, 2018). A number of different aspects of a match can be covered, including technical analysis, physical overview, or the ranking and contribution of a given player during a match (Casamichana *et al.*, 2014), as well as analysis of possession or passing at individual or team level (Di Salvo *et al.*, 2007).. More detailed KPI can also be extracted (J. Liu *et al.*, 2013). This could entail analysis on passes, which might produce insights into numbers of passes, ratio of successful and unsuccessful passes, or numbers of passes made backwards or over short or long range (Hughes and Franks, 2005b; Cochrane, 2011; Sampaio *et al.*, 2012; Carling *et al.*, 2014).

The comparison of the Opta measurement with an independent measurement in the Spanish league found that the average difference of event time was 0.06±0.04 s for OPTA, with a kappa value of 0.92, indicating a high level of reliability (H. Liu *et al.*, 2013). Other independent studies have demonstrated the reliability of Stats (formerly ProZone) (Rampinini *et al.*, 2007; Di Salvo *et al.*, 2010). Given their acknowledged reliability, this affordable and accessible data has been utilised in the current research (Cobb, Unnithan and McRobert, 2018).

Nevertheless, the technical limitations of these databases makes them insufficient for KD and data mining tools, leading to the recommendation that datasets must be developed *"further to compete with the array of additional parameters offered by new technologies such as global or local positioning system technology"* (Casamichana *et al.*, 2014, p. 701). For this reason, teams must create and maintain their own primary databases to supplement secondary databases. The second technology to collect data is the optical devices.

Optical devices, primarily in the form of automatic video tracking and electronic transmitters (O'Donoghue, 2006; Carling *et al.*, 2008; Camerino *et al.*, 2012), have a well-recognised role in the collection of team performance data (Groom and Cushion, 2004; Mara *et al.*, 2017). These optical devices are fitted with algorithms that are capable of differentiating players in terms of their faces and shirts, enabling speed and type of movement to be measured and categorised (Assfalg *et al.*, 2003b; Farin, 2005; Ding and Fan, 2006; Schlipsing *et al.*, 2017). Automatic video tracking records the movements of each player, whether during training or match conditions (Zhou and Zhang, 2017), with newer optical devices enabling real-time auto-scaling data capture (Ryoo, Kim and Park, 2018). Importantly, optical devices only capture movement indicators, rather than information on internal factors or the external environment.

Environmental sensors measure external factors that can influence individual and team performance, including temperature, altitude, pressure and humidity (Hiscock *et al.*, 2012; Bradley *et al.*, 2014; Fernandez-Navarro *et al.*, 2018b). However, although these factors have been recognised as influential over the success of business operations (Jagadish *et al.*, 2014), the literature has neglected their use in the KD process. As the current research takes a prospective approach to KD, the data collection technologies will focus on those environmental factors that may directly or indirectly affect performance, rather than focusing exclusively on player behaviour.

The final data sources technologies are wearable devices that are attached to the bodies of players to measure their external behaviour (movement) and internal behaviour (circulation) (Chambers *et al.*, 2015). There are number of well-known examples of these technologies. For example, the Geographic Positioning System (GPS) relays data via space satellite (Rangsee, Suebsombat and Boonyanant, 2013) and Local Positioning System (LPS), which allows activities to be tracked via a nearby machine that monitors the wearable device (Frencken, Lemmink and Delleman, 2010; Leser, Baca and Ogris, 2011). Another form of wearable device is the accelerometer, which measure the number of steps taken by an individual, and heart rate monitors, which count and record heartbeats (Casamichana *et al.*, 2014; Li *et al.*, 2016; Bowen *et al.*, 2017). GPS, accelerometer and heart rate monitors are often integrated into a single wearable device called an 'Integrated wearable device' (IWD) (Dellaserra, Gao and Ransdell, 2014; Li *et al.*, 2016), many of which are capable of using a locomotor to measure the frequency of certain categories of movements (e.g. sprinting and jogging) (Dwyer and Gabbett, 2012) or measuring the frequency of contacts (e.g. closeness to other players) (Macutkiewicz and Sunderland, 2011). Finally, textile wearable devices contain integrated sensors to monitor body kinematics and physiological signals (Coyle *et al.*, 2009; Dalsgaard and Sterrett, 2014), enabling coaches to monitor players during training sessions without requiring the use of external devices.

2.5.1.1.2 Data Analysis Technologies

Data analysis technologies generate quantitative and qualitative analyses of individual players and teams, providing rigorous feedback to athletes and coaching teams (Booroff, Nelson and Potrac, 2016). In the context of this research, the chosen data analysis technologies are software-based annotation technologies and data mining technologies.

The function of annotation technologies is to enrich collected data, thereby enabling the analyst to process it with the chosen KPIs to reach the desired goals, often including enriched visual data (Cobb, Unnithan and McRobert, 2018). Annotation analysis is the most popular analysis among coaches (Booroff, Nelson and Potrac, 2016), with the majority of professional teams worldwide using this approach in the discovery and measurement of performance knowledge (James, 2006). Annotation is perceived to be relatively straightforward (Booroff, Nelson and Potrac, 2016) and able to cover numerous vital movements, including shots, corners, aerial challenges, crosses, tackles and passes

(Martin *et al.*, 2018; McKenna *et al.*, 2018b). The annotation of movements can grant coaches a deeper insight into their players, enabling them to give better, more targeted feedback (Ives, Straub and Shelley, 2002; Stratton *et al.*, 2004; Groom, Cushion and Nelson, 2011). These insights have also provided additional understanding of the relationship between injury occurrence and in-game behaviour (Carling, Gall and Reilly, 2010); the factors influencing reductions of skill in skilled physical performance (Carling and Dupont, 2011b); and monitoring load in both training and competition (Gaudino *et al.*, 2013).

As a sole performance analysis approach, this approach can become a bottleneck in the KD process (Carling *et al.*, 2013). Prior to the advent of wearable devices, non-annotated actions were not analysed or considered in terms of match strategies (Wright, Carling and Collins, 2014). Classically, notational analysis during games involved manually annotating each event recorded on camera during a match (Martin *et al.*, 2018). This traditional reliance on cameras was high inefficient, leading to the adoption of other qualitative tools, like Quintic, Dartfish, Sportscode and, MatchViewer (Wright *et al.*, 2013; O'Donoghue and Holmes, 2014; Kite and Nevill, 2017; Martin *et al.*, 2017). The objectivity of annotation analysis has been significantly improved through the introduction of specialised software applications, such as SportsCode, TRACAB, Focus X2, ProZone, and Sport Universal Process AMISCO Pro (Carling, Williams and Reilly, 2005; O'Donoghue and Holmes, 2014; Fernandez-Navarro *et al.*, 2016; Martin *et al.*, 2017).

Currently, wearable devices provide a degree of automatic annotation, although reliable capture of specific movements requires a programmer to set an appropriate algorithm. Both research and applied settings commonly utilise this approach to record incidence and outcomes of behaviour, which enables the investigation of certain technical aspects of football performance (Assfalg *et al.*, 2003b; Canales, 2014; Stein *et al.*, 2016; Xue *et al.*, 2017). However, an important criticism of annotation analysis is the inability to precisely track complex biomechanical, physiological, tactical or technical aspects of sport (Sampaio *et al.*, 2015). Annotation analysis is also reductionist, meaning that its analysis ignores important contextual factors (Groom, Cushion and Nelson, 2011; Booroff, Nelson and Potrac, 2016), and reactive, because of the unstructured focus on critical moments in a performance, (Groom, Cushion and Nelson, 2011). Because of this, irrespective of its advantages, annotation analysis, should be supplemented with other data analytic technologies (Stein *et al.*, 2017a).

The main roles of data mining technologies are grouping and correlating data, or uncovering patterns, influences and effects manifested in a certain data set (Olson, 2018), which enable new insights to be extracted by analysts. Data mining can use a number of different programming and analytical languages, including R, Python, and Java. Tools, packages and visualisation tools typically utilise Python, R, or Structured Query Language (SQL). Meanwhile, the various packages and Application Programming Interfaces (API)s used to collect and process data are generally in Python and R, with extraction and processing normally involving XML data feeds run through analytics platforms like RapidMiner, WEKA, KNIKE RStudio, and SPSS, as well as through visualisation platforms like Tableau, QlikView, Crystal Reports, D3.js, or Alteryx (Thuraisingham, 2014; Slater *et al.*, 2017). Statistical analyses in the literature are typically conducted using software applications and packages, such as SPSS, SAS, RapidMiner, WEKA and RStudio. These analyses can be most efficiently integrated using programming for data and analytics, such as R, Python, or MATLAB (Slater *et al.*, 2017; Olson, 2018). Given the array of available software and options, one of the main challenge for data analysis technologies, which includes both data mining and annotation analysis, is the cost involved in the purchase, deployment and utilisation of such technologies (Martin *et al.*, 2018)

2.5.1.2 KD Human Resources in football

KD is a socio-technical process (Ho, 2017), arising from the interaction between individuals and technology. Because of this, the successful functioning of KD requires the people involved to have the correct skills and competences, otherwise the technological outcomes will not produce the expected benefits (Groom and Cushion, 2004; Carling, Williams and Reilly, 2005). This requirement extends to all individuals involved in the analysis process, such as coaches and team managers, rather than just the analyst (Medeiros, 2017; McKenna *et al.*, 2018a). The following section will present and examine the roles involved in the KD process, then outline the way that the interaction between these roles in the agile value co-creation process results in the discovery of new knowledge.

2.5.1.2.1 Football Team Management Role

Proper teamwork requires clarity of roles (Bray and Brawley, 2002), otherwise effective teamwork will be compromised and group satisfaction is likely to fall (Eys *et al.*, 2005; Fletcher and Arnold, 2011). Clarity of roles does not mean that each role is isolated, however. Instead, it means that all members of the team should be aware of the responsibilities and requirements of the others. Analysts enquired about preferred playing style and key priorities, but have knowledge about concepts like goals, chances and set plays. This perhaps help communication and brainstorming among the analysts and the coaching team (Lyle, 2003; Nash and Collins, 2006). In the context of the management of a football team, the key roles are team manager, coach, and data analyst, each of which can be a single individual or a group, depending on the particular needs of the club (Zambon Ferraresi, Lera López and García Cebrián, 2017).

2.5.1.2.2 Team Manager Objectives and Competencies Role

The primary responsibility of a team manager is to oversee the financial performance of the team (Watts and Wruck, 1988; C. P. Barros and Leach, 2006; Kelly, 2008; Hamil and Walters, 2010; Zambom-Ferraresi, Lera-López and Iráizoz, 2017; Kilpatrick, 2018); or to maximise profit (El-Hodiri and Quirk, 1971; Szymanski and Smith, 1997; Rohde and Breuer, 2017). Extensive research has investigated the topic of maximising the financial returns of football clubs (Szymanski and Smith, 1997; Garcia-del-Barrio and Szymanski, 2009; Hamil and Walters, 2010; Kuper and Szymanski, 2018), although recent research has tended to emphasise sustainability over profit. There is an established assumption that sports managers maximise utility to achieve non-profit goals, consuming resources in pursuit of satisfaction rather than profit (Sloane, 1971). In this sense, it is important to distinguish between performance success, which refers to the ability of a coach to win matches, and profit success, which describes the ability of a team manager to ensure financial sustainability and profitability (Carlos Pestana Barros and Leach, 2006).

(Plumley, Wilson and Ramchandani, 2017) state that there are three primary cases that might arise in terms of the relationship between financial success and winning match success. In the first scenario, greater profits might improve team performance, or more successful teams might become more profitable. In this case, no conflict exists between satisfying the desire of shareholders to obtain profit and the desire of fans to win. This relationship is typical of the situation in the stock market model of ownership of privately owned clubs (Wilson, Plumley and Ramchandani, 2013). In the second case, successful performance does not necessary result in increased profitability. A correlational study into the relationship between profit and the league positions of 40 football clubs (1978-1997) found no significant evidence that changes in league position brought a corresponding change in profit (Szymanski and Kuypers, 2000, p. 22). Finally, in the third scenario, successfully winning matches might cause or be attributed to lower profits, such as when players are overpriced or there is poor investment at the club. This relationship would require shareholders to decide upon an acceptable balance between profit and performance. In all cases, there is a fundamental link between sporting and financial activities and this association is essential for the operation and sustainability of football clubs (Szymanski and Kuypers, 2000, p. 22).

In summary, the role of the team manager is to balance performance and profit, although with an emphasis on profit in order to satisfy stakeholders. There is generally a more positive relationship between financial performance and team performance among teams listed on the stock market than teams that are either privately or publicly owned. Nevertheless, poor investment can harm teams, even when they are successful. However, examination of the team manager is beyond the scope of this study, because concentrating on financial aspects could adversely affect the quality of this research.

2.5.1.2.3 Coach Objectives and Competences

The sole objective of the team coach is to help the team to win matches (Cushion, 2001; Ingle, 2013; Vilar *et al.*, 2013; O'Donoghue and Robinson, 2016). As a consequence of this, coaches invest heavily in analysis of performance and associated problems using a range of data, reports and videos (Wright, Atkins and Jones, 2012). Some coaches utilise sophisticated, objective data, while others rely more heavily on personal intuition and judgment (Adjei *et al.*, 2013; Medeiros, 2017). Many models exist to conceptualise and investigate the myriad competences required by team coaches. The first is Santos *et al.*'s (2010) theory, which focuses on a number of competences: annual and multi-annual planning; practice and competition orientation; and personal and coaching education. Additionally, coaches who are cooperative and work effectively with data analysts invariably use data more effectively to develop advanced plans and training scenarios (Martin *et al.*, 2018).

In many clubs, data analysts, and particularly performance analysts, play an instrumental role in the coaching process (Groom, Cushion and Nelson, 2011; Nelson, Cushion and Potrac, 2013). Coaching involves guiding players, but also leading and building trust between the coach and his players, which benefits from transparent, objective performance analysis technologies (Nelson, Potrac and Groom, 2014). Coaches also sometimes act politically with the motivations and intentions of the team (Booroff, Nelson and Potrac, 2016). In this scenario, analysis can become a tool to assert power, which can harm the perceptions, relationships and culture of the club (Booroff, Nelson and Potrac, 2016).

2.5.1.2.4 Data Analyst Competences

Performance analysts work within the football coaching team to ensure that all data is utilised efficiently and effectively (Davenport and Harris, 2007). Data analysts play a critical role in team success, with research demonstrating that coaches supported by data analysts receive more information and are therefore better able to understand match dynamics than when coaches attempt to fill analytical roles themselves (Martin *et al.*, 2018). In some teams, the data analyst role involves teams of specialists, working in recruitment analysis, opposition analysis, and even academy analysis (Hatton, 2013; Wright *et al.*, 2013, 2016). However, despite this growing prevalence, the role of data analyst is relatively recent within team management as a whole. For example, according to a recent survey on Australian football, only 13% of the coaches have access to data analysts, which limits their advanced planning potential (Martin *et al.*, 2018).

It is important to note that the role of data analyst is different from that of sport scientist. A performance analyst at a large club, such as in the English Premier League, will focus on examining match strategies and team performance, whereas the sport scientist will be responsible for the physical aspects of performance (Garganta, 2009a; Wright *et al.*, 2016; Sarmento *et al.*, 2017). Data analysts must demonstrate statistical and technological competences, enabling them to effectively utilise sophisticated data analytics technologies (Wright, Carling and Collins, 2014; McKenna *et al.*, 2018a).

2.5.2 Modelling Development Approached: Agile Value Co-creation Approach

In modern football teams, data analysts produce data and the coach or team manager consumes that data. This relationship benefits from close cooperation and interaction, in order to ensure that the analyst properly understands the needs of the consumers and is therefore able to translate them into statistical models for the testing or exploration of certain aspects or issues. As summarised in Table 2-2, there are two main model development approaches: Waterfall (also called Push), which is a relatively simple process that fits clear outputs, and Agile, which is more suitable for outputs that are complicated and difficult to express.

Knowledge creation is fuzzy and challenging to articulate clearly in advance (Du Chatenier *et al.*, 2009). Therefore, development of tailored, needs-based solutions requires collaboration between the model producer and model consumer. In other words, the discovery of new useful knowledge requires constructive positive cognitive sharing and interaction among different stakeholders (e.g. data analysts, team managers, coaches, physiotherapists) (Jones, Harris and Miles, 2009; Martindale *et al.*, 2010). This collaboration is known as the value-co-creation process (Prahalad and Ramaswamy, 2004). The following sections outline the model development approach to illustrate the use and validity of the value co-creation approach. This is followed by an in-depth discussion of agile value-creation models and the various tools involved in agile models.

Table 2-2: Push versus value co-creation production created by the researcher

	Push Production	**Value Co-creation Production**
Waterfall	Traditional project management approach	Client is involved in designing the solution but not involved in producing the solution
Agile	Client is involved in the production, but the scope is ambiguous, but the client is not involved in the production	Client is involved in designing the solution and involved in producing it. Knowledge Discovery Agile value co-creation approach

2.5.2.1 Knowledge Development Approaches: Waterfall versus Agile

The traditional waterfall approach is most appropriate and efficient when working with a clearly defined and deliverable scope in a stable environment, often over repeated projects (APM, 2015). In contrast, the agile approach is more suitable with vague scopes or requirements, which need flexibility and regular stakeholder feedback. Agile methodologies benefit from clear, scheduled tasks, carried out quickly, flexibly, in phases, and with adaptation following a clear well-understood plan. As an example of this, the digital services in the United Kingdom government utilise an agile approach (GOV.UK, 2018).

Development of tailored, needs-based solutions requires collaboration between the model producer and mod el consumer. In other words, the discovery of new useful knowledge requires constructive positive cognitive sharing and interaction among different stakeholders (e.g. data analysts, team or measure key metrics (Carling, Williams, et al. 2005; Hughes 2004; O'Donoghue 2006). The use of waterfall depicts a simple, linear process in which the consumer clearly articulates their requirements and the producers fulfil those needs. However, given the complexity and iterative requirements of coaching (Lyle, 2003), agile approaches may be more useful. This approach encourages close collaboration between client and producer, which is especially useful when the needs are not clearly identified and the producers therefore do not have clear guidelines. For instance, telling stories as an agile based tool can improve collaboration in football teams at the management level (Perin, Vuillemot and Fekete, 2013). This perspective argues that the job of the data analyst is therefore to listen to the coach about the stories, to tell stories and to express findings, rather than to provide an exhaustive list of statistics about games or players. This is reflected in the review of literature, which did not find explicit research to demonstrate how agile development can develop new models in the knowledge discovery approach.

2.5.2.2 Agile Based Approach

Modern dynamic digital services utilise iterative approaches to manage complex challenges, such as those discussed above. Agile offers a way to overcome the rigidity of the traditional project management approach, which suffers from "too much planning" (Boehm, 1996) and is challenged by the inability of specifications to differentiate and clarify deliverables from prototype. In addition, early specification of requirements can lead to extraneous features being added, the lack of opportunities to alter or develop functionality, and the immutability of focus, which is especially problematic given the likelihood that requirements or environments will change. In a study of 1386 projects, the relationship between planning and delivering promises was found to be an inverted U (Serrador and Rodney Turner, 2014).

Agile approaches share certain values and principles, as underlined in the Agile Manifesto (*http://agilemanifesto.org/*) (Collier and Highsmith, 2010; Sutherland and Schwaber, 2017), emphasising flexibility, leanness and engaging the clients (Conboy, 2009). Traditional project management methodologies experience difficulties in dynamic environments (Collyer *et al.*, 2010), leading to increased reliance on Agile, which utilises minimal documentation to make the approach more flexible, while also increase responsiveness to changing conditions (Serrador and Pinto, 2015). Agile methodologies encourage iterative user engagement throughout the developmental cycle (Serrador and Pinto, 2015), with daily meetings to ensure that clients are updated, involved, and satisfied throughout the process (Mann and Maurer, 2005).

Historically, these kinds of methodologies when software developers sought better practices and key values with which to manage the development process (Beck *et al.*, 2001).

Establishing solid theoretical foundations for the definition of agile methodology in the specific context of the current research requires a review and synthesis of the three most relevant definitions in the literature. The first definition is a software development practice that seeks to manage issues relating to high levels of uncertainty, dynamic and frequent changes, short development cycle, digital deliverable and custom based systems (Abrahamsson *et al.*, 2002; Dingsøyr *et al.*, 2012; Hobbs and Petit, 2017). The second definition focuses on the 'evolutionary' aspect of the development process:

"Agile software development is an evolutionary (iterative and incremental) approach which regularly produces high quality software in a cost effective and timely manner via a value driven lifecycle" (Ambler, 2009, p. 6).

According to this definition, agile methodology is disciplined and self-organising, with a high degree of collaborative from active the active involvement of stakeholders to ensure that their diverse, evolving needs are met. The final definition transcends the narrow understanding in software engineering to encapsulate the diverse needs of the market and technology. In this sense, Agile refers to the ability of a team to respond quickly to the technological or market needs of customers or stakeholders, enabling "better project and product performance in an innovative and dynamic project environment" (Conforto *et al.*, 2016, p. 547).

As the concept of required knowledge is fuzzy in terms of usability, usefulness, and fitness, different definitions are required for the projects used to uncover or develop knowledge. Building on previous definitions, this methodology is a co-created iterative approach to the development of customised solutions to fuzzy problems. This research is informed by the Agile approach to the discovery of knowledge as a deliverable, which is produced by data analyst in conjunction with continuous interaction with the coaching team. The Agile approach can utilise a number of different tools and techniques: user stories, on demand scheduling (Kanban), sprint, retrospective, and burn down charts. These will be discussed in more detail in the following sections.

2.5.2.2.1 User Stories

'User stories' refers to a technique for modelling and understanding the multitudinous requirements of users in an agile project. These stories serve as building blocks to conceptualise and inform projects (Inayat *et al.*, 2015), utilising the stories to divide up the work to be completed by the team, working in consultation with customers or owners of a product (Agile Alliance, 2018a). User stories were first introduced as a part of the traditional XP practices (Beck, 1999) and later as a core component of the XP2 evolutionary practices, reflecting the importance of obtaining and understanding user requirements to make meaningful improvements to software or application quality (Beck and Andres, 2004).

A user story is a way to capture a technology application or software functionality. Each story should address: who (the type user or consumer of the piece of technology), what (the need to develop or use the technology), and why (the benefits and outcomes) (Patton, 2014). User stories are scheduled and extracted from backlogs that sort and rank according to their particular importance, relevance, category or scope within the cycle or iteration (Dimitrijević, Jovanovic and Devedžić, 2015).

2.5.2.2.2 Story Mapping

User Story Mapping is a usage-centric approach in which agile teams visualise the stories that they are working on (Rubin, 2012), using terms like 'activity' or 'epic' to reflect on the primary categories of the task, and 'task', 'theme' or 'subtask' to reflect on less important categories (Rubin, 2012; Patton, 2014). Using a Story Mapping approaches encourage user-centred design and decomposition of story requirements in the workflow context (Rubin, 2012; Taibi *et al.*, 2017). The effect of this is that agile teams can obtain a better overview and understanding of the stories at a low level, as well as a high level understanding of the entire project to ensure commonality of vision (Taibi *et al.*, 2017).

2.5.2.2.3 Agile Release Planning

The purpose of the release planning technique is organising, categorising, and prioritising user stories during the mapping process. Effectively, release planning is a roadmap of the release plans for a particular project (Dimitrijević, Jovanovic and Devedžić, 2015).The release planning technique groups related user stories in terms of the area of functionality within the final application, product or service (Heldman, 2011). In Scrum (an Agile approach), this approach is referred as Scrum Resales Planning, which focuses on what will be delivered and how that aim will be achieved (Sutherland and Schwaber, 2017). All members of the Agile team should be involved in these types of planning activities, thereby ensuring consistency of approach to user stories (Alliance, 2018) and agreement on deadlines and the number of releases required (Cohn, 2004).

2.5.2.2.4 On-Demand Task – a Kanban Technique

Kanban is the method that Toyota devised to implement an Agile methodology (Ahmad, Markkula and Oivo, 2013; Saltz, Shamshurin and Crowston, 2017; Agile Alliance, 2018b). In this approach, tasks are scheduled on-demand or as a Work In Progress (WIP) (Ahmad, Markkula and Oivo, 2013). Kanban focuses on visualising the WIP and associated work iterations as fully transparent (Matharu *et al.*, 2015). In contrast to Scrum, Kanban allows iterations to be changed (Wang, Conboy and Cawley, 2012), with WIP enabling stories to be delivered in other ways, as each piece of work is updated as it is completed.

2.5.2.2.5 Sprint

Sprints is the most common short Agile technique (Baird and Riggins, 2012; Hobbs and Petit, 2017). It is mostly used in Scrum because iterations are time limited, with work being forbidden on additional User Stories or changes (Rubin, 2012). Every Sprint includes specific Sprint Backlog items that are prioritised based on the decision of the Scrum Product Owner and the Scrum Team decided which work to carry on and for how long (Adjei *et al.*, 2013; Sutherland and Schwaber, 2017).

2.5.2.2.6 Retrospective

The retrospective technique enabled teamwork to be improved by reviewing the feedback, advantages and disadvantages after every Sprint (Stellman and Greene, 2014). The process of sharing feedback with the team is a crucial final step of the Scrum or XP. This enables plans and improvements to be carried forward to the next spring, improving the output and performance, as well as increasing trust within the team. The development of intra-team trust is the main goal of this stage in the iteration (McHugh, Conboy and Lang, 2012). However, because retrospective enables the verification and validation of team progress, if all members are not present at these meetings then the team may be adversely affected (Drury, Conboy and Power, 2012; McHugh, Conboy and Lang, 2014).

2.5.3 Agile Value Co-creation

Value co-creation is a client-centred strategy (Nambisan and Baron, 2009) that originated in marketing literature as a way to conceptualise the design of services through and based on the client (Prahalad and Ramaswamy, 2004; Auh *et al.*, 2007). This concept was later utilised in the development of service-oriented architecture in IT research (Ordanini and Pasini, 2008). In terms of football literature, value co-creation has been employed in the design of strategic governance models to oversee the integration of local trusts and football clubs (Castro-Martinez and Jackson, 2015). However, value co-creation has not been specifically defined in terms of sport management. Therefore, a definition has been adapted from other disciplines to match the current context. Accordingly, this research defines value co-creation as the process of collaboration among the members of the coaching team (team manager, coaches, data analyst and sports scientist) to create new analytic models and use new technologies to discover knowledge in the datasets. This strategy seeks to blend different perspectives to obtain a mutually valued outcome (Prahalad and Ramaswamy, 2004). In this vision, all participants (i.e. data analyst, coaches, team manager, and other stakeholders) have their own views, needs, and interpretations of the data. For instance, while a coach manager might have a preference for visualised techniques, such as video analysis, the data analyst is likely to be more quantitative oriented. Combining these views may produce deeper, more insightful analysis of data through the development of new models (Mackenzie and Cushion, 2013). Presentation and interpretations may also be affected by social environment, the philosophy of individuals or their roles, and the particular qualities of recipients (Groom, Cushion and Nelson, 2011; Barbour, Treem and Kolar, 2017). By extension, any proposed intervention of video analysis from an analysts would entail careful consideration of the format, design of session and delivery, and specific targeted outcome (Groom, Cushion and Nelson, 2011). Hence, communication during the value co-creation process is vital to ensure understanding of the reports and associated technology outputs (Booroff, Nelson and Potrac, 2016), as misunderstandings can result in incorrect or unwanted consequences, lack of commitment, and limited or incorrect understanding of the various metrics (Wright, Atkins and Jones, 2012).

Much of the literature stresses the importance of trust and respect in the collaboration between the members of the team, including manager, coach, and data analyst, as well as including athletes, assistant coaches, and administrators (Potrac, Jones and Armour, 2002; Jones, Armour and Potrac, 2004; Cushion, Armour and Jones, 2006; Potrac and Jones, 2009; McGarry, T., O'Donoghue, P., & Sampaio, 2013, pp. 175–186). Trust can improve understanding and reduce conflict between stakeholders (Groom, 2012; Groom, Cushion and Nelson, 2012), ultimately improving the value co-creation process.

In summary, stakeholders collaborate to produce a fuzzy output (knowledge), based on fuzzy requirements (knowledge requirements for taking a proper decision), creating the need to combine concepts (the agile approach and the value co-creation process) to create the Agile value co-creation process. This new process facilitates understanding of the creation and discovery of knowledge, ultimately improving the co-creation development process.

2.6 KD Maturity Models (MMs)

Maturity Models (MMs) are developmental models that describe the ability of an organisation or system to produce a specific outcome or logical relationships between the development routes of certain dimensions, attributes, or processes (Kuznets, 1966). Early forms of maturity are evident in the work by Maslow (1970), Kuznets (1966), and Nolan (1973; 1979), who created a hierarchy of human needs, economic growth, and IT progression in organisations, respectively. Maturity models assume that organisational development is predictable and structured. For this reason these models are extensively used in Information Systems (IS) literature, especially in data analytics (Chen and Nath, 2018). The current research is primarily focused on these models in the organisational context.

MMs help organisations to meet performance objectives by providing valuable insights into current levels of capability, process, and resource development (Cosic, Shanks and Maynard, 2012), as these theories offer a systematic overview of organisational capacities along a particular projected path (van de Ven and Poole, 1995; Gottschalk, 2009). In other words, MMs are *"a set of characteristics, attributes, indicators, or patterns that represent progression and achievement in a particular domain or discipline"* (Caralli, Knight and Montgomery, 2012, p. 3). In IS literature, MMs demonstrate the process through which organisations attain certain levels of technical competency and strategic alignment (Becker, Knackstedt and Pöppelbuß, 2009a).

MMs are utilised in the current research. In order to provide a coherent understanding of the rationale for this and a theoretical basis for the use of this model, the following section discusses the purpose for the development of maturity models. This is followed by an overview of the structure of MMs, including key mechanisms, components, and the main aspects in the design, after which the section presents the presenting different approaches and types of MM. This discussion concludes with a critical examination of the literature on MMs in the field of data analytics, which is believed to be the closest form of MM that can utilised within the context of KD in football.

2.6.1 Maturity Model Purposes

MMs have three possible purposes of use: descriptive, prescriptive, and comparative (De Bruin *et al.*, 2009). In other words, MMs are used to describe current situations, predicting possible futures based on identified areas of weaknesses, or comparing different cases based on a particular set of measures. Each purposes of use is described in more detail below.

A descriptive purpose for MMs uses diagnostic tools to investigate certain attributes and practices in order to identify areas for development and provide an informative assessment to stockholders (Becker, Knackstedt and Pöppelbuß, 2009b; Maier, Moultrie and Clarkson, 2009). This enables MMs to evaluate or control progress and inform developmental initiatives (Iversen, Nielsen and Norbjerg, 1999), utilising sets of characteristics, goals, indicators, practices and processes to better understand and assess the patterns of work in an of the organisation (Rosemann and Bruin, 2005; De Bruin *et al.*, 2009). In contrast, a prescriptive purpose evaluates the current maturity of an organisation to create viable strategies and paths towards desired levels of development (Becker, Knackstedt and Pöppelbuß, 2009b). Finally, a comparative purpose compares data from a current MM with historical data in order to benchmark internal and external performance and progress (De Bruin *et al.*, 2009; Maier, Moultrie and Clarkson, 2009).

2.6.2 Maturity Models Structure

In broad terms, MMs are measures that create a sequenced progression path from one state to a desired mature state (Becker, Knackstedt and Pöppelbuß, 2009a; Gottschalk, 2009). This involves two main components: Maturity Levels and Measured Components.

Maturity Levels, or stages, represent different levels of progress or improvement over time. These levels are characterised in terms of stages-of-growth models, stage models, or stage theories (Prananto, McKay and Marshall, 2003) and must be aligned with the culture, strategies and structure of the organisation.

Measured Components are the processes that deliver the needs of the proposed Maturity Levels (Pöppelbuß and Röglinger, 2011). These components are often organised hierarchically into multiple layers (Rosemann and Bruin, 2005) and include competence objects, maturity levels, criteria, and methods for data collection and analysis (M.C. Paulk *et al.*, 1993). Fraser *et al.* (2003) state that these components usually consider the following, as part of the activities undertaken at certain levels of maturity: levels, descriptors, descriptions for each level, capability areas (dimensions), activities for each capability area, and a description of each activity. Finally, general frameworks exist to inform the structure and function of MMs, creating a practical approach for the design and use of these models (Pöppelbuß and Röglinger, 2011).

2.6.3 MM Approaches

There are three main approaches taken by MMs: progression, capability, and hybrid (Mehravari, 2014). A progression model is a lifecycle approach that focuses on improving organisational maturity, with no relation to process or capability. A capability model focuses on improving performance in terms of process and goals from one maturity level to the next through the assessment of processes and capabilities (Wendler, 2012). Finally, a hybrid model mixes both models, with maturity being constructed to reflect on development in terms of improvements in performance (Eppler, 2014).

Maturity models can be either focus on a single process or the entire set of available processes (Proença and Borbinha, 2016). In the former scenario, the MM investigates the capability to complete a specific task, such as obtaining or designing a technology, whereas the latter approach examines the ability of the entire organisation to complete tasks efficiently (Rosemann and Bruin, 2005; Hammer, 2007).

2.6.4 Capability Maturity Model (CMM)

The Capability Maturity Model (CMM) was one of the most common MMs in literature and in professional contexts. This framework was designed to assess and develop software processes and performance in the software industry (Caralli, Knight and Montgomery, 2012). CMM examined three components: Key Process Areas (KPAs), Process Capability and Maturity Levels (Mark C. Paulk *et al.*, 1993). The CMM was adapted by companies and universities, and was extended to better focus on certain organisational requirements (Dawson, 2009). The CMM was replaced by the Compatibility Maturity Models Integration (CMMI) framework in 2010 (CMMI, 2010; CMMI Product Team, 2010, 2018).

The Capability Maturity Model Integration (CMMI) was created in 2000, with the creation of a single framework from three integrated MMs. This framework, the Capability Maturity Model for Software, System Engineering Maturity Model and the Integrated Product Development Capability Maturity Model, has subsequently informed the development of other MMs, such as the People Capability Maturity Model (P-CMM). Versions of the CMMI framework exist for acquisition, development, people and services, and a new version (V2.0) of the CMMI Development Framework was recently released(CMMI Institute, 2018).

The adoption of the CMMI framework results in improvements in key processes areas, increased organisational capability and higher levels of maturity (Software Engineering Institute, 2005, 2010; CMMI, 2010; CMMI Institute, 2018). CMMI assesses organisational change in terms of the match between business strategies and capability levels, which are specific developmental goals, or maturity levels. The function of CMMI versions is to provide information for adaptation or modifications based on a specific score to meet the organisational or team needs in the fulfilment of specific sets of strategies.

2.6.5 Data Analytics Maturity Models

MMs for data analytics systems measure the ability of organisations to integrate and utilise knowledge in organisational decision-making (Popovič, Coelho and Jaklič, 2009; Popovič *et al.*, 2012; Chen and Nath, 2018). For instance, Chen and Nath (2018) investigated management perceptions and attitudes. They discovered that the maturity of business analysis influences both process performance and organisation performance. As will be discussed in detail below, Business Analytics Maturity Models are generally classified into technical focused, organisation focused or mixed.

2.6.5.1 Technical Focused Maturity Models

Technical MMs focus on technical aspects of IT infrastructure in terms of connectivity, data warehousing, integrability and security, with earlier versions focuses on those aspects most relevant to enterprise data architecture and Business Intelligence (BI) applications. Examples of technical MMs include Watson *et al.*'s (2001) Data Warehousing Maturity Model, which uses levels of growth to classify technical capabilities into three stages (initiation, growth and maturity), which are defined by nine characteristics of enterprise data warehouses. Another example is Eckerson's (2004, 2009) six-stage MM for data technology implementation, which was inspired by human growth. The final example is Tan *et al*.'s (2011) Enterprise BI Maturity Model, which measures four dimensions (analytics capabilities, data warehousing architecture, information quality, and master data management) to determine five maturity levels.

These technology focused maturity models are criticised for a failure to recognise the relationship between BA technology and the culture, powers, processes, strategy and structure of organisations (Lahrmann *et al.*, 2011).

2.6.5.2 Organisation Focused Maturity Models

Organisation MMs are the other category of BA, with an exclusively non-technical focus on people aspects of a company. The first example of this kind of MM is Gartner's Maturity Model for Business Intelligence and Performance Management, which uses a five-point scale to evaluate dimensions including availability of performance metrics, levels of business sponsorship, organisational structure support, and scope of the BA initiative (Rayner and Schlegel, 2008). The second example is Capgemini's (Capgemini, 2012) Predictive Analytics Maturity Framework Assessment which seeks to maximise business benefits by the evaluation and optimisation of the maturity of the predictive analytics environment of an organisation in terms of its competence, deployment, enablers, governance, strategy and vision. The third example is Davenport and Harris's (Davenport and Harris, 2007) DELTA model (Data, Enterprise orientation, analytics Leadership, strategic Targets and Analysts) which focuses on a number of analytical factors in an organisation: "Analytically Impaired, Localized Analytics, Analytical Aspirations, Analytical Companies and Analytical Competitors". Another organisation MM was developed by Harriott (2013) to assess the effectiveness of analytics strategy and then develop structured development paths to optimise value output from investment in business analytics. Harriott's MM uses seven dimensions, which are "business challenges, data foundation, analytics implementation, insight, execution and measurement, distributed knowledge, and innovation". The final example is The Data

Warehousing Institute (TDWI) model, which looks at readiness for analytics, culture, data management, internal politics, and skill sets, in order to categorise an organisation in terms of five levels of analytics maturity. This enables identification of business drivers and cultivates a positive BA environment, in which analytics are properly integrated and strategically aligned (Halper and Stodder, 2014).

These kinds of BA MM are criticised for ignoring technological aspects of business. This led to the development of the third stream of BA MM, which focuses on the integration and alignment of technical and organisational dimensions.

2.6.5.3 Integrative Maturity Models

One of the most notable capability-focused MMs is the BA Capability Maturity Model (BACMM) (Cosic, Shanks and Maynard, 2012). The BACMM focuses on assessing capability in governance, culture, technology and people, evaluating a range of technical, organisational and strategic issues on a five-level scale of maturity from ‘non-existent’ to ‘optimized’. This comprehensive approach has resulted in the BACMM being criticised for its generality, as the model is broadly applicable to most IS contexts and phenomena. There is also little evidence of empirical testing to validate the claim that the BACMM leads to a sustainable competitive advantage.

In general, impact-focused BA MMs focus on organisational performance and decision enablement. As an example of this, Teradata’s BI and DW Maturity Model examines the impact of analytics on certain business processes and decision capabilities in terms of five maturity levels: reporting, which seeks to categorise events; analysing, which looks at the reason for events; predicting, which tries to determine likely future events; operationalising, which looks at current events; and activating, which describes the push to make events occur (Olszak, 2016).

The IDC’s Big Data and Analytics Maturity scope examines organisational development towards the effective and efficient use of data in decision making (Vesset *et al.*, 2013). This model examines quality of data, strategic clarity, people (skills and culture), process improvement, and sophisticated of technology. These are graded in terms of five stages, from ‘Ad Hoc’ to ‘Optimized’, to predict maturation of organisational capabilities. IDC states that technological and data capacity develops faster than strategic intent and people.

Similarly, the Business Intelligence Maturity Hierarchy (BIMH) illustrates the knowledge management capability of organisations in terms of data, information, knowledge and wisdom (Rajterič, 2010). Finally, Lahrmann *et al.* (2011) studied an impact-focused maturity model of BA with 103 business and IT practitioners. Their study validates the theory that a MM based on deployment of BA technology lead to greater internal process efficiency and overall performance in the adopting organisation. The assessment of BA maturity should involve the measurement of those areas most affected by analytics(De Bruin *et al.*, 2009; Souza and Gomes, 2015). However, the review of MMs suggests that many models focus on certain aspects of BA maturity, rather than comprehensively examining all related aspects and considerations.

2.6.6 Criteria for a "Good" Maturity Model

MMs face certain inherent challenges which should be overcome during the development of a model. Ahlemann *et al.* (2005) state that MMs should have a solid empirical base, software tool support, standardization, flexibility/adaptability, benchmarking applicability, certification, disclosure of potential for improvement, evidence of correlation between maturity model adoption and performance. Good capability assessment models should be cost-effective, reliable and valid, as well as using good academic evidence (Simonsson, Johnson and Wijkström, 2007), however many MMs are overgeneralised and do not have a sufficiently rigorous empirical base (Benbasat *et al.*, 1984; King and Kraemer, 1984a; Rosemann and Bruin, 2005; McCormack *et al.*, 2009). Additionally, MMs are not applicable for all industries or sectors (Mettler and Rohner, 2009). Even when they are applicable, the design must clarify the need for continuous improvement before prescribing a set sequence towards a specific "end state" (King and Kraemer, 1984b) leading some authors to design MMs as lifecycles or continuous processes (Becker, Knackstedt and Pöppelbuß, 2009b; De Bruin *et al.*, 2009; Maier, Moultrie and Clarkson, 2009; Mettler, Rohner and Winter, 2010; Solli-Sæther and Gottschalk, 2010; van Steenbergen *et al.*, 2010).

2.7 Synthesis of the Literature Review

The literature review for this research covers the following areas to aid in developing and understanding the width and depth of the research. Additionally, to aid in improving the current Football Data Analytics practices within the coaching team. Table 2-3 highlight the major research subjects that are investigated in this research to develop the models, framework and the maturity model.

Table 2-3: Research Subjects used in this research

Subjects	Related Paper Subjects	Sections
Knowledge	To understand the definition of knowledge and the key differences between Data, Information, Knowledge and wisdom.	2.2
Knowledge Discovery	To look at the definitions and the descriptions of KD in the computing, informatics, information technology, information systems	2.3
KD in the Football Industry	This is to review the related applications on KD in the domain of football. Also, the objectives of using KD, Data Mining, Data Analysis and related subject in football data analytics. Also, to reflects on the current needs of developing performance analysis applications in football based on the variations of the KPIs (i.e. psychological, physical, technical and tactical). Finally, to look at the subjects of FDA used in football in order to understand the analytical model used in this research area.	2.4
Knowledge Discovery Value	Most of the studies focus on the what would football data analysis would benefit researches with minimal focusing in what would be the value of FDA. The review in this subject addresses these concerns. That aided in the development of the initial framework.	2.5
The initial KDV Framework in Football Data Analytics	The scope of the area of the literature it to build the framework, the models and sub-models needed to address the needed of the research. The subjects covered here are the Technological Resources in football (i.e. data sources and data analysis technologies), The KD Human Resources (i.e. Team management roles, competences for the different roles (i.e. team managers, coaches, data analysts, and the members of the coaching teams). Additionally, it covers the Agile approaches, tools and artefacts that are best suitable to use in addressing the research needs. Finally, it reviews the principles of developing Maturity Models (MM) (i.e. purpose, structure, approaches, the variant application of MM and the criteria of developing good MMs)	2.6

2.8 Summary

This chapter sought to review and synthesise the literature relevant to the knowledge discovery process and associated resources, with particular reference to football. Based on this review, the Melville framework has been adopted to structure our understanding. This paradigm argues that technological and complementary resources are important for the delivery of outcomes, with consideration of human resources, technological resources and value. A definition was provided of the concept of value in the context of KD to develop a new functional definition for the sports industry. As the main mechanism for the realisation of value through the KD system is performance analysis, a review was then conducted into analytic methods and KPIs. The second section models for use by football teams, the literature in this area was outlined, with particular reference to MMs and data analytics. The next chapter will introduce the methodology utilised as this research aims to operationalise the results into a maturity model for use by football teams, the literature in this area was outlined, with particular reference to MMs and data analytics. The next chapter will introduce the methodology utilised to extend, improve and validate the Melville framework, as outlined in the literature, to fit the needs of the football industry.

Chapter 3 Research Methodology

3.1 Introduction

This chapter aims to provide a detail examination and discussion of the research philosophical stances to answer this research question and fulfil the objectives of the current study. Based on the question and the philosophical stances embraced, the research strategy is developed to inform the adoption of the research methods and analytical approach. This chapter begins with a discussion of the research philosophy, following this with the resultant research strategy, presented in terms of research methods. This is followed by the research analytic approach proposed to provide insightful knowledge from the research activities. Finally, the chapter concludes by looking at the research ethics governing the data collection and analysis process, and the process by which the quality of the current research was maintained.

3.2 Research Paradigm

This research aims to develop a framework for understanding the value co-creation process in the football industry through the use of knowledge discovery systems. In order to develop the philosophical stances governing the research strategy by which to fulfil this aim, it is necessary to first identify the nature of knowledge (ontology) and how to obtain this knowledge (epistemology).

The two main research concepts are the interpretive paradigm and the positivist paradigm, each of which is built upon certain ontological, epistemological and axiological stances (Creswell and Miller, 2000). The ontology defined "what" is the knowledge and characteristics of the knowledge (Teddlie and Tashakkori, 2012). This can be a single global reality or numerous different contextual realities (Walsham, 2014). Ontological stances can characterise the definition of science in terms of relationships between concepts (Poli and Obrst, 2010) or the understanding of a given phenomenon (Walsham, 1997). The positivist paradigm defines knowledge as a set of relations between different concepts (Venkatesh, Thong and Xu, 2012), whereas the interpretivism paradigm believes that knowledge cannot be understood through relationships and requires in-depth investigation. Because of these beliefs, positivists define a framework as a set of propositions and models as sets of tested relations while interpretivists define a framework as an abstraction of reality and models as sub-sets of that framework

(Tashakkori and Creswell, 2008). The model is defined as a set of tested relations for the positivists while interpretive defines the model as a sub-set of the framework (Gregor and Hevner, 2013). The aim of the current research is to develop a framework for understanding the value creation process, rather than testing it. Therefore, the knowledge shall be framed based on the interpretive ontological stance, in which reality is abstracted in terms of value creation in the knowledge discovery process, rather than testing relationships between concepts.

Ontology discusses whether reality is external and unknown, or internal and known. In other words, ontology governs the question of whether respondents are assumed to 'know' the knowledge, which the researcher must grasp, or the respondents are assumed to not 'know' the knowledge, meaning that the researcher should discover the relationship between concepts. Positivism primarily believes that knowledge is unknown and that correlations should be derived to test propositions; interpretivism mainly believes that knowledge is known and so researchers should capture the insights of participants. Because the KD process happens intentionally, the respondents shall be informed of the intentions and rationales of their activities, meaning that the interpretivist ontological stance is most appropriate for adoption in this research.

Epistemology is concerned with the question of 'how' to gain knowledge (Lincoln, Lynham and Guba, 2011). Here, positivists believe that the best way to gain knowledge is to take an active position in setting propositions, from the literature, and testing it. In contrast, interpretivists believe that researchers should understand the knowledge, enabling them to draw the abstraction of reality in a framework, in its context (Walsham and Waema, 1994). The interpretivist believes that the researcher shall understand the knowledge, to draw the abstraction of reality in a framework, in its context, which is called social construction of reality. The current research follows the interpretivist paradigm to socially construct reality in the context through face-to-face discussions with each participant, supplemented by examination of their practices and behaviours. This is important because the different financial support and resources available to coaches in each team creates differences based on context. Furthermore, each manager has an individual rationale for the various practices involved in their role, making reality different in each context. This is important because the contingency theory stipulates that there is no correct prescription for all managerial and decision making issues, because the best mechanism should be used to fulfil specific aims in specific contexts (Drazin and de Ven, 1985). Accordingly, it could be important to understand each coach practices, rationales, and intentions alone then consolidating different views in different contexts to develop a comprehensive framework.

Axiological stance defines the level of subjectivity or objectivity in a given piece of research. Positivists believe that researchers are fairly objective and that they use objective tools to test the propositions of their studies (Mertens, 2007) . In contrast, interpretivists believe that a researcher will inevitably have a subjective understanding of contextual factors and, by extension, reality. From this perspective, the background and education of the researcher influences how the perception and interpretation of interviews and facts surrounding them. Accordingly, the researcher has taken many courses in coaching and data analytics to be able understanding the participants thoroughly. Although this can provide insights to a problem, too much subjectivity can destroy the credibility of the research, which is a risk inherent to interpretive research, such as the current study. For this reason, this research will adopt a conceptual framework derived from the literature to guide the data collection, data analysis, and reporting process (Aliseda, 2006). This framework is not intended to limit or propose certain relations, but rather to highlight the concepts that need to be investigated to ensure less subjectivity in perception and understanding. This is supplemented by use of validation techniques, to ensure that respondents have similar understanding of the researcher, and the use of a verification tool to construct new arguments for those with less knowledge or awareness.

3.3 Research Strategy

This research is a multi-phased (three) study based on a design science research methodology (March and Smith, 1995), meaning that it seeks to address and develop a solution for a certain problem (Peffers *et al.*, 2007). The aim of the current research is to answer the following question:

“Why are some teams better able to get value from investing in knowledge discovery technologies than others in the football industry?”

A maturity model was required to assess the abilities of teams to realise the value gained from investment in KD technologies. In the specific context of this study, design science differs from traditional research approaches in the sense that it not only attempts to understand the reasons for differences in realising the value, but also seeks to develop tools for teams to benchmark their capabilities. The development of such a tool requires that research concepts be identified, taxonomised, and operationalised into scales for assessment (Gregor and Hevner, 2013). In the current research, this process involved operationalising the expected value of KD to the coaching team, identifying and categorising KD resources, and depicting a model of the role of football technologies in improving coach performance. This was carried out to enable the research to identify and frame the role of different knowledge, skills and competences required from producer (i.e. data analyst) and consumer of the knowledge (i.e. coach), thereby enabling the expected value from KD to be realised.

As recommended by design research (Hevner, 2007), this research is organised into three phases. The first phase sought to understand the AS-IS to develop a framework that explains variations in understanding to develop the initial framework, models, and tools based on an assessment of coaching awareness and use of KD in developing football related strategies. The second phase involved the development of the maturity model. Finally, the aim of the third phase was validating the framework and verifying the maturity model, in order to ensure the quality of the research outputs. The interviewees listed in Table 3-1, Table 3-2, and Table 3-3 will be discussed, analysed, referred, and discussed in more details in Chapter 4 Chapter 5 Chapter 6 .

3.3.1 First wave of interviews: Developing the framework

Development of the framework started with in-depth interviews with experts, coaches, data analysts and coaches. The following sections outline and discuss the sampling method, interview guide and analytic approach adopted in the development of the research framework utilised in the current research, as well its subset models and tools.

3.3.1.1 Sampling

The sampling approach adopted in this research is purposeful and selective (Suri, 2011). This means that the selection of respondents is based on strict criteria, in order to inform the development of a constructive framework to aid teams for improving the value realisation from investing in KD technologies. Because of this aim, well-informed opinions were required, which means that participants needed to be experienced. Therefore, the first criteria were three years of experience in football. The second was that experts had senior positions in their teams (only team managers, coaches, and data analysts). The third criteria were that participants had to be based in the chosen geographical scope of this study: i.e. Saudi Arabia. Interviews with experts from the British League were used to advise on the current status of Saudi practices, so that a constructive framework can be developed. A pilot study was conducted and then interviews were held to discover current practices in utilising the KD technologies in Saudi Arabia. Participants were coaches, data analysts and team managers from the premier league, youth league, second league, and Olympic league in Saudi Arabia, as well as certain high-level decision makers in the Saudi Arabia Football Association. Since 2018, there are sixteen teams in the Saudi Professional League (SPL) (GSA, 2018), as well as one Olympic team, a youth team, and a national team (SAFF, 2018). These teams constitute the population of this research. Invitations were sent to all eligible coaches, team managers, and data analysts in Saudi Arabia. Interviews were scheduled for a duration of 1-2 hours, in an attempt to understand their perspectives on optimal usage of KD resources.

Table 3-1: Wave 1 - Initial Participants – Framework Development

Code	Team / Bodies	Role
W1TD	Football National Teams	Technical Director & Expert (Coach, Player in Different Leagues)
W1FC2	Football Club - 1st Team	Coach
W1DA3	Football Club - 1st Team	Analysts
W1DA4	Football Club 1st Team	Analysts
W1FC5	Football Club - Olympic Team	Head Coach
W1DA6	Football Club - Olympic Team	Analyst
W1FC7	National Olympic Team	Coach
W1FC8	Football Club - 1st Team	Coach
W1FC9	Football National Teams	Assistant Coach
W1DA10	Football Club 1st Team UK	Analysts
W1BM11	Football Organisation - UK	Performance Analysis Team Member
W1BM12	Football Organisation - UK	Performance Analysis Team Member
W1BM13	Football Organisation - KSA	Technical Committee
W1RS14	Rugby Club	Director of Performance Analysis
W1PSC15	Sports Data Consultancy	Data/Video Analysts
W1BM16	Football Organisation - KSA	Technical Committee
W1PSC17	Sports Data Specialists - UK	Representative - Sports Data Specialist
W1PSC18	Sports Data Specialists - International	Representative - Sports Data Specialist
W1PSC19	Sports Consultancy - KSA	Manager – Football Data Specialist
W1PSC20	Sports Consultancy - KSA	Representative - Football Data Specialist
W1PSC21	Sports Data Specialists	Live Scouting Administration

3.3.1.2 Interview Guide

The invitation was accepted by five teams from the premier league, the Olympic team, the youth team and the national team. The research utilised semi-structured interviews, examining components of the conceptual framework. As a brief summary, these components are value (i.e. benefits), outcomes (enhanced use of data analytic models and key performance indicators in planning and coaching), the technological resources, human resources (required skills, competences and knowledge), and value co-creation process and tools. The questions focused on the current and required knowledge of coaches and data analysts regarding the effective utilisation of KD technological resources. Since KPIs are the main outputs of KD, questions also discussed the main KPIs used by the team manager and data analyst, how they were developed, and how they benefit from KD resources. Finally, interview questions focused on the value co-creation process across the stakeholders, looking at issues like communication, tools, and mechanisms used in listening and understanding the needs or expectations of stakeholders, and the types of knowledge required by the team.

3.3.1.3 Analytic Approach adopted

As the sample size in the current research was too small for thematic analysis, other analytic approaches were evaluated for adoption. The closed coding was used to guide the data collection and analysis process (Charmaz, 2006). The theoretical lens of this research was provided through a combination of the Melville framework, benefits mapping, value co-creations, and Agile frameworks, which are discussed in depth in the final chapter. Closed coding does not mean rejecting other interesting ideas (Urquhart, Lehmann and Myers, 2010), instead providing a flexible, open starting point for the analysis. The significance of the rationale is weighted in terms of the plausibility and feasibility of a statement, as perceived by the researcher, rather than number of respondents. Although this approach has an obvious inherent bias, the results of the research were contrasted with the literature to ensure the validity of the research findings, as well as being subjected to the aforementioned validation and verification process in the final phase.

3.3.2 Developing the Maturity Model

Maturity Model (MM) were developed using the results from the previous phase. The MM was adopted for this development process and customised to meet with the specific needs of this research, as they, e.g. CMMI and DELTA (see section 2.6.5) was originally intended for use in software development, therefore requires adaption for new analytic contexts (Kim and Grant, 2010). However, this research aims to developing new analytic models to develop new technologies are similar process. This research borrowed the CMMI from the software engineering literature to apply its approach to KD literature. Questions were prepared on the Likert scale (5 items, from strongly disagree to strongly agree). The maturity model was designed immediately prior to the framework being completed. The face validity of the model was ensured by having three interviewees answer the questionnaire, to ensure that any misunderstanding or miscommunications were eliminated, which improved question clarity and focus for the respondents.

3.3.3 The Second Wave of Interviews: Validating the Framework

The second wave of the interviews were intended to validate the results of the first wave, as well as to validate the maturity model. This wave focused on obtaining data from experienced individuals in senior positions, due to the belief that they would have greater insight into the applicability and usefulness of such technologies. Interviews were conducted with those in the Saudi Arabian Football Federation positions, such as the executive manager of the technical committee, technical committee members, and the director of the Academy of Football. Senior figures from local teams were also interviewed to gain their perspectives on results.

Table 3-2: Wave 2 - 2nd Participants (Framework Validation)

Code	Team / Bodies	Role
W2TD1	Football National Teams	Team Director – Former Player – Former Coach
W2EM2	Football Federation	Executive Manager of the Technical Committee
W2TCM3	Football Federation	Technical Committee Member – Professional coach
W2FC4	Football Federation - Football Club Academy	Professional Coach – Academy Director – Former National Team Coach
W2FC5	Football Federation - Football Club Academy	Professional Coach – Academy Director – National Youth Team Coach – Scouting & Talent Identification
W2FC6	Football Federation - Football Club Academy	Professional Coach – Professional Player Mentor
W2FC7	The UK Football Association	Professional Coach
W2FTM8	The UK Football Association	UK Team Manager
W2SC9	University	Principal Lecturer in Sports Coaching Science
W2TD10	Football Federation	Ethics Discipline Committee

3.3.4 Third Wave of Interviews: Verifying the framework

The last wave sought to assess the weaknesses and strengths of each team regarding the technological and human resources required to use KD effectively. Data analysts and coaches from five teams completed the assessment and were sent the analysis, after which their feedback was received and analysed. The five teams represent different leagues in Saudi Arabia, in order to achieve a representative view of teams in different categories. Thus, two teams were selected from the professional league, Olympic national team, under 19s national team, and one team from the secondary league.

Table 3-3: Wave 3- 3rd Participants (Verification and MM - Application)

Case	Code	Team	Role	Team / Bodies
Case 1	C1P1	CT1	Video Analyst	Football Club - 1st Team
Case 2	C2P1 C2P2	CT2	Assistant Coach Data Analyst	U19 National Team
Case 3	C3P1	CT3	Data Analyst	National Olympic Team
Case 4	C4P1	CT4	Assistant Coach	Football Club - 1st Team
Case 5	C5P1	CT5	Football Coach	Football Academy Club

3.4 Research Quality

The research quality process serves to ensure that a study produces outcomes that reflect reality and that the data obtained are suitable to address the research question, especially given the subjectivity way in which human understand and process ideas, which is integral to interpretivist research. During this process, five main indicators are considered in order to determine quality: reliability, validity, credibility, reflexivity and transferability. These criteria will be briefly outlined below in general terms, and then discussed in detail in the following sections.

Reliability describes the truthfulness of participants in a study (Rossman and Rallis, 2003), which is important because people can become inclined to misrepresent their perspectives or to give intentionally mislead with their answers for a variety of reasons, including a dislike for being observed, a feeling of shyness, or even because of a perceived lack of security (Kirk and Miller, 1986). In recognition of this tendency, a number of specific measures were adopted to ensure the integrity of the interview and to guarantee the ability, and willingness, of participants to speak freely on the topics under investigation.

Validity describes the accuracy with which a researcher has understood the statements and utterances of the participants in their study (Arksey and Knight, 1999; King and

Horrocks, 2010). Therefore, I took extensive notes and paraphrased the answers of respondents, then checked these interpretations with the interviewees in order to assess whether my understanding of their meaning was a fair representation of the meaning that they had intended to convey.

Credibility describes the correctness of any records made of participant contributions, in terms of accuracy in the `observations and transcripts (Lincoln and Guba, 1985). Throughout the three waves of interviews, there were prolonged engagements with experts in this domain in order the understand the context and dialects of the coaches, team managers, analysts and relevant stakeholders. Additionally, I took professional analysis courses, official coaching certificates, attended workshops, conferences and professional training to gain as much as possible of up to date experts' knowledge within the field. Moreover, I met with football journalists, football associations and football federations members to gain knowledge of current trends and current practices and issues of this area of the research (Lincoln and Guba, 1985). In order to ensure that a high degree of credibility was achieved, all interviews were recorded, transcribed and translated. Exceptions were made in those situations where participants explicitly forbade recordings, such as for reasons of security. In these cases, a degree of credibility was sacrificed in return for access to valuable data.

Reflexivity describes the relationship and the reflection of the researcher on his research. It is a process of which the researcher engages with his research, communicate with interviewees, develop and improve knowledge in the research area, observe and analyse interviews and questioners. This should lead to maturing the knowledge gained from aliening that with literature readings to consolidate concepts and understanding. As well to which the framework utilised in the study is trustworthy and the rationale for the interpretation of data is suitable for its intended purpose. In consideration of this issue, the literature was evaluated to ensure that the researcher was cognizant of the salient facts.

Finally, transferability, which concerns the applicability of the research practices and finding outside the research context and how this research could aid in other research areas.

Table 3-4: Summary of research qualities

Research Quality	Definition	Measure used
Reliability	Participants are telling the truth and their discourse is constant over time.	Asking the same question in different ways at different times. Showing a consent form to confirm that all data gathered are confidential and will not be shared with anyone.
Validity	Ensure that the understanding of the researcher matches that of participants.	Paraphrasing the answers and ensuring similar results. Emails were sent to give confirmation of the interviews.
Credibility	Ensuring that everything written is correct, truthful and trustworthy.	Consistency of the report with few contradictions between findings by using a recorder and recording interviews, then checking transcripts.
Reflexivity	Ensuring that the researcher's understanding is correct, and her interpretations are the most suitable in the context.	Evaluating different possible understandings of the facts using literature review and different rationales.

3.5 Research Ethics

This research study targets experts in the domain of football coaching because the study involved human participants, it was necessary to consider ethics and gain ethical approval from the researcher's university. Ethical approval was granted based on that. Towards this informed consent was conducted whereby participants were informed about the purpose of the study and their consent was gained. The participants were also informed about their right to withdraw from the study at any time.

3.6 Chapter Summary

This chapter aimed to discuss and set the methodological foundations for this research. This is an interpretive research adopting design science strategy to develop a framework for understanding the value co-creation process of the Knowledge discovery resources in Football so that a maturity model can be used to assist the team manager evaluating their teams' abilities to realise value from investing in the KD. The literature is used to set the theoretical lens for this study and set the methodological basis for defining the sample, interview guide and analytic approach of this research. This research follows three phases: developing the framework, developing the maturity model, and validating and verifying the maturity model and the framework. The next chapter will be the first of three in depicting the findings.

Chapter 4 Knowledge Discovery Resources

4.1 Introduction

The analysis is presented over two chapters while the validation and verification are devoted in a separate chapter. This chapter aims to investigate the required resources for gaining value from the knowledge discovery activities while the following chapter focuses on the value of the knowledge discovery activities. These couple of chapters are ended by value co-creation knowledge discovery maturity model to operationalise these research findings into an assessment tool that can help team managers for gauging their capabilities to realise value from knowledge discovery.

This chapter adopts Melville et al. (2004) framework in identifying and classifying the required resources. According to Melville et al. (2004), the value from investment in technology comes from IT resources and complementary resources (i.e. people/human resources). The same framework is adopted in this research to understand the required resources.

This chapter structures as follow. After spotlighting the required IT resources as an infrastructure for the knowledge discovery activities, Human resources and their competences are identified. Based on the common challenges faced in the HR communications, proposed Agile methods for improving the knowledge discovery process.

4.2 The KD Technological Resources Model

The first model of this research is to understand the role of IT resources in the knowledge discovery. In this model, it shows that there are five types of technologies are perceived to be critical for the knowledge discovery. They are tracking technologies, body sensors, annotation software, database interfaces, and knowledge discovery analytics. They have been classified into hardware and software categorise as visualised in the Figure 4-1. Data capturing technologies in terms of tracking technologies and body sensor aim to capture live data in the match time and in the training time. The annotation software is to give meanings to different data taxonomies and ontologies. The historical data are combined in the analysis through having an analytic interface to retrieve and use historical data. Finally, data analytics systems consolidate these data, after cleaning them, to develop new analytic models or KPIs for discovering new knowledge.

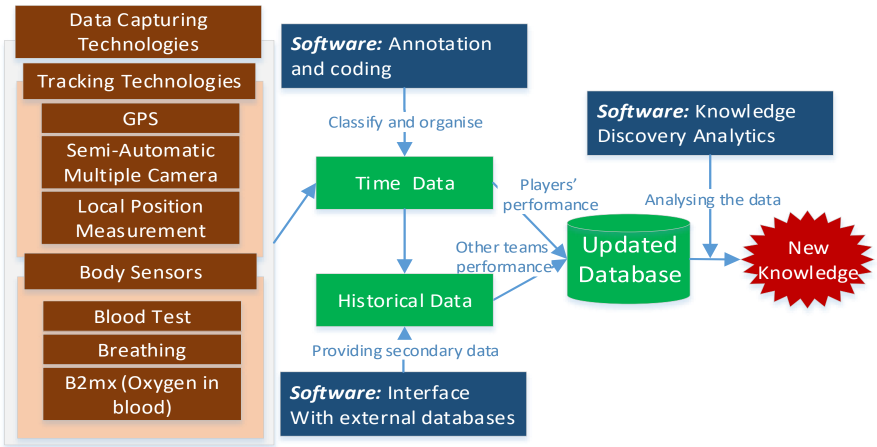

Figure 4-1: IT Resources model for enabling knowledge discovery - © by the researcher

4.2.1 Hardware required to collect the data

The KD process in the football industry requires technologies to record and track the players' movements and to measure the external environmental factors. The technologies can be classified into body sensors and tracking technologies. Body sensors are those wearable devices that track the body physical performance. The body sensors outputs include the heart rate, VO_2 max, and B2mx (Oxygen in blood).

> *"Yes, maybe I know where you are going. I have many positions in the field, but also I have many kind of measuring VO_2 max, I can check if the player breath under masses, have all kind of information. I want to show you know, let's see what happen"* ***W1FC2***

In contrast, tracking technologies measure and report the positions, movements and actions of players, in addition to weather indicators such as temperature and humidity. Tracking technology generates massive data that can motivate the coach to explore and discover the implications and uses of these data. This argument is conditioned by certain capabilities required from the coach, as will be discussed in team manager and coach competences sections.

Not all teams in the sample were found to have access to similar technologies: two teams out of eight have all technologies, with seven having tracking technologies, and one team (T3) having no access to any form of technology at the time of interview. Two months after the interview, the researcher was informed by the team analyst that they had bought tracking technology. Limited or no access to tracking and annotation technologies can be perceived as a disadvantage that constrains the KD process, however manual data collection is a viable substitute to other technologies.

> *"We do that manually. We do very primitive analysis due to limited access to first hand data. Through my assistants, we can calculate number of successful and unsuccessful passes and number of shooting. We cannot do more due to the technological constraints."* W1FC8

The managers or the coaches of teams without KD technologies must often rely on secondary data or analytic reports published by specialised companies. However, these commercial secondary data have certain inherent limitations, because the data are not updated, not in-depth, and not customisable. Outsourced analysis from external sources is limited to camera-based data, which still lacks the use of sensors in tracking physical performance. The outsourced analysis can feed in tactical and technical performance and basic physical performance.

> *"Just the one I show you before, Stats. With Olympic team we use video and trying to get GPS data" W1DA4.*

> *"We use InStat before with national teams but now I only use visual observations." W1FC5*

4.2.2 Software: Knowledge Discovery System

Software applications required for KD are three: data base interfaces, annotation, and analytics. The three technologies are perceived to be important. The first software required, which is usually web-based service outsourced from external vendor, is the interface for accessing the vendor data of other teams and other matches in the league. This is the most accessible and prevail across the teams that are affordable to subscribe.

> *"I provide the data in different format to reflect in his view. We use Opta reports and InStat to access secondary databases for getting information about players and teams in the league" W1DA4.*

> *"Yes, that is the problem I had, when I first got Opta data about last year, and when I got it last time, I was amazed about it, what is this. It was 90 minutes of events-based dataset of everything happening in the Match. What will I do with this, I have not seen dataset like this before. I said ok, that is a good thing, it is a good structure and good quality." W1TD.*

Using this data, a coach or data analyst can model and understand the performance and behaviours of opponent teams in a variety of different situations. The second software application is for annotation, based upon code data received from the sensors and tracking technologies. These technologies generate huge quantities data, which can be coded and annotated for comparison with external data, or which can be modelled and analysed by analytic applications.

> *"With Olympic team video analysis and observations. Stats, ProZone when I was the analyst of the first team." W1DA6*

> *"Regarding the methodology, I was thinking about linking the data between the 1st team and the Olympic team, not only using one tool or application, but using any suitable, useful technologies that could provide a future benefit. All the data we have starts from the 1st team, though. There is nothing from the teams before." W1DA4***.**

The main benefits of annotating the primary data is the availability and its depth, which are not available in the secondary data. However, it needs more technical human resources, as will be discussed later. The reason is that it implies more coding and customisation abilities than the standard reporting system such as Opta and InStat. Thus, fewer teams are adopting this type of applications.

> *"We have software to annotate movements. It gives us the information about the real time and game we can see that the midfield covered more distance then the forward player, the midfield they covered the medium speed in the game 5km per hours and the forward covered less distance that speed in the game use 10 or 8 km in the average so that the different." W1FC2*

Finally, the data analytic applications can facilitate the development of sophisticated analytic models to enable the creation of effective, targeted knowledge (e.g. predictions, estimations, probabilities, scenarios, confirming and verifying certain believes or plans) to meet the specific needs of each team.

> *"We use Top Sports Lab to predict performance and injuries" W1TD*

> *"We use fitness data, we work also with InStat football (InStat Scout) very nice algorithms and key performance indicators for players and teams' performance (technical and tactical data)." W1TD*

In summary, all of the teams utilise software applications that provide access to secondary data. Four of the eight are using the annotation technologies. The reason for this choice seems to be less concerned with the technology and more with the perceptions of the team managers and the specific capabilities of the data analysts, as will be discussed in the human resources sections below.

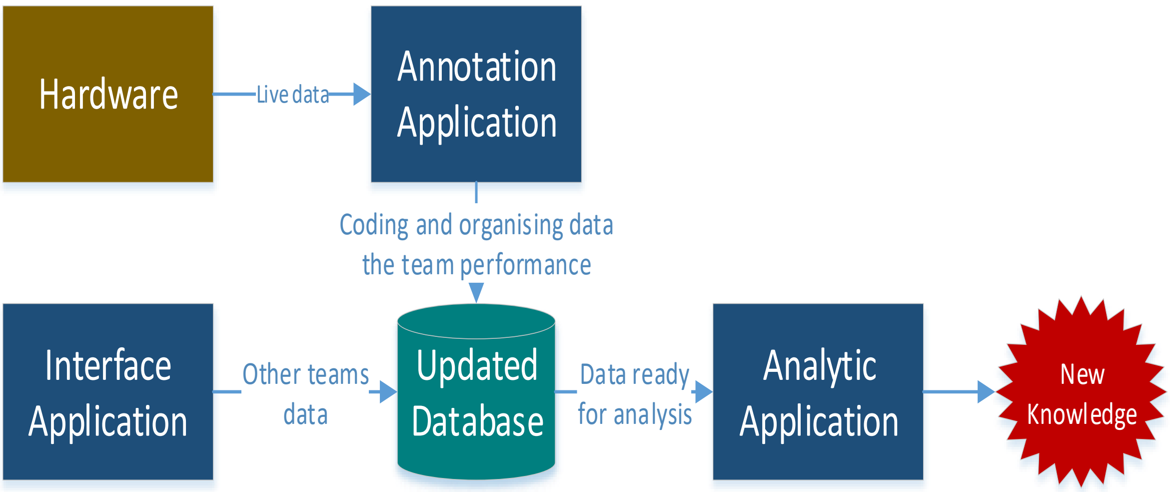

Figure 4-2: A model to show the relationship between different software applications and hardware in discovering knowledge - © by the researcher

4.3 The KD Human Resources Model

The main actors in the value creation process are the consumer of the knowledge (i.e. team manager) and the producer of the knowledge (i.e. data analyst). The various capabilities and the relationships between these parties in the KD process are outlined in diagrammatic form below in Figure 4-3.

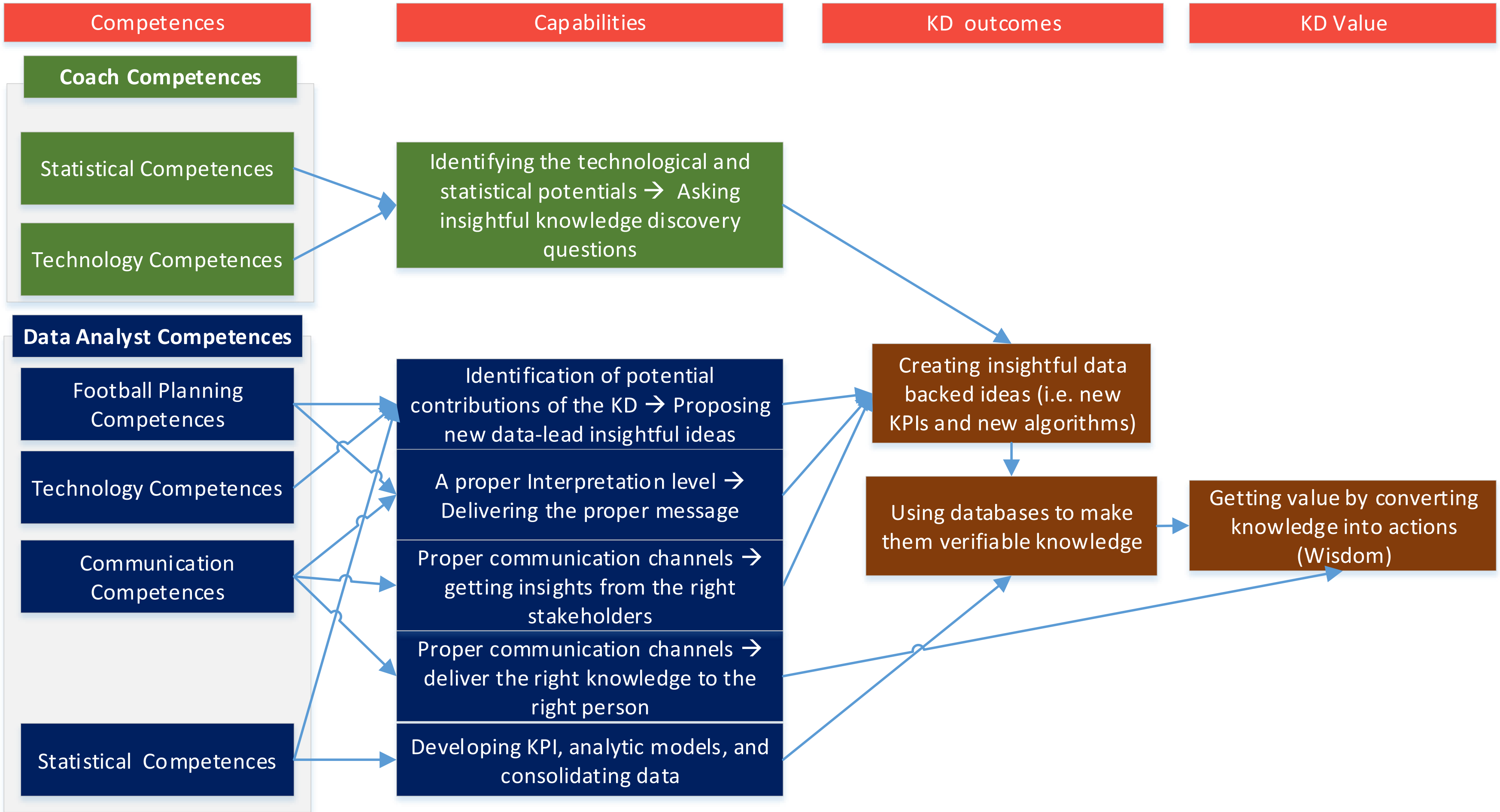

Figure 4-3: A model to explain the role of different competences for discovering knowledge for football teams - © by the researcher

4.3.1 Consumer of the Knowledge: Coach Competences

The head coach is expected to have complementary skills that enable him to communicate with the data analyst, to understand the data and, to recommend new exploratory questions in such a way that new, pertinent, useful knowledge can be discovered and utilised in the fulfilment of team aims. Without such competencies, communication is likely to be influenced negatively, resulting in the KD process suffering.

> *"Honestly the board members they did not have sport technical background, so in this case you can only offer basic details. On the other hand, I was developing some reports, and I email it. But there was no feedback and there was no specific methodology, there were no time for this, and the time was limited and only for one season." W1DA4.*

The main competences required here are statistical competences are to read the reports, which refers to the ability to interpret the reports and to translate their strategies/ideas into hypotheses/questions, and technological competences, which involve knowing the limitations and capabilities of the systems. Although data analysts have a responsibility for analysis, mutual understanding is instrumental in improving the KD process. It can be difficult to establish mutual understanding when the team manager does not possess the requisite competences.

> *"[There is a] lack of knowledge among head coaches. This is the main reason for no engagement in the knowledge discovery process from the systems." W1TD*

The summary of key findings is summarised in Table 4-1.

Table 4-1: Summary of key findings regarding the role of the coach competences on the effectiveness of knowledge discovery process

	Findings
1	The team coach perception of the usefulness of the knowledge discovery and positive attitude towards the knowledge discovery technologies play a role in utilising benefits.
2	The problem formulation is based on the team coach's ability to comprehend the problem
3	The team coach is bounded in his ability to comprehend the problem by his perception and his understandings
4	Team coach who has more experience and awareness of the knowledge discovery tools and knows more about the data science, are able to articulate the problem in a more detailed and data driven way
5	Team coach who are aware of relevant data and have analytical understanding of available data are able to address their team performance needs precisely.

6	Team coach who has more closed relationship and more frequent meetings with the data analysts are more able to define their needs in a more specific and clear way. Also the reports used are richer than others
7	The problems are structured over the time. Each coach by the time has certain needs and certain problems. This can hinder the team manager to be able to discover and explore new insights from the data.

4.3.1.1 Statistical Competences

KD axioms are based on the discovery of insights from data that enable the discovery of new knowledge. Research states that the attitude of team managers regarding statistics can determine the intention to use KD practices. According to the theory of reasoned action, when users believe that a system could improve performance and productivity, their intention to use the system improves (Ajzen and Fishbein, 1980).

> *"So, what I believe is that we are not ready yet, with data science and only few coaches use it or either afraid of it, they do not use it because they are afraid of it but I believe that its will be one of the most important aspect of football" W1TD.*

> *"Couches are too afraid, there are no secrets" W1TD.*

The knowledge and awareness of the statistics and acknowledging the importance of it plays a significant role in shaping the attitude toward the use of statistics in discovering knowledge.

> *"Were to board members were not aware of the benefits these tools or this information could help and supports them, were thy naïve about it, don't know what the outcomes of it, what they could achieve of this, what opportunities of could lead to, the technical staff were worried about what data could leak or exposed or the players could not understand it and cannot digested it, many things really, and my responsibilities were very limited as an analyst." W1DA4.*

On the other side, some coaches have a belief in and understanding of statistics, enabling them to do more through the KD process.

> *"Statistics are all information that we know about the players. We can rely on it. We process and clean data to be used by data analyst and myself. I am repeating that statistics are very powerful and can change the game rules, only if you understand, read and able to interpret them. In this way, it can transform the team manager thoughts, expectations, and strategies" W1FC9*

If the coach knows statistics, he will be able to propose questions and ideas that can be answered through the data.

> *"Depends on the coach, for example, other coaches may ask more about players data because he is into analysis and technologies" W1DA4.*

> *"It is honestly depending on the coach and what information he wants to use to his advantage, and fully know how to use it and utilise it." W1DA4.*

> *"When I was working in Marseille with "Marcelo Bielsa" and he is crazy about statistics and performances, we collect all of the data and based in these data we talk about fitness. Marcelo knows very well what he wants from the data and how to deploy them in his match strategy development" W1TD.*

The coach can recommend how analysis should be done, in order to ensure that he can access the required outputs.

> *"It depends what I need from the data. I direct the data analyst how to analyses to get what I want. The more the classifications of the data, the more I will be able to get what I want" W1FC7.*

4.3.1.2 Technology Competences

More useful and relevant knowledge is created when team managers are better equipped to use and understand the functions and capabilities of data analytic systems.

> *"[We are] Happy about the system used in the Saudi Team. I think in general that data mining can be much more successful, and I think the issue is a lack of knowledge among the head coaches can be a bit of a problem." **W1TD**.*

In other words, coaches must believe that the system constitutes an effective mechanism with which to improve their job as coaches.

> *"I take all this information. Then I take decision depends on how my player need sprint session or strength session, fortunate. I have all this information to help me. So, when I make my planning the main aims is the game." W1FC2*

4.3.2 Producer of the Knowledge: Data Analysts Competences

The modern game in football has been influenced by the emergence of numerous technologies over the last decade, which have had far-reaching repercussions for the reading of results and prediction, through complex analysis across various levels of interpretation. These data gathering and collections practices, collaboration and processes are generally accepted as enriching the data available to coaching staff. However, the demanding, high-pressure nature of football competition requires practices to fulfil the required tasks meaningfully, efficiently and effectively while still meeting ongoing yet critical weekly deadlines. The producer of such knowledge is required to understand the needs of the knowledge consumers, which requires familiarity with football knowledge and the ability to construct reliable and effective communication channels with the consumers. In addition, analysts are expected, by default, to have strong statistical and numerical competences that enable them to effectively exploit the data and translate them into knowledge that meets the needs of consumers. The summary of competences are listed in Table 4-2.

Table 4-2: List of competences required by the data analyst to have an effective knowledge discovery process

Competence	Rationale
Communication Competences	*For collaboration* Identifying/understanding the requirements and needs To identify which information shall be shared with different stakeholder (Motivational, envy)
Football Planning Competences	1) Communication/collaboration 2) Proposing new ideas to the coaching team 3) Interpreting the reports 4) Improving Active Listing 5) Expediting understanding required task.
Statistical Competences	Data mining / modelling for converting data into insightful reports, deriving insightful interpretation and reports from data (i.e. translating requirements into data and statistical algorithms)
Technology Competences	To identify/use the best hardware and software with lowest cost and highest effectiveness. Also improves the ability of use technologies more effectively and efficiently

4.3.2.1 Football Planning Competences

In order to have effective communication between the data analyst and team coach, it is essential for the data analyst to have good knowledge of football, as this can help in the communication/collaboration process, as well as with interpreting reports and proposing new ideas to the coaching team.

"For me, before anything else, he shall have good knowledge and passion of the football technical, tactical, and physical aspects" W1FC7

The consequence of this is that coaches sometimes set certain requirements in terms of education and background, while others give specialised training to their data analysts to get the right knowledge about football

"Having knowledge of football is critical. Also, having a technical and tactical perspective is important for me, because this helps me to communicate with him and can help him to give me interesting ideas through the data. Sometimes, I prefer if the data analyst has experience in coaching as well" W1FC8

"It is vital to have a profound knowledge of the football. The analysts are working with team managers and others; he shall be able to see things differently. It is not only about data" W1FC7

Communication not only comes from talking the same language, but also denotes the ability of the data analyst to translate and explain data in more useful ways (i.e. wisdom).

"That is why this needs to go step by step and as a sport scientist. The most important thing is when you talk about data mining/science is to show people understandable data." W1TD.

Theme	Sub theme
Knowledge in football	Communication (improve value creation process)
	Proposing new ideas
	Interpretations

4.3.2.2 Statistical Competences

Data analysts also require sophisticated numeric ability. Although this seems natural, in the context of the Saudi teams, some of the data analysts demonstrated a low level of familiarity with statistics, which resulted in the need to outsource reports from professional firms. However, it is generally argued that data analysts should be able to model data in appropriate time.

"He shall know statistics and familiar with SPL statistics to identify different useful KPIs" W1FC9

This statement is interesting because the understanding of the concept statistic is limited to the KPIs without modelling. In other words, the concept of modelling the data is not prevailing, with only two team demonstrating knowledge about the modelling process.

> *"When you have millions of data, you have to put them in a system, and you have to start looking for relations and correlation between the data. That's your work." W1TD.*

Other teams demonstrated a limited understanding of the statistics, with their apparent perspective being confined only to a perception of the role of the data analyst being to generate descriptive data.

> *"Faster analysis, qualitative insight than the stats we collect." W1DA3*

Across all teams, a serious gap was identified between the analytic models discussed in the literature and the actual knowledge or practice of the data analysts in Saudi Arabia. No team used simulation models or sophisticated analytic models. This can be perceived as a weakness in their data analytic knowledge regarding quantitative analysis models, techniques, and software applications. None of the data analysts interviewed were aware of any data analytic models, as they relied exclusively on Excel software to perform basic mathematical calculations. Ironically, no data analytic staff came from statistical or mathematical backgrounds, with all noted analysts coming from sports, business, or physical background, with only a few having had training in statistics and numbers. This may be a factor undermining the value of KD resources in this context.

4.3.2.3 Communication Competences

Communication competences are another important area for data analysts.

> *"Communication is the key, it will be easier to work with him (coach) and do my job, you understand him. You know his goals, objectives, he is clear, you understand how he work, what he wants it will be easier for me to do my job. It is better than working with someone who does not have clear idea of what is he doing, or not organised it will be hard to be to do my job." W1DA4.*

This research defines communication competences as the ability to listen actively and understand question in such a way that problems can be translated into sets of knowledge requirements, in addition to the ability to explain findings to the users of the data in meaningful terms and circulate them to the right people with a level of trust. Trust and mutual understanding are complementing each other.

> *"This is a compulsory competence. He shall be trustfulness. Trust shall be in communication and circulating the knowledge, and in the quality of information presented. Without such trust, communication will never be established. Also, data analyst shall be able to understand the team managers' information needs" W1FC9.*

Communication is critical to the knowledge co-creation in the coaching team, including the data analyst.

> *"You as a data analyst, sometimes you can see things differently. Also, could be against the beliefs and assumptions of the team manager. If there is a mutual trust between you and the team manager, he will listen to you. Communication is all about mutual understanding and trust between you and the team manager. W1FC9*

There are two main competences that data analysts should develop in order to construct effective communication with their team managers: developing proper communication channels and determining the appropriate level of data interpretation.

- Developing communication channels

Data analysts need to construct proper communication channels to enable them to identify which, when, and to whom information should be released. Communication also involves circulating and distributing reports to the right persons at the right time.

> *"The best data analyst for me is the one who understands what I want and knows very well which information can and shall be shared with the players and which are no" W1FC8*

> *"These data have high level of privacy. Data analysts shall not disclose or share any information in formal or informal meetings with anybody" W1FC7*

Certain information is also believed to have the potential to have negative psychological impacts on some players. For instance, in scenarios when the performance of the players on opposing teams are significantly better than the team, some coaches feel that arbitrarily sharing this information about their weakness could have a negative influence on performance and morale.

> *"The reason why I hate the data analyst share information to players is that players are comparing each other's too much. This has negative influences on their morale" W1FC8*

According to the perspective of this team manager, telling players about their weaknesses in a more convenient way influences their morals.

By having proper communication channels, the right person is expected to receive the right information and to inquire the useful information. This can lead to the delivery of the right knowledge to the right person, potentially improving the use and value of the knowledge. In addition, the interaction between required knowledge and what is available could stimulate the data analysts to think differently, leading to the discovery of new knowledge.

- Interpretation level

The reports created by data analysts are the ultimate knowledge with which team managers can improve performance. Even the presentation of this data is important, in order to maximise its usefulness.

> *"No, the collections are good but the way of representing the data is not that good." W1TD.*

> *"And the same for data scientist, you can come up with the best data ever but if you cannot convince the head coach to use those data to change his tactics what are you going to do with it. Then you are just analysing data for the sake of analysing data, which is not wrong at all - Because it is also a scientist". W1TD.*

In order to be useful, reports must present findings in a comprehensible format that is easy to read and process. The findings illustrate that the overreliance on specialised jargon adversely affected the ability of some participating data analysts to effectively communicate their knowledge.

> *"So you see interpretation of data is very successful but yet again I may think people like you, data scientist, will be probably one of the most important people in a team but the biggest problem now is that people like you they are presenting their KPI's to coaches while they should ask coaches, listen to the coach, what do you want to know, which KPI do you want to receive and then you need to make these KPI's understandable and that is your challenge" W1TD.*

This indicates the importance of data analysts giving useful interpretations of the results in order to help the head coach to make the right decisions. At the same time, it must be remembered that excessive subjectivity of interpretation can also be misleading.

"Sometime as an analyst there are boundaries, you don't push too much, the head coach does not want too much interference with him. So, know it's not providing information but interference in his work. You will find yourself ignored or even kicked out if you push it too much. There is thin line, provide information, back off, give him space and let him work with the data." W1DA4

These findings are an effective summary of the relative pros and cons of the interpretations that data analysts perform of the data. The pros are primarily related to the ability to help the coaching team understand data and obtain insightful ideas from reports. The cons pertain to the interpretations that are bounded by the knowledge that data analyst has in their specific field (here, football), which is closely related to the ability to inform or mislead the coach in terms of reaching effective decisions.

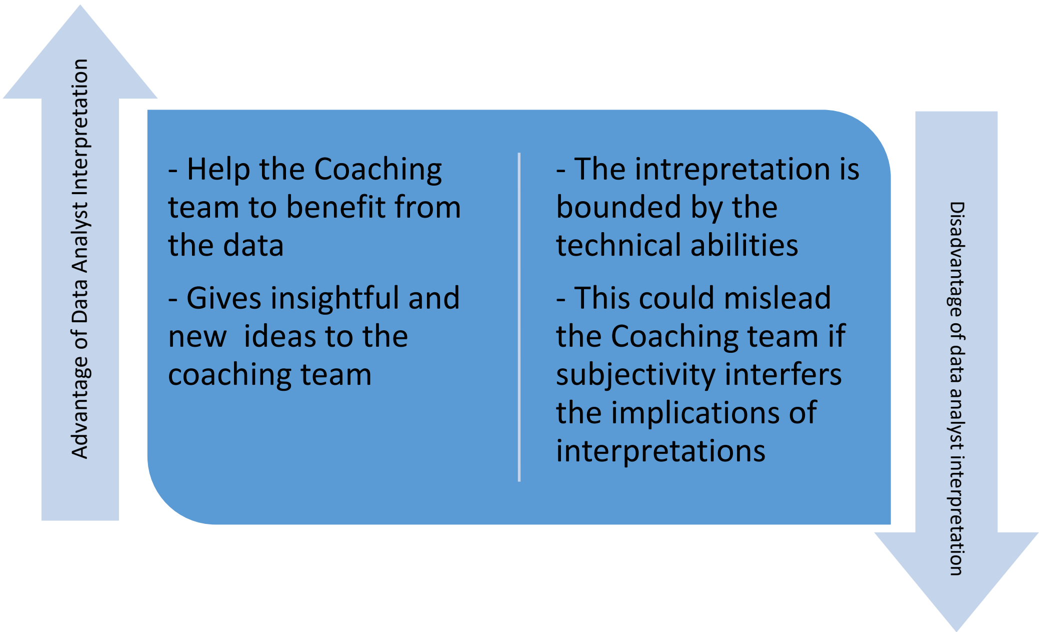

Figure 4-4: Pros and Cons of data interpretation by the data analyst

4.4 Proposed Value Co-creation Process Model

The last section clearly advised that the key in the discovery of knowledge is communication between data analyst, coach, and other stakeholders. In other words, value is created through discursive and constructive communications: this is called the value co-creation process. In the classic approach, data analysts produce reports, regardless of the real needs of the head coach. This is a challenge perceived by the head coach.

"But most sport scientist they go to the raw data and develop some KPI's and they say to the head coach. It should work the other way around" W1TD.

In other words, the KD process traditionally begins with the production of the reports without filtering the knowledge to different actors, or even identifying their specific needs and requirements.

"Analysts record a game and then send the analysis to the locker room. All the information about the tactics and what happens in every match half. Then we try to fix our play or change our tactics." W1FC2

"Mostly Reports for the technical staff as well for the players." W1DA4

This approach limited the KD practices and abilities of the participating teams, since communication was one way and was not perceived as an effective co-creation process in discovering knowledge, resulting in harmful rigidity in the formulation of team strategy.

"There is no flexibility to change the team positions / game model. The change is for limited positions. The determination of the communications between the coach and data analyst is fixed and rigid." W1TD.

This even restricts the data analyst from discovering new knowledge, as there is no reason for that event to occur.

"Also, I was very limited in scope by what the needs and requirements of the team manager and I cannot do as I wish. If I had more responsibilities from the board member then it would be a different scenario." W1DA4.

However, this can be addressed by proper co-creation of the knowledge among the stakeholders. There are three proposed methods for improving the value co-creation process between data analysts and coaches: user stories, sprints, and backlog. These strategies are all borrowed from Agile methodologies literature and are discussed in more detail below. The process is visualised in Figure 4-5, and detailed in the following sections.

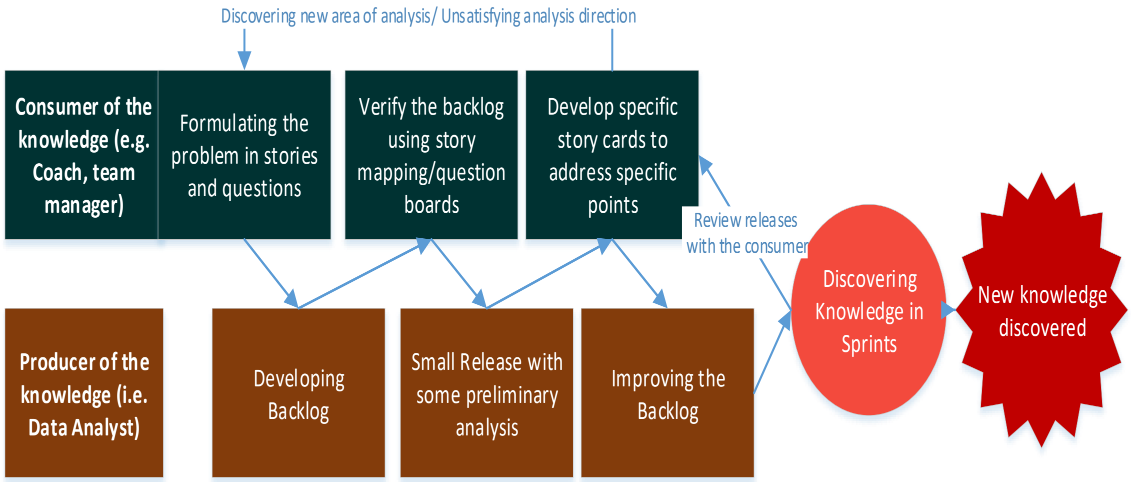

Figure 4-5: The proposed Value Co-creation Process Model - © by the researcher

4.4.1 User Stories / User Question

In an Agile process, user stores are a technique for the development of the features required to meet the specific goals of users. User stories capture what needs to be discovered, based on their specifically articulated acceptance criteria (requirements, questions, and visions), in order to enable new insights to be achieved in the necessary domains.

> *"I tell the data analyst different scenarios of the match. Then I explain to him what my preferred scenarios is. The data analyst validates what I am saying using his data"* W1FC5

> *"You as a team manager, articulate your point of view in stories to simplify the identification of the required knowledge from the data analysts. As data analyst, you have to understand the knowledge required, the head coach objectives of the analysis, and understand the reason for asking of this thing in depth so that you can do your analysis"* W1TD.

In this way, user stories help to create a clear written list of what needs to be achieved, by whom and why, then allows that to be tracked and progressed further. There are many stakeholders involved in this process, including: players, head coach, assistant coaches, fitness coaches, data analysts and others (e.g. team manager). This process is based on training or match activities, scenarios, and practices that reflects the performances of players or the team.

> *"You need to understand the head coach philosophy and approach in training and setting match strategies. How can you know that? It is by meetings and listening to his stories"* W1DA3.

This Agile collaboration technique helps the stakeholders achieve the following (Cohn, 2004; Drury, Conboy and Power, 2012; Patton, 2014; Orłowski, Ziółkowski and Paciorkiewicz, 2017):

- **Identifying** the promised scope for reaching the intended result by writing related questions to reach new insights.
- **Acceptance** criteria and understanding about certain features during specific sprints to reach the intended insights of the analysis within the coaching team.
- An approach of **documenting**, **recordings** the analysis process to **maintain** and **preserve** the **processes** and **approaches** taken, as well as the knowledge learned by the different sprints (approaches and processes).
- **Clarifying** the problems to be analysed, breaking down larger questions or request into smaller manageable clearer questions/stories/requests, which can then be further divided into smaller analytical questions (stories dealing with a highly specific purpose).
- **Insights** are then **studied**, investigated, evaluated and validated against questions, stories, and backlogs for confirmation of insights.
- The insights reached are then used in the **learning** process, as well as for **improving** the development of new stories, questions or requirements.

They are the simulated moments required by the head coach from the data analysts.

Table 4-3: Generic Agile Story Template

As <user> I want to <do something> So that I can <get benefits>

Table 4-4: Proposed Agile Story Template - © by the researcher

As a <PLAYER> In this role <ROLE>, In this location <POSITION>, When the team is <Moment of the Game>, I want to know <expected performance KPI> , So that I can <UNDERSTAND THIS SCENARIO>

4.4.2 Stories mapping / Questions board (mapping)

Story mapping can also be an effective way to address limited understanding or knowledge about KD tools on the part of coaching team. Through story mapping, the data analyst can translate requirements into hypotheses to be tested or elaborated using statistics and data.

Story mapping starting by a certain objective, then investigates possible scenarios that could influence whether or not these objectives are met. An example of this approach is provided below:

Coach: I believe our team players can perform longer than the competitors. Thus, I can bet over the last 10 minutes of the match. My players can cover more distance faster. I believe that we can play long ball in the last 10 minutes to score goals.

Data analysts can operationalise this story into a set of arguments to be tested: Do our players perform well in the last ten minutes? Can our players perform competent long passes effectively? Do our attackers fall in off-side traps often? Are the defenders of our competitors always coming in front? By breaking down the story into quantitative questions (or cards), an analyst can gain a better understanding and translate the requirements of the coach into required data led information.

4.4.3 The Story/Question/ Analysis Card

As noted immediately above, stories can be structured using cards. This is an Agile artefact to capture, documents and organise conversations about stories to address questions and concerns about the analysis. The proposed story cards contents from a recent study by Patton (2014) which has been tailored to fit with the research scope:

- **Author:** Stakeholder name for reference and also to clarify any additional information about this card.
- **Dates and time:** When this card was born.
- **Short title**: The story analysis/question card should include a short title reflecting that story/question. It should be meaningful and reflective, focusing on the task or question under analysis, enabling the conversation to run smoothly. It should reflect on the analysis task the stakeholders want to learn about.
- **Description**: One or two sentences should briefly describe the action or subject required to examine. It should highlight who is this card about, as well as the action and the purpose for that action (benefits, values and importance).

- **Purpose**: The purpose of this card, the intended way that it will help, and its link to the analysis.
- **Story tracking number:** A number for easy tracking and future referencing.
- **Estimate size or budget:** The estimated time or duration of take, with weight and budget if needed.
- **System used:** The tools or systems proposed for use in the discovery process, as well as applications, software or hardware requirements that assist in this process.
- **Value**: The maximum time and effort accepted for getting the requirement. It is of the story/question in this sprint and how it is reflected in the goals of the intended sprint. Also, to reflect on if this value shared with another card.
- **Importance:** The criticality of the card and its priority in this sprint, or other sprints, using a scaling system (numerical or alphabetical) or coloured indicator**.**
- **Dependencies**: The link between the card and other cards.
- **Status:** A record of the progress of this card.
- **Requester:** The stakeholders from the coaching team who requested the analysis.
- **Related Cards / Stories:** Any relationship between this card and another one.
- **Acceptance Criteria**: A number of criteria, usually 3-10, to enable a clear scope to be defined, as well as to ensure no ambiguity and uniform understanding across the team.

The proposed examples here are to aid in showing how the FDA process can be done to ease in gathering the needs by coaches, data analysts and the coaching team. They are listed in the next page to ease of use.

These are three proposed example cases for the use of story cards to identify knowledge requirements. These examples story cards are provided below:

Table 4-5: Example 1 - Story/Question Card

Author	Analyst 1	**Story tracking number**	S12	**Importance**	2
Title	Defensive Third ability for player 5	**Dates and time**	18-02-2018	**Value**	
Dependencies	Story 1	**Estimate size or budget**	Light	**Data used**	Statistical data
Purpose	Analysing the defensive thirds players and their abilities for next match Metrics			**Requester**	Head Coach
Description:	**As a** <PLAYER #5> In this <Centre Back>, **At this** <Central defending Zone >**,** When the team is <Losing the ball>, We want to know <% of tackles>, **So that we can** <know his defensive ability/strength in the team defensive third>				
Acceptance Criteria	• The zones/location where the tackles occurred • The frequencies in which these tackles occurred in the relevant locations • The players engaged in the tackles • The time stamps these tackles occurred with respect to match result				

Table 4-6: Example 2 - Story/Question Card

Author	Analysts 2	**Story tracking number**	S13	**Importance**	1
Title	Next match midfield attacking strategy	**Dates and time**	18-04-2018	**Value**	
Dependencies	Story 2	**Estimate size or budget**	Light	**Data used**	Statistical data and technical data
Purpose	Analysing the best strategies for creating attacking opportunities for next match.			**Requester**	Head Coach
Description:	**As a** <midfield players> **In Role** <Midfield line>**,** At this Zone <central zone >, When the team is <in ball possession>, **We want to know** <attacking opportunities>**,** **So that we can** <possible attacking scenarios>				
Acceptance Criteria	• significance level • Tested and verified using empirical data • Weakness of the opponents defending line • Strength of next match midfielder and attacking line				

Table 4-7: Example 3 - Story/Question Card

Author	Analyst 1	**Story tracking number**	S01	**Importance**	2
Title	Midfielders #8 attacking build up passes	**Dates and time**	20-03-2018	**Value**	
Dependencies	Story 1 and Story 2	**Estimate size or budget**	Medium	**Data used**	Tactical and technical data
Purpose	Analysing the midfield players passes behaviours when building up attack			**Requester**	Assistant Coach
Description:	**As a** <PLAYER #8> **In Role** <Central Midfield>**,** **At this Zone** < Central Midfield Zone >**,** When the team is <in ball possession>, **We want to know** <distance covered during the 1^{st} and 2^{nd} half >**,** **So that we can** <the effective distance covered when the player is building up attacks>				
Acceptance Criteria	• significance level • level of accepted error • Tested and verified using empirical data • Best collaborating players • Pros and cons of previous matches				

4.4.4 Sprint

The sprint is a method used to improve communication and gathering requirements. A sprint is a time boxed Agile technique, with each time box determined in advance. The idea of the sprint is to ensure continuous, iterative data gathering and analysis.

Matches are played weekly. Most teams asked the data analyst to develop one report after the match and 1 report before the match (answering queries).

> *"I do not give all reports one time. This is useless, if I gave all of the information one time, all of us will be confused. I will not be able to address his issues, and he will not be able to fit these analyses in his work. Different reports are produced in different times to ensure the mutual understandings and to address the real needs. The timing of reports is identified at the beginning of the week" W1FC7*

> *"I do give daily reports for the match and the training, based on the needs and requirements. For the match for example, about the fitness, there is another person who gives report an out the tactics etc. I only give about fitness" W1FC2*

> *"One of my tasks is, after every match I make an analysis of what the team made, what we did well and what we need to improve to the next match. I always do this analysis after the match and we always have a plan for next match. So, we work on that and we try to achieve these objectives for the next match" W1DA3.*

The main assumptions for these teams were that the data required should be structured and fixed through matches. However, the findings suggest that this did not always, or often, occur. Besides blocking KD practices, the matches and contexts are different, which by nature pushes team managers to look at new information for new matches.

> *"Also, it depends on the match from game to game, depends which categories of the match (A, B, C) which depends on the opponents, some matches you need more details and information, other ones not that much. With time and experience you really will know what you are looking for. "W1DA4.*

The proposed method is the sprint. In the sprint method, it could be expected to have 5 sprints. Starts by a meeting with the team coach to identify the requirements using stories. The following day, 4 or 5 hours as a time box, the data analyst is working alone for working on the questions developed from the stories. Once the questions are identified, the next day meeting is to verify the questions and the potential use of the answers of the questions.

> *"We have several meetings to elaborate the understandings. It is very important to ensure both of you are on the same page. It is important to define appropriately what is the required information and how will be used" W1FC8*

The second time box is intended to derive answers to the questions. The function of the third day meeting is to discuss these answers and to produce any new questions. This case was only seen on one occasion in the current research, but not structured in the typical sprint structure outlined here.

> *"There are two separate processes here. There is a time for data analysts to do their analysis and other time for discussing the results". W1FC7*

> *"I used to work alone and sometimes I have meetings with the head manager, sport science, assistance coach. We usually have technical meetings before each game (a day or two days before) we explain the performance simple." W1DA4.*

> *"What if Scenarios?" I.e. "if we have this information, can you resolve the problem" W1DA4.*

Small releases in the sprint can also be a way to avoid misunderstandings or poor interpretation of the data.

"P2" for example is a player who always finishes the game with almost 100% passing rate, he never ever loses a ball, but he never passes the ball upfront. He recovers the ball and then he passes the ball to "P1", it's, done. So, you can say based on passing rate he is our best player, no of course he is not our best player. He does not lose the ball and that's important because he is the link player." W1TD.

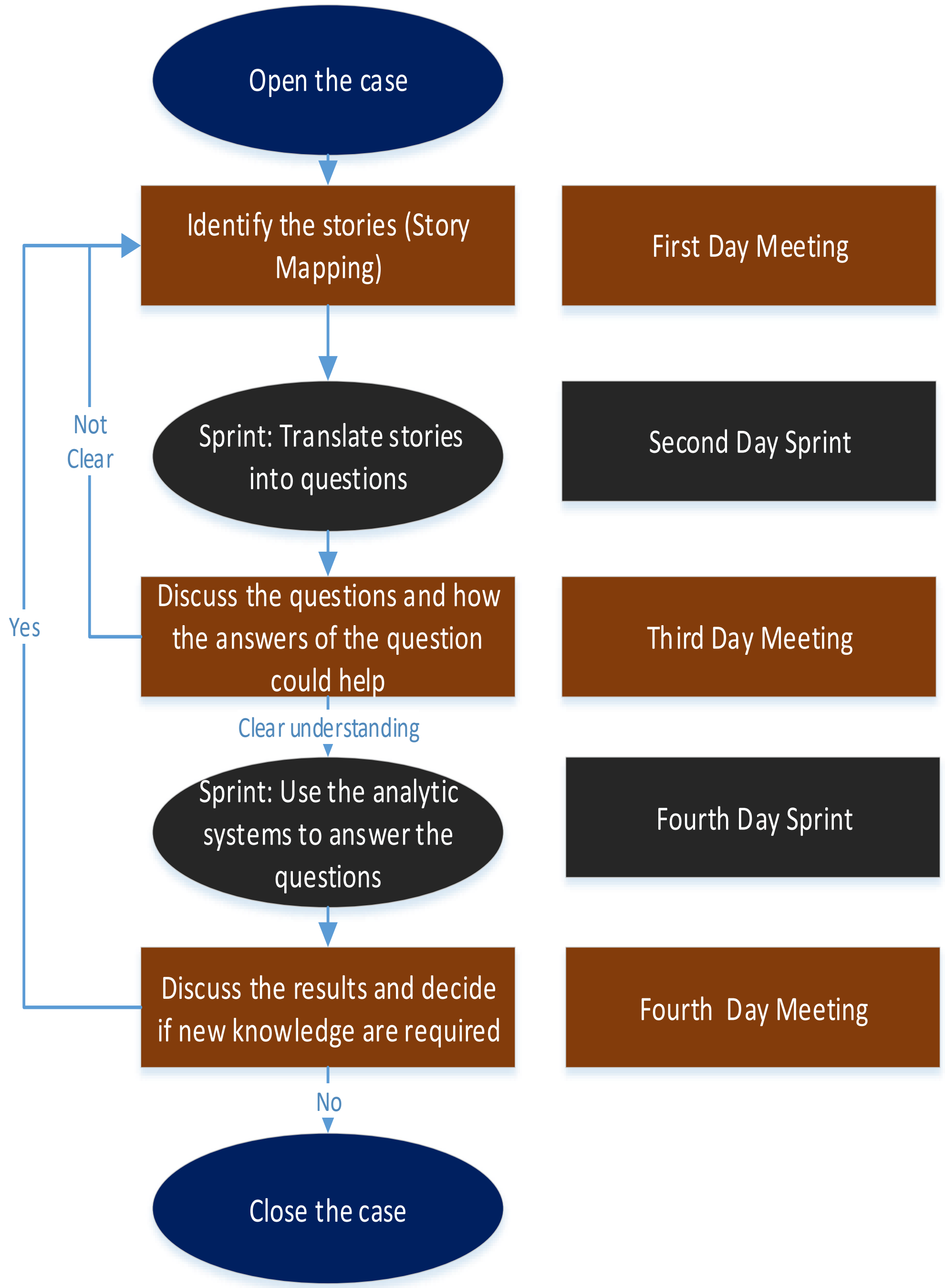

Figure 4-6: Sprint Model for KD value Co-creation framework - © by the researcher

The developed sprint model shown in Figure 4-6 was inspired by the SCRUM Agile methodology. A diagram of the SCRUM framework shown in Figure 4-7 to show where the sprit model should fit within an Agile methodology.

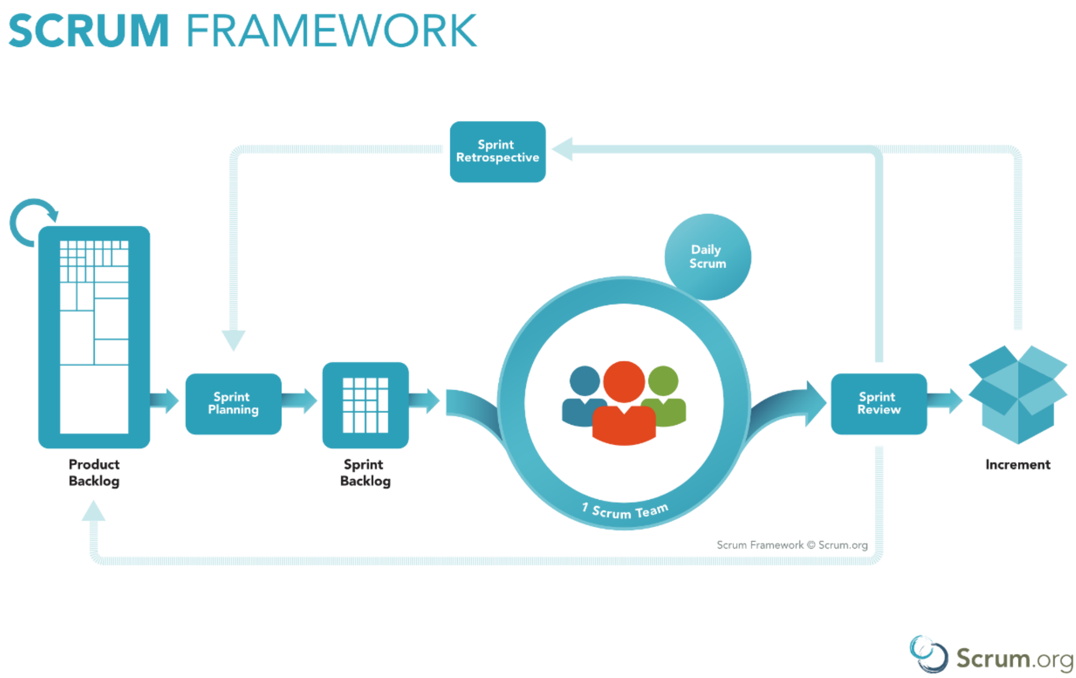

Figure 4-7: SCRUM Framework

Sprint is organised by a backlog that identifies the objective of the analysis, breaking it into small releases with certain acceptance tests. This backlog is revisited at the end of each release to set directions. The following section explains the application of the backlog, small releases, acceptance tests, and retrospective approaches in the specific context of football analysis.

4.4.4.1 Backlog

Backlog is a file utilised to document the objectives of the analysis. This includes a number of factors: the knowledge required (needs), the required software/applications, the required type of analysis, and the overall intended function of the data. The backlog is expected to contain all the thoughts and ideas that the team manager needs to be further explored. The team manager is responsible for formulating such a document with the assistance of the data analyst.

> *"The organisation of the information exchanges is the key. The documentation also improves communication between data analysis and team managers. In each document, there are*

fields for the objectives of the analysis, the knowledge required and other things we need" W1FC8

Despite the theoretical application of this document, the backlog is not always complete and comprehensive. Instead, it is a dynamic document that changes over time, as new stories or questions arise to be addressed, as reflects the analysis needs. On many occasions, team managers do not know the exact problem or knowledge required, so exploration of knowledge from data can potentially be a relatively unstructured process. An example of a proposed backlog is provided below from T3. This backlog concentrates on time, as this was the information that was useful to that team, at that point.

"This process can help to identify all the required information for each scenario, and for each match." W1FC8

Table 4-8: Example of Backlog file - © by the researcher

Objective of the analysis	Identify the weaknesses in the team X					
	Day 1	Day 2	Day 3	Day 4	Day 5	Sprint Review
Story 1: Defence gaps						
Task 1: Comparison in **speeds** of defence of the opponent with attacker of our team						Day1
Task 2: Comparison in **tactics abilities** of defence of the opponent with attacker of our team						
Task 3: Identify best and weakest player in the defence						Day 2
Task 4: Identify the weaknesses in potential passing in the defence						
Task 5: Review the plan and find out further investigative						Day 4
Story 2: Midfields passes						
Task 1: Identify the potential weaknesses in passing between defence and midfields						Day 2
Task 2: Comparison in **speeds** of midfields of the opponent with attacker of our team						Day 3
Task 3: Comparison in **tactics abilities** of midfields of the opponent with attacker of our team						
Task 4: Identify potential opportunities and threats in the expected opponent strategy						Day 5
Story 3: Attacks go through						
Task 1: Identify the weaknesses in passing between midfields and attackers						Day 4
Task 2: compare attackers speed of the opponents with the defenders						
Task 3: set the possibilities of the match win under different scenarios						Day 5

2.5.1.1 Small Releases with simple designs

Instead of finishing the whole match analysis in one report, the data analyst breaks the task into several, iterative reports to ensure the continual progression towards the required knowledge/understanding of the problem. As discussed in earlier section on user stories, working on small releases uses a narrow, effective scope for the analytic approach. In other words, rather than focusing on a large, complex task, the analysis is conducted on small tasks in short sprints, which maintains the work-and-confirmation basis. This helps to engage the whole coaching team and stakeholders, especially given the 'story-telling' session after the sprint enables the current state of the analysis to be clarified, ensuring that the visions and requirements of stakeholders are met.

> *"Our analysis is conducted through layers. I do not do all the analysis and knowledge discovery once. I break down the questions into 5 main questions covering different aspects such as the space, attacking style, corners, fixed balls, and develop probability-based*

reactions and consequences for each proposed event. I trained on this way when I was in Belgium" W1TD.

"When we do the analysis of the team, we don't take it separately we have to consider these actions with the team. When I start making the analysis after the game, I try to see the most information possible and focus on specific actions. Also look at the dynamics of the team as see each player as well. We need to consider several aspects of the match." W1DA3

Because knowledge required sometime vague and not well specified, the team manager can address the problem and data analyst can propose simple designs - initial information to address the problem

"Similar as we are doing now we meet with the head coach, one to on, effective communications, and I get his request and provide it to him later once it's done." W1DA4.

"Head coach, assistance coach, fitness coach, sport science, goal keeper coach by the way. And I provide it the info for the players. Sometimes they ask about more info and I provide it to them based on their requests." W1DA4.

4.4.4.2 Acceptance Test – Story Acceptance Criteria

After each release of data reports, the team manager validates and verifies the results to ensure that they contribute to the objectives. By defining acceptance criteria, the questions that are similar in scope can be grouped to ensure that issues are worked on effectively in sprints. This also helps to ensure that sufficient understanding of the outcomes of the KD activities are maintained throughout the process.

"Another time for me to replicate and verify the processed knowledge through watching by myself the moment. Usually, analysis is supported by recorded events or simulations to help me verifying the analysis". W1FC9.

"With some data you can have some understanding, but the data is somehow is a good way to start but the not give you the full picture. The statistical data won't give you the full picture but would be the starting point for your research. To make a good decision or good analysis you need to look at some videos to deliver to get the full picture." W1DA3.

4.4.5 Retrospective

The backlog enables to have effective retrospective meetings. Retrospective technique will help in maintaining the iterative need between the questions, research and result so that level or collaboration is achieved as will leading enhancing maturity level in the collaboration process over time. It occurs after each sprint to collect any improvements by the team. Receiving the team feedback. Linking the reached insights with the discovery process. Revisit the acceptance criteria and work on any enhancement or feedback about them to improve next sprints discovery process.

> *"So, we know we have the log book and TM goal and objectives is clear (but people have different interpretations than the team manager)" W1FC2.*

Retrospective sprints provide an opportunity for the team to reflect on previous sprints, and then suggest plans to improve future sprints. In addition, this stage can help the coaching team find ways to increase the quality of analysis by improving work processes. Improvements and enhancements may be implemented at any time, so the sprint retrospective provides a formal opportunity to focus on inspection and adaptation to perform the next sprints with improved quality of analysis and understanding of the KD process.

4.5 Summary

This research has found that the value of an Agile system can be summarised into the use of new KPIs, which enable the coaching team to develop well-informed recruitment strategies, training strategies, and match strategies. These improved strategies then influence the main objectives of coaching teams, which are the financial return on the player and the match results. The beginning of the value story is the existence and usage of these new KPIs. In order to deliver these KPIs, two conditional capabilities (Agile and KD) should be considered. Agile capability refers to the ability of stakeholders to collaborate in such a way that the development process is lean and flexible, based on a high level of mutual understandings in the team. The Agile capability is developed through effective data governance systems and collaboration requirements, which include mutual understanding between stakeholders, frequent meetings, and the mutual acceptance of who shall interpret the data and to what level. The second conditional capability, KD, is a blended approach using technical and human resources. Technical resources include software and hardware, as well as the required technical abilities to use these technologies. The technical resources serve to collect, analyse and report the required KPIs at an affordable level of effort and cost, in a convenient time. The human resources in KD identify, develop, interpret and integrate KPIs into new practices, based upon specialist skills, knowledge, and abilities (i.e. statistical, technological, and technical football competencies).

Having outlined KD resources in detail, the following chapter seeks to critically discuss the value that these resources and approaches offer for the football teams who integrate them into their systems.

Chapter 5 Knowledge Discovery Value

5.1 Introduction

The aim of this chapter is to operationalise the value of the knowledge discovery. If the knowledge discovery uses and benefits are not aligned with the mission, objectives and tasks of the team manager or the head coach, there is no value of it. As can be deduced from an extensive review of IT business value literature, the capabilities involved in using technology are intimately linked with the ability to derive value from that technology. Value is defined as the sum of the tangible and intangible benefits realised from the change in the current routine due to the existence of a new technology. Related to this, capability denotes the ability to realise the expected value from a certain resource (i.e. the technology). Thus, first, this section covers performance metrics leading his knowledge discovery direction. Based on this, as will be detailed in the second section, the main team manager or head coach strategies will be mapped. Since strategies are formulated based on data (i.e. raw facts), information (processed data) and knowledge (i.e. processed information), the next following sections are to identify and estimate the key performance indicators (as information) of the players and to identify the analytic models that could process these KPIs to deliver knowledge. At the end of this chapter, findings are summarised into the knowledge discovery framework and operationalised into a maturity model.

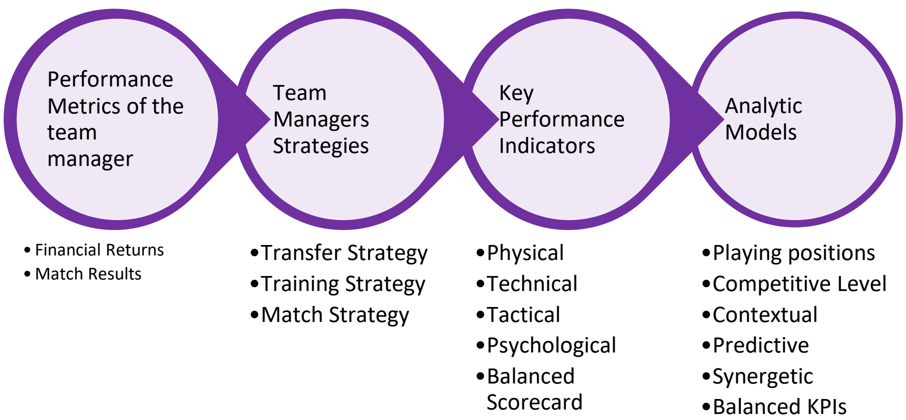

Figure 5-1:KD Value - © by the researcher

5.2 Performance metrics of the Team manager

There are two main objectives for the managers of football teams: maximising the results of that team, measured in terms of winning ratios in championships and leagues; and optimising the return on investment with players. While significant, this latter objective is less commonly discussed, despite the fact that some team managers are searching for cheap, high performing players, often from South American or African countries, who can be recruited and then sold after development at vastly higher prices. These objectives are commonly achieved through three main strategies: transferring, training, and match strategy. These are discussed below.

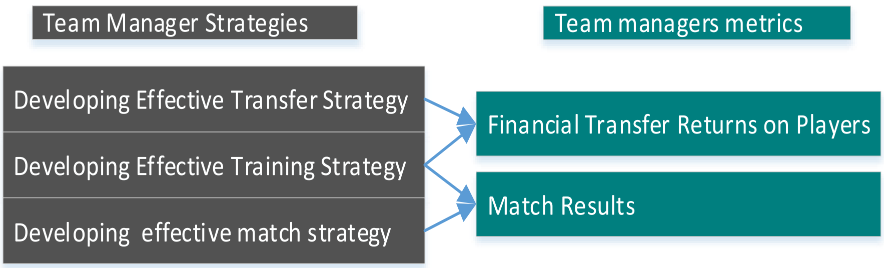

Figure 5-2: Team Manager Strategies leading to metrics - © by the researcher

5.3 The KD Outputs: The Role of KD in Developing Effective Strategies

The three aforementioned strategies that team managers (transfer strategy, training strategy and match strategy) use to achieve their objectives are not developed and operationalised at the same time. Knowledge Discovery outputs in terms of new KPIs and new data analytic models could help the coach capture more of the dimensions on the SWOT of his team and the opponent team which enables him to develop a better, knowledge based, and more insightful transfer, training, and matching strategies.

Data analysis in professional sport occurs pre-match, during the match, and post-match. Pre-match analysis aims to set match strategy based on the current information and knowledge of the team and their opponents. During the match analysis aims to monitor and assess that match strategy. Finally, post-match analysis closes the loop by determining the feedback that informs training and transfer strategies.

> *"Different knowledge required different times. Some of them before the competitions, within the competitions, or even after the competition. The coach could not start his work without having some information about players' KPIs."* W1FC7

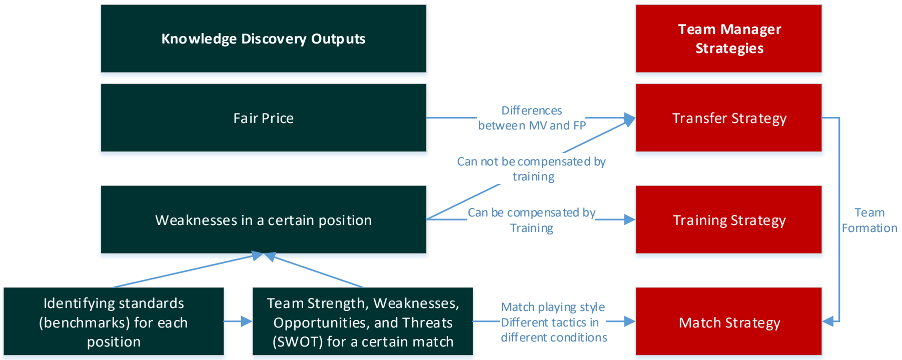

Figure 5-3: The role of the Knowledge Discovery in formulating team manager strategies Model - © by the researcher

5.3.1 Transfer Strategy

In this research, transfer strategy is defined

> *"I use statistics to search for players. They allow me to value players in terms of number of matches played, number of scores, and overall performance records." W1FC8*

According to this strategy, the optimal player is defined in terms on the specific objective, with variations in desired outcome informing the choice of the most appropriate methodology. There are two main objectives in player recruitment, namely to complete a Transfer for Investment or to Transfer for Match Results.

5.3.1.1 Value-based transfer process: Transfer for Investment (Money, Exchange)

In terms of Transfer for Investment, the optimal player should be chosen based on the differences between the actual market prices of players and the precise value of that particular player. The difference is the profit from buying players cheaply from a remote location and exposing him to the market through matches and games. Synthesis of interview data indicates that the steps were: determining the most appreciated KPIs in the market, locating a player who matches/exceeds these requirements, and identifying the highest possible price for that player.

> *"We already know that data driven approaches in sports can let you do a lot of important things such as finding undervalued talent to hire for the team or assessing player performance with things like GPS locators and heart rate monitors, and so on." W1FC9*

> *"It also allows you to analyse gameplay by looking at the predictors of scoring or potential weaknesses in defence and while the first of these, finding undervalued talent, is typically*

at the domain of the team manager, the other two along with many others are of direct concern to coaches." W2FM8.

In summary, the value-based process to transfer players is illustrated below (see Table 5-1). KD is an effective way to identify the most valuable KPIs in the market. Data analytics can correlate between the market prices and KPIs per position, helping the team to locate and purchase undervalued players. KD can then help the players offering the highest potential expected ROI to be identified, by identifying those players with the highest required KPIs at the lowest price in the market.

Table 5-1: Summary of value-based process to transfer players

Step	Step	Evidence
1	Defining the most appreciated KPIs in the market	"Each position has its main requirements and KPIs. Some of them are more appreciated than others depend on the position". *W1FC9*
2	Identifying the players who possess these KPIs	"So, you look at those data, you look at the technique of the players, how is their passing rate, do they lose the ball very quickly". *W1TD*
3	Identifying the actual market prices	"Financial wise, full data about the player, you know the value of the players, salaries, and bounces performance wise, all of these measurements. So, these data help not to be subjective, not a point of view, data, facts." *W1DA4*
4	Identify the fair market price	"When you renew players contracts, know how much they worth in the market, plan B, ultimate players." *W1DA4* "All of that can be used to assess his value" *W1FC8*
5	Identify the gap	"determine the difference between the price and what should be" *W1FC8*
6	Buy the player	
7	Expose him to the market	

5.3.1.2 Value-based transfer process: Transfer for Match Results

In terms of Transfer for Match Results, the optimal player requires an in-depth understanding of the preferred strategy of the team manager, the required KPIs in the identified positions, the KPIs of the players currently holding positions, and the gap between the required and current KPIs. These metrics can help team managers to identify the best players to fulfil these requirements.

"The roles determine the rates, not the other way around. When you put "Coach 8" as a midfield defender, his passing rate will be 99% when you put his as 10 then it will be 60% and you don't say because '"Coach 8" is 60% then we put him in 10! He had some skills which makes him for the 10 position, such as creativity, agility – these kinds of things. And based on his position, the rate starts to change. When you have a player at number 10, you don't look at his passing rate, but you look at how many assists, goals, etc. These are all that really counts. When you speak about a player at 6, you talk about passing rate being very important, so if he loses the ball many times, then every time counts. This is why I believe that the role determines the rates." W1TD

The process for transferring a player based on match strategy is as follows: the team manager identifies his preferred strategy, then he defines the targeted KPIs for each position, based on his preferred strategy. Once this has been completed, the current KPIs of the current players are assessed and insignificant differences dealt with by training and strategy. Otherwise, the player will be replaced in that position by a more suitable alternative.

The KD system can also help managers to identify the targeted KPIs relative to the indicators of other team players. For instance, defenders should run at a faster speed than the average speed of the attackers in the league. Midfielders should have a higher ability to run for long periods of time than the average of competitors. In this way, KD systems can identify the main KPIs required for different strategies, based on the KPIs in the current league. The benchmarking process can even be multi-dimensional, enabling coaching staff to optimise the players or their positional performance, thereby improving the overall performance of the team.

KD systems can also define 'significance' based on historical performance and patterns of improvement. Furthermore, KD can correlate body measures with the different KPIs in an attempt to identify the maximum potential of each player, even after they have received training.

Table 5-2: Value based transfer process: Transfer for match results

The step	Evidence
Identifying the team manager preferred strategy	*"So, it depends again in the game model that you are playing but to get something in general it is very difficult of course, Central Defenders are taller than your full backs. So these things are normal but in general no, it depends on your game model." W1TD* *"Also depends what the coach goals and objectives from the players of the team and team needs. Coaches some time like fast players, strong player and so on. Depends on the playing style of the team manager.*

	Also, Defensive aggressiveness and offensive aggressiveness which can be analysed from videos and matches. Also, and this has to reflect each positions and role." W1DA3. *"Attacking player: (Assist and goals) - attacker - offensive = productivity score. Winger; how much he can pass, one-against-one, to create overlaps so that's important. Midfield: there are two kinds of midfield player - defensive midfield player (6) and offensive midfield player (8). But it is difficult, everything depends on your playing model!"* W1TD
Identify the KPIs required for each position	*"On average wing back covers distance more than others. But even when you talk about high look at Barcelona FC, they are all small, look at Bayern FC they are all tall"* W1TD *"It depends, if you are a winger or central striker, look to "Andy Carol" he is 2 meters, but he cannot play as winger. So when you ask about it again, you cannot determine like this, because you also you need to have this, it's the size goal keeper need to be tall and fast, CD: tall, not fast, side defence, not tall, you need to run, striker should be tall, winger should be small but fast and based on this you can start to work."* W1TD *"Attacking player: (Assist and goals) - attacker - offensive = productivity score"* W1TD
Assess the current players KPIs	*"I see some details about some player and later we tell them what they did well or not. Also, I analyse in team level and we show the team what they did good and wrong. All we provide feedback for the players and the team."* W1DA3**.**
Identify the significance/insignificance of the gap	*"You look at fitness data (meters run over 24km/h this is very important factor) if you don't have this kind of players because it is genetically it is not something that you can train on you have physically fit player, so you do not have them. In this case you may need to substitute him"* W1TD
Substitute the current players	*"If you have two different players. One of them is faster than the other. The slower one has bigger body than the faster one. It is critical to allocate players on the positions to fit the match strategy. If the ball is*

with significant gaps by others	*expected to be most of the time in centre line, who shall be the defender and who shall be in the midfield? W1FC7*

5.3.2 Training Strategy

Training can be based match feedback or based on a trend in performance. This research argues for training to improve performance based on trends, rather than on feedback from a single match. One reason for this is that psychological factors can be an element in suddenly reducing the performance, so feedback from a single game may provide useful insights into psychological situations or for showing the level of progression in performance.

> *"Also, I see some details about some player and later we tell them what they did well or not. Also, I analyse in team level and we show the team what they did good and wrong. All we provide feedback for the players and the team." W1DA3.*

Therefore, this research seeks to utilise the advice of coaches to create training programmes based on a clear profile created for each player that ensures that they meet the minimum standards required and that they are the best fit for the team.

> *"yes, for the forward player, because this kind of player make a lot of sprint all the time, and this one move like this (tic) so the player will make longer sprint than this one" W1FC2*

> *"Also, the data we have is from match to match, A, B, C nothing in between there should be something between these matches link the training sessions, between A to B there should be a link between them, B to C there should be a line as well and so forth. You could compensate these limited by other technologies in order to have a consistence flow of data." W1DA4.*

> *"All the information I get for the games for session training if I want improve, I would improve sprint – improve his sprints with respect to his positions" W1FC2*

> *"I take all this information and make session I want train another day strength then another day the speed. So that what I see the fitness in football then another sport" W1FC2*

If players demonstrate significant gaps between their own performance and the desired KPIs, then the team manager will buy new players. Otherwise, the head coach will train these players to better fit their roles, with training primarily focusing on fitness and technical skills, like dribbling and interventions. However, there are no clear guidelines for when differences should be classified as significant. Although KD can support this decision-making process, ultimately the decision is dependent on the judgement of the managers.

> *"Software gives us different kind of information first they cover distance is different and the sprint are different also, so the session trainer has to specific for them I can't make a session training the same for the forward and midfield or the back player, so I need to make deference with the distance covering the sprint for every kind of information the software gives me". W1DA3.*

> *"The capacity to make a lot sprint and recover faster, when I say recovers faster is to make another fast sprint. For example, I make 20m high intensity 30km per hour that's kind of movement maybe about 20 sec to recover to make another one. That's important. Strength, to be strong all the time because in the forward he has to support, hold the defence". W1FC2*

> *"When we came here we take the software we analysis the game and the training session what I saw the player doesn't cover 76m per min they cover 52 or 56 less then hour in their area in specific game, I take my excurses in each session they cover 52m per m so I need to improve that I need my player cover over 70m/m over ok, now how many sprint they make per session training maybe 24 I need to improve it 30 up over 30 so that can of meaning is reality that kind of information I take I make new excurses to try make the stress for them like this what it means I need to make one exercise to make the player make over 30 sprint so with the staff a lot sprint with the ball definition cover cross, finishes, I don't know like real movement I say Ramon I need that kind of excurses to improve the sprint in the game but for improve we have to train it not just say you need to do it." W1FC2*

5.3.3 Match Strategy

In this research, match strategy is the process of using a match model to understand the strength, weaknesses, opportunities and threats (SWOT) of opponents in the match environment, in order to help the team winning the match. Based on this definition, the first step in devising the strategy is to do a SWOT analysis and the second is to use that analysis to devise the match model.

> *"If I can understand my team KPIs very well, my training path will be right and fit with the match strategy. My tactics are developed based on KPIs and capacity and limitations of*

the players. By setting the weaknesses and strength of each player for each position, I can set the plan and define tasks for each players". W1FC7

SWOT analysis is to identify the strengths, weaknesses, opportunities, and threats for the team to win the match. All of these aspects are relevant and not fixed. They are relevant to the opponent situations. Thus, it is important to identify, compare and analyse these dimensions for both teams, which can be developed through knowledge discovery systems. Indeed, it has been observed by most of the team manager starting point to formulate the match strategy is identifying the relative power and performance metrics of the competing team before anything else.

"The first step I start with is to identify the relative strength and weaknesses of the opponent team relative to my team. Measures I use are number of successful passing, speed of covering, empty spaces, number of winning matches, how it plays in its home, abroad, when it plays with big team, with small team, formulating its attack, strength and weakness points, and sources of strength and weaknesses points" W1FC8

"I start by identifying the main strength and weakness points of the opponent team relative to my team. I take care of detailed and general information about sources of strength point in the tactics of the opponent teams. I rely on the videos, statistics and other reports from my team. Believe me, if you missed any of these details you can lose the match easily". W1FC9

From the interviews, the most important dimensions can be classified into internal factors for identifying strength and weaknesses, and external factors with which to identify opportunities and threats. The internal factors can be classified into the performances of players in different positions in the team, as well as the overall level of team cohesion. This is important because different positions need different skills and abilities, which enable each position to fulfil certain functions in the match. These resources enable the team manager to select an optimal mix, based on the level of talent in the opposite team in each position.

"For example, you ask a Right Back (RB) that he cannot attack and only cover the Right back zone and he gave two assistances and score a goal maybe I'm not happy. This is taking in my mind, as I know the capacity of the opponent positions of the right back". W1FC2

This gives a unique importance of the use of KPIs to measure the relative endowment of the skills required in each position with taking into consideration the opponent facing positions to each of them. The second internal aspect is the team cohesions and the predicted consistency of the players' performance in the match. This is also not a fixed measure, this relevant measure as it requires to assess the passing rate with taking into consideration the opponent team ability to intervene the ball. Likewise, the ability to do forward play and possess the ball for period of time can be relied on the dribbling ability and speed of the players, in comparison to the opponent team position players' abilities. This gives another uniqueness of the importance to measure the team cohesion with taking into consideration the other team's ability to intervene and to stop the team possession of the ball in the match. Currently, there is no unified approach to do that. It is based on the experience and the coach team knowledge and views. This gives a clear importance to use KD capabilities to build certain heat dynamic maps for simulating different scenarios in different conditions, as will be discussed later.

> *"To know his team performance, only." W1DA4*

> *"So, it depends on the personality of the Head Coach. For example, if we have similar to this information with Fabio we could perform much better. It is honestly depending on the coach and what information he wants to use to his advantage, and fully know how to use it and utilise it." W1DA4*

> *"For Forward Players, I think is to know really the stress the player has. I mean maybe is important for me to know how many stress has the player after the game or after the session training for to know how many time for them to recover, I can give know chart for the player how he is stress to that, the software give a lot of information but maybe I need another support about it always there is room for improvement" W1FC2.*

The heavy use of the data analytics makes the team as mechanics with high harmony and coherent performance. Because, as it is perceived by of the team managers, European leagues use the knowledge discovery and data analytic models extensively, there is a perception that it looks like "Chess" in how they formulate match strategy and how the match is played.

> *"I prefer watch a game between Brazil and Argentina in opposite of Europe match because they play like chess". W1FC9*

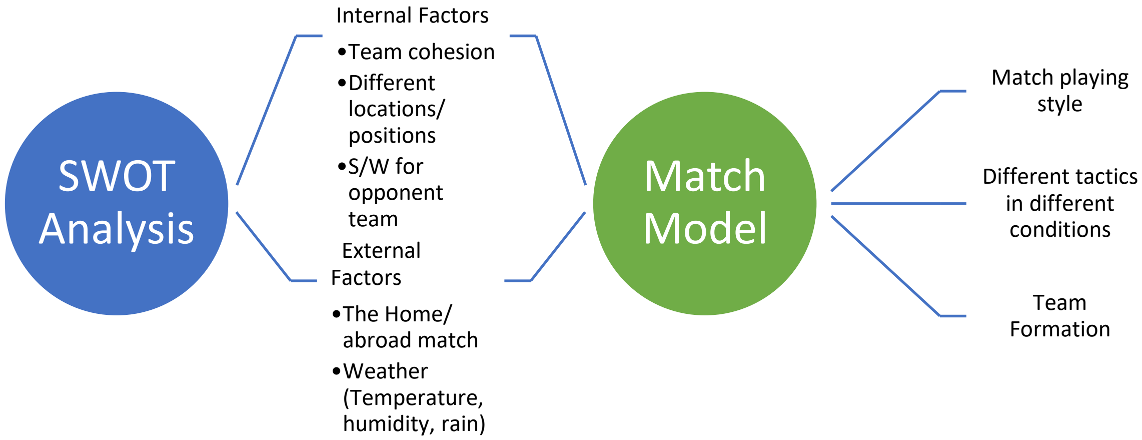

Figure 5-4: The role of the Knowledge Discovery Indicators on the match analysis model - © by the researcher

5.4 The KD Outputs: Balanced Key Performance Indicators Roadmap

This section seeks to develop a road map to help team managers and data analysts to effectively process historical data to improve the effectiveness of team strategies and related policies.

> *"I believe anything can be measured. If it is measured, it can be theorised, valued and assessed. If you understand and measure how things work, you can control it. If you can control it, absolutely, you can win" W1FC7*

There is an insightful argument that the best way to understand any KPI or any analysis is to understand the context, taking into consideration other KPIs that can contribute to, and enrich understanding of, the variation in match performance.

> *"For examples, you may have a player that have high accuracy of passes, for example %90 pass accuracy. Then when you look at the details of the players passes you see most of them to the side or to the back, it is different than a player who passes forward most of the time. You really need to have a lot of things when you one to consider some aspect of the analysis." W1DA3*

The balanced scorecard of KPIs (Norton and Kaplan, 1998) is based on reading, analysing, and interpreting historical data and information based on a structured approach. Structured analysis can make KD activities more valuable by facilitating the use of Agile methods. In other words, structured analysis can help each step to be clearly formulated in each sprint, in order to improve match results by improving the

opportunities of scoring more goals and conceding fewer goals than the opposition teams, ultimately improving match performance as measured by the criterion of winning each game. These match performance indicators are constrained by other KPIs. Therefore, by building a map of indicators, the root reasons for key metrics can be investigated.
In this study, the main factor cited by interviewees was tactical KPIs. These are influenced by the technical and fitness KPIs. Fitness KPIs influence technical KPIs. However, fitness KPIs are not sufficient to improve match performance without the addition of technical and tactical KPIs. Psychological KPIs influence all of these dimensions. The following sections provide an in-depth explanation of these relationships, using supporting evidence from the interviews.

> *"The most important KPIs are speed, tactics, technical, fitness. Sometimes you look at passing rate, the amount of recovery, distance run over 24 Km/h these kinds of thingsm, but it depends" W1TD.*

> *"All of the KPIs are correlated and interdependent. Speed is required to create successful passing. Successful passing is required for penetrating opponents team lines. This, if utilised successfully, leads to scores. Thus, all KPIs are required and complement each other's" W1FC7*

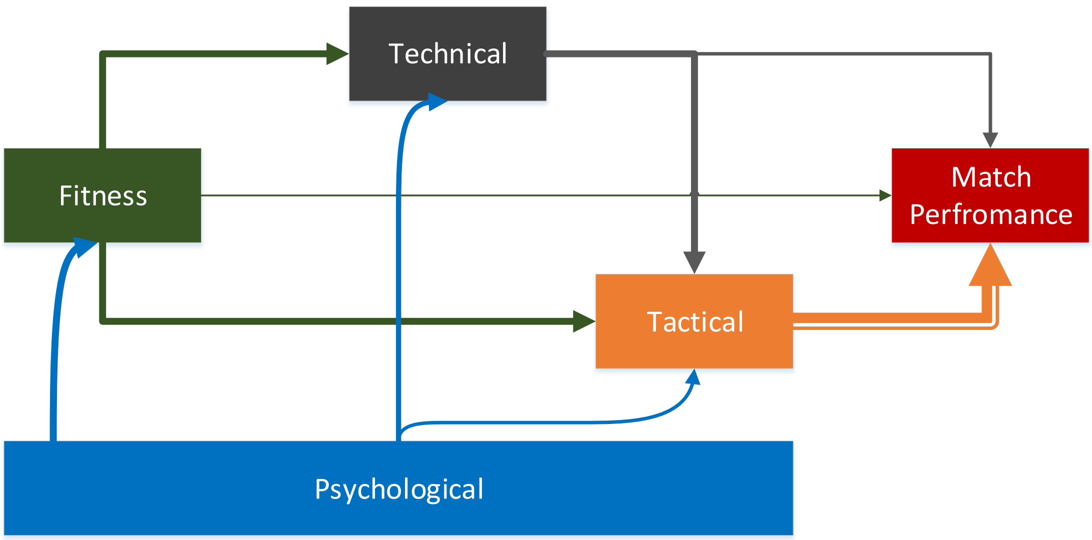

Figure 5-5: KPIs BSC - © by the researcher

5.4.1 Tactical KPIs

Tactical KPIs are metrics that are intended to measure the ability of players to position themselves effectively in such a way the probability of passing, possessing, scoring and intercepting are improved. Tactical KPIs are measured in terms of players, units of play (set of players), tactical lines (e.g. attacking, defending, or midfield line), or by the team. These KPIs are then classified into passes, possession, and playing style.

> *"Number of passes making significant attacks, number of constructive passes, number of goal keepers touches, making significant attacks, number of crosses and overs, all of these skills make much difference in the match results". W1FC8*

> *"The most important KPIs for winning the match is the players' movements. How the player intervenes, receive and shoot the ball, which come from positioning in the right time and the right place during the match. All of that depends on the players' abilities in being able to see himself in the pitch" W1FC9*

> *"Tactical skills are all about movements with ball and without the ball, and utilising spaces" W1FC7*

Tactical skills are perhaps the most important skills for modern footballers, with most valuable activities in the match being connected to these skills, even leading to 'man of the match' decisions.

> *"Who is the best player? If you want to know who the best player is, it is not the one runs most, or the fastest. He is the one who has highest successful passes with least missing. The one who can receive the ball and send it back successfully. To identify the best player, you need to have KPIs and analytic system that can find him. You cannot find him by your eyes, since this can be illusion. Many things are taken into considerations such as number of constructive attacks, successful long balls, and initiating successful counter attacks" W1FC8.*

> *"The player ability to play within a team is the key here. His ability to create new space, preparation for the successful attack, good possession of the ball, ability to intervene the ball and return it back to the attacker in short time. All of these skills make the team plays better and the team scoring abilities improve" W1FC7*

It is difficult to measure the quality of movement or positioning performance in the match through quantitative indicators. Thus, other metrics key factors are used as proximities to this ability.

> *"I think that's most important, and the you look at their tactical skills, and that something you can measure (how many times they lose the ball, how they use their right/left foot, etc..)*

and then you look at their tactical qualities. This how you determine a role in a team" W1TD.

These key factors are the passing rate, scoring from assists, scoring from faults made by the opposition, interceptions, and stopping counter attacks quickly.

"So, these are the things I were looking at. Then there are of course some underlying data like how many passes that we gave, what was the success rate we knew that with "T10" if the passing rate was less than 80% then we are not doing good. But as I already said before if P3 successful passes rate was less than 95% then he played a very bad game because he was a link player" W1TD.

Tactical skills are important for all positions, but especially crucial for defenders to create successful counter attack, for the link player (e.g. midfielders) to build a successful attack, and for attackers to score.

"The link player should not have less than 95% successful rate. And then you have "P6" (Number 10) he is the one who has to create chances, for example if he has more than 80% passes rate then for sure he is playing a bad game which means he is always looking for easy solutions, he should take risks, he is the genius, he has the creativity so he should take risk, he should look for possibilities." W1TD.

"Maybe the location the player has, when I saw in the game to P5 playing, P5 have different movement then P4 because P5 can play back to goalie but P4 need to play forward. That kind of movement take you give to take good decision. But I can imagine I need to P4 playing like P5 also. P5 playing like P4, but P5 has more tactic to play with the ball. W1FC2

"So that means if you have 5 occasions and you score 2 or 3 goals and those are the most successful team. When you look at Chelsea FC or Leicester City FC this year they don't have many chances, but when they have a chance they score and that's very important." W1TD.

Head coach job is to understand and to predict the players' capacities and position them of his team and the opponent teams.

"Tactical performance is based on head coach ability to absorb different players KPIs in his team and the opponent team to fit players in the right places" W1TD.

Effectively, this consideration describes the ability of the head coach to comprehend different KPIs and to situate the players in different circles or domains on the pitch, thereby improving the controllability of the match. In this way, following the directions of the head coach can enhance the tactical abilities and performance of the players, resulting in better overall results for the team as a whole.

> *"Player commitment is the key in tactical performance. I set circles to play for each player in such a way my tactics can win. Any leakage could have negative consequences. I wish if we can invent a technology to control players' minds to ensure that" W1TD.*

The reason for this position is that the tactical performance of players is arguably more a function of the team manager than anything else and should therefore be assessed more in terms of the team than in terms of individual players.

> *"Tactical performance is solely determined by the team manager capabilities to understand the match parameters and the players commitment to the training managers' directions."W1TD*

> *"the best player who understand and follow the train managers instruction with taking into consideration the match dynamics. this is very important to be able to see the opponent and his team movements. it is for me not a fixed calculated thing. it is a chemistry" W1FC9*

However, others who believe that tactical performance can be assessed per player as well as per team face this argument

> *"It is important Information about the individual quality about the players of the team. It covers Tactical information about the team." W1DA4*

> *"It is usually when he plays a good game it means that his successful passes rate was about 50%. Again, you have to look at player by player and that depends on the objective the head coach given" W1TD.*

Tactical performance also encapsulates the ability of a player to read the dynamic, fast-moving situation of a match, including the movements and intentions of players and their positions. Without predicting the opponents and the performance of their players, it is difficult for a player to demonstrate tactical performance in terms of constructive long passes or crosses or the creation of a successful attack utilising a certain pass at the right time to the right player. All of these KPIs do not only come from the tactical capabilities of individual players, but also from their fitness and technical capabilities, as the next quote highlights.

> *"Finally, to measure the player performance, we looked at occasions, occasions like "clear cut chances or clear chances" and approaches to the goal. Then you calculate them and of course the performance is related to how many occasions you can create but according to me the most successful team in the world is specially how many occasions do you convert in a goal and the most successful team are the ones with more than 40% conversion rate" W1TD.*

Sources of tactical performance information are the players' commitments to the team manager directions, in addition to their specific technical and tactical skills, as will be detailed in the following sections.

Table 5-3: Sample of noted Tactical KPIs from the interviews

Sample of Tactical KPIs	
Passes Indicators	
Overall all passes performance index	% of successful passes per match (e.g. spontaneous passes, 1 to 1 passes, unit passes, constructive passes, and long passes)
% of successful spontaneous passes	SP is defined as the passes without having a clear intention to build a constructive attack (i.e. due to pressure from opponents)
% of successful 1 to 1 pass	1 to 1 pass is the several passes between two players only aiming to construct an attack, penetrate defensive line or shift the direction of the play
% of successful unit passes	Unit passes are the several repeated passes between more than two players.
% of successful constructive passes:	Constructive passes are more than 2 passes with more than 2 players aiming to construct an attack or shift the play direction. (e.g. second ball and third ball)
% of successful long passes	Long passes is a movement of the ball from a zone to another zone or from tactical lines (e.g. from back to front, from the left side to the right side or from defending to attacking line). E.g. successful crosses/ counter attack
% of successful interceptions	from short passes or long passes (crosses or counter attacks)
Team Playing Style	
Time player with/without ball	minutes played with or without the ball
Time played per position	in offence, defence, and midfield
Ball recovery time	Average time required to regain the ball
Total Possession	% of the time the team hold the ball
Distances between attackers and defenders	The average distance between the attacking and defending lines.
Maintain distance between players (close down space):	The % of the time that distance between players within the ball range is lower than the coach defined space in each zone
Offside (Tolerance) Management	(such as % of the successful deliberate offside (avoidance) and % of the successful avoiding opponent deliberate offside)
Player Positioning Performance	
Role rotations	% of successful (constructive change) changes of players' positions in the pitch during the match.
The duration of a player being in specific zone.	The duration of a player being in specific zone.
Player density: % of time played in the player specified zone	The position where the player(s) playing in during the match.
Marking (man to man marking – Zonal marking) :	The ability of a player to mark an opponent's players – or zonal area of the pitch

5.4.2 Technical KPIs

In this research, technical skills are the different physical competences required by different positions in the game. It is the ability to control the ball for the sake of accomplishing the required tasks effectively and efficiently. It is defined in this research as different individual football physical competencies required to control or to regain the control, to direct the ball, and to build constructive movements during the match. They are classified into off the ball competences (ability to regain the control) and on the ball competences (ability to direct the ball towards a constructive movement). Examples of technical KPIs could be the ability to save the ball for a goalkeeper, interceptions for the defence players, or aerial skills for midfielders.

> *"It depends a positions by positions, you have goal keepers, defenders and so on." W1TD.*

The one who cover the most important spaces in the ground is the one who has the fitness and technical skills. They are most important to be able to intervene opponent passes.

> *"It is also a technical skill to be able to stop the ball in the right time in the right way" W1FC5.*

> *"You need to consider the position of the player, different aspect different characteristics and to see which player is best in which position. Also depends what the coach goals and objectives from the players of the team and team needs" W1DA3.*

> *"For each position, there are certain essential technical skills. For instance, flanks should be able to control the ball and able to dribble. Also, defenders shall be able to play with head, aerial skills, and tackle the ball. "W1FC7*

Technical skills are essential compliments for tactical skills. Without good technical skills (e.g. dribbling, intervening), there will be less possibility to control the ball, giving fewer opportunities to score or contribute to goals.

> *"We can separate between the fitness and the tactics." W1FC2*

However, these skills are not sufficient for tactical performance and match performance (scoring and guarding the goal).

"Two players are different in their body size with different KPI indicators. one of them is big but heavy and slow, while the other is thin and fast. Fitness indicators can be misleading here. The heavy person can be positioned in the right place so that he could score better as his shoot is strong. But he has weakness in the speed. The other person who is thin, he can run fast, but he does not have such ability to shoot as strong as the other but can score from penetrating in the opponent lines" W1FC7

Table 5-4: Sample of noted technical indicators from the interviews

Indicator	
Ball Regain	% Success rate of the attempts to regain control on the ball (e.g. tackles or interceptions)
Dribbling	% Success rate to take on (e.g. dribbling)
Aerial Interaction	% the players ability to win aerial interactions
Ball control with speed	Significant change in the speed with the ability to build a constructive pass or goal. i.e. 80% change in speed within 1 min leading to successful attack.
Free Kicks	% of successful shots towards the goal in different situations (in plenty area, outside the plenty area, when marked by 1 person, by more than 1 person).
Free Kicks Goals	% of successful free kicks towards the goal from different zones (e.g. right, left, middle zones).
Innovation index	Number of innovative movements in the match (new dribbling, tackles, passes or movement)

5.4.3 Physical KPIs

In this research, Physical KPIs are those physiological and fitness measures for the players' abilities. Some of them are traits that cannot be changed, such as the height and ambidexterity while others can be improved by training such as speed, high/moderate intensity running and recovery rate. These factors can be preliminary indicators for predicting match results

> *"As an example, normal team they run 800/900 meter in more than 24 km/h and the more successful teams they run 4/5 Km. That's already a very important parameter. "W1TD.*

> *The most noted and observed by all participant as they are published online and relatively stable, although they can not be changed from match to match. W1DA3`*

> *"I take all the information about my player how many km they covered in the session how many sprints made in the game how many crosses how many tools. So, I take all the information then I make my decision then I know because I read many papers in football strength sprint speed condition" W1FC2.*

Some experts claim that these factors are relatively fixed for most teams, except the number of sprints and high intensity movement over distance, which means that these factors can help a team outperform their opponents.

> *"and when you speak about fitness it is specially about the distances they run more than 24 km/h so the total volume they run is not important at all because if you look at the last 20 years the total distances has not increased the only thing that was increased was the number of sprints and the distance in high intensity." W1TD.*

Physiological measures can provide the basis for technical and tactical skills, as these skills are insufficient without them to get match results.

> *Without the fitness aspects, talking about the technical and tactical aspect would make no sense. The ability to follow the ball depends on the ability to run easily and speedy, with taking the ability to observe others". W1FC9*

> *"The technical and tactical skills are based on body movements. If the player does not have the ability to do these movements fast with high level of concentration, these skills can be demonstrated in the match. To do good passes and receive balls, you have to run and move faster than your opponent. Once the fuel finishes, the team will be defeated easily. "W1FC2*

Several factors were noted as being likely to improve the probability of better match results, in terms of scoring goals, or preventing opponents from scoring goals.

> *"but for me I knew that when we ran more than the opponents (24 km/h) the likelihood of us being more successful is higher, when we recover more balls in the final third, more occasions; specially the conversion rate." W1TD.*

> *"The critical KPIs for me are Meters in high intensity, 24Km/h, amount of occasions, the conversion rate; how many occasions you score, %of occasions you score, recoveries in the final third of the field." W1TD.*

The interviewees suggest that fitness is only a contributor to tactical performance but is insufficient on its own to score in the match.

> *"There is a confusion here. Player X can have good sprints but number of unsuccessful passes. is it a tactical issue or physical issue? I think relying only on distance run per match could be misleading as a proximity for the tactical skills." W1FC9*

There is some evidence to suggest that physical KPIs and tactical KPIs are sometimes mixed, because there is a high level of association between the two factors, with fast and fit players having more likelihood to possess the ball and make successful shots on goal. Additionally, fitness metrics are published and accessible, while tactical are not easily quantified (relying on video analysis rather than statistics) and therefore much less frequently published.

> *"Here is the issue. There is confusion between tactical and fitness aspects. for example, if you find a certain player has not run much in the match, you can translate that as fitness*

issue; but indeed, it can be tactical issue, and vice versa. To avoid such confusion, I prefer to use the computer for measuring the KM run in the match, but I prefer it based on the videos recorded. Statistics is difficult to help here". W1FC7

Table 5-5: Sample of noted physical indicators from the interviews

Physical Indicators	Descriptive
Player Speed Index	Average player speed per match in different modes (low, moderate, high speed and sprint) with and without the ball
Player speed in different running categories with the ball	In low, moderate, high speed, and sprint with the ball
Player speed in different running categories without the ball	In low, moderate, high speed, and sprint without the ball
Distance covered	The total distance run during the match
Distance covered with the ball	The total distance run during the match with Ball
Distance covered without the ball	The total distance run during the match without the Ball
Distance covered in different speed categories	In low, medium, high speed, and sprint
The maximum speed of shooting the ball	
The maximum distance of a throw in	
The maximum height of aerial action (i.e. jumping for header)	

5.4.4 Psychological KPIs

These indicators measure the volatility in other KPIs in different contexts. Psychological KPIs referees to the ability to play in the standard performance under different psychological pressures, which can be called "resilience indicator". As mentioned before, the physical performance of players is fixed and stable over time except some situational fluctuations. These fluctuations are reasoned to psychological issues.

"I can give you an example. One player has 99% success of the intervening opponent passes as long as within 5 meters. I can rely on him. But, from my experience, any sequential missing the balls in this area is an important flag for psychological issues. Once they are resolved, the player performance return to his normal rate" W1FC7

In this way, mental factors can affect all other measures in certain contexts.

"All of us has a fear of the psychological pressures. We have a serious fear of failure, which can influence our performance in a positive or negative way. But fear can increase the

possibility of mistakes which can be translated into goals. Team manager shall be able to manage the level of psychological parameters such as stress and fear of players to overcome them" W1FC7

Environmental contexts can be influential in psychological factors and some individuals are psychologically affected by other players, which can affect their performance.

"It is crucial to understand the psychological factors affecting the players. Not even individual psychological issues but also psychological issues as a group. If the chemistry between players is not as should be, the performance will go seriously down" W2EM2

Personality is an important factor here, with players having different attitudes to risks and opportunities: some are risk averse and have a defensive style under pressure, while others are risk takers who adopt more aggressive response in pressure. These personal characteristics can influence players in different positions and at different times.

"Ibrahimović is egocentric but every striker in the world is egocentric. You cannot but an egocentric player as central defender because he will take risk just to show off, so you cannot do this." W1TD.

Table 5-6: Sample of noted psychological KPIs from the interviews

Indicator	Description
Resilience	% of change in the performance indicator in different contexts (e.g. opponents, home/away, fan support, get paid well)
Ethical indicators	number of cards or injuring other players
Discipline indicators	% Body language/facial expressions of anger against the coach/referee decisions
Manipulative indicators	Number of free kicks against opponent

5.5 The KD Outcomes: Analytic Models

Analytic models are used to combine different indicators for revealing and discovering some of new knowledge. There are different and integrative analytic models are underlined in the interviews. They are predictive, simulations, context based, comparative and synergetic analysis. Predictive models are to predict the probability of scoring in a match for different models. Predictive models are shortcuts of the simulation models which aim to identify weaknesses and strengths of each match model before the match. Simulation models can use sophisticated applications or based on scenarios and comparative analysis. Context based analysis aim to understand the players' performance under different cases. Synergetic analysis is to find out the incremental performance of certain player when plays with a certain player, team or in a certain position. Indeed, all of these models complement each other, and it is argued to work together at the same time.

> *"The data analytic systems enable me to see the situation better. I can set certain scenarios, and hypotheses; then testing them through the data. This helps a lot in setting the match model to improve the possibilities of winning"* W1DA3**.**

> *"Data modelling made the teams can read each other's before the match. it seems like a machine."* W1FC9

5.5.1 Predictive and Simulation Models

Predictive models are equations or estimations used to estimate the probability of scoring in a variety of different situations. In effect, these models estimate the probability of delivering the objectives of the coach, in terms of scoring goals and obtaining a desired match result.

> *"If you play next game make sure that you play better because otherwise, I will be taking the decision next time to take you out of the field. So, he was using all of these data very well. His system was impressive. He uses this equation: occasions = goal attempt - approaches to the goal. Let's take a look at this last one in gameplay. Now data science and gameplay are when you start trying to model what's happening on the field to find the predictors of desired outcomes"* W1TD.

There are two main outcomes for simulation analysis: predicting the outcome of games in different scenarios (i.e. match model), and identifying the potential strengths, opportunities, threats, and weaknesses for each scenario. This analysis can enable a team manager to train the players or change his match model to improve the possibility of obtaining the desired results.

Interviewees noted that simulation analysis can be achieved in a number of different ways. In fact, some did not even use any type of information technologies, using KPIs to mimic the match two days before it took place, which enabled the team manager to watch the simulated match, identify weaknesses and pressure points, and then ensure they are dealt with in the real match.

> *"In the last technical training, I ask the team to have a simulated match 48 hour before the real match. I ask the players to simulate the planned scenarios in fixed balls, building up*

> *attacks, counter attacks, and corners. This can help the team and myself to identify the weaknesses in the expected match." W1FC7*

This approach has many positive and weakness sides. The main advantage over the virtual one is it can be seen as training players on the expected match model. It can be expensive, costly, the simulated match may not fit with the real one, training coach may find this match model is not the best and needs to change it again. Thus, it is believed that the use of virtual simulation models can help to identify and anticipate the weaknesses, strength, opportunities, and threats before the match, or before the on-field-simulation. The main weaknesses of the virtual simulation that teams are not affordable or accessible to different team managers due to financial and people resources.

> *"In pioneering teams, like in Europe, they use virtual simulations. This is very beneficial for them to identify the weaknesses and strengths based on the opponent team. It is used in Real Madrid, Barcelona, and others. These tools can help them but needs people who can use it and extract the required knowledge from it. Also, they are expensive" W1FC9*

5.5.2 Context based Modelling

The context-based modelling is defined in this research as the identification and measurement of the players' KPIs in different training and match context. Context here can be game location, quality of opposition, match status, and match timing (e.g. Match Half or extra time). The reason for contextual analysis is the performance of players can be sensitive to certain contexts which shall be considered in setting different scenarios or in simulations.

> *"We do different of series of comparisons through the application. Indeed, from my experience, the player performance changes from context to context. The KPIs are relevant to the context. By understanding these contextual factors, I can optimise the team composition KPIs to get the best. Also, all measures are identified with upper limit and lower limit to set for other unknown factors. This is the work of both train manager and data analyst." W1FC7*

This modelling is not a one-time analysis, but rather it is based on a series of analyses to ensure that the measures used are reliable and valid.

"And then I'm interested to see if P3 is playing a good game or not. Then I go layer by layer. and see how many meters, where did he run his meters, was it the first half or the second half, what was his average position, what was his opponents' positions and go deeper and deeper and deeper. But when you ask me what should I do when I make my first analysis, which data I look at, these are the ones" W1TD

According, to do that, the categorisation process is required to categorise the different states that players' performance can be sensitive to.

"He will study it and meeting with the staff, assistance coach, fitness coach, based on each game, match to match, categories of the match, so in Cat A match P3 performance in this way, in Cat B match he perform in this way and so on. Home or away, team performance will be low because of the "pressure" crowd, audience. He defines the categories based on previous data, experience and so on." W1DA4

5.5.3 Comparative Modelling

Comparative modelling is a statistical method for the comparison between players or teams utilising different KPIs. This form of analysis covers playing positions and competitive level to incorporate data from measures such as game result, tactical tisposition, or influence of fatigue.

"Also, specific data about each player performance. Also, opponent's analysis. Also, information about scouting new players." W1DA4

"Comparisons is a strategic tool to identify the weaknesses in the opponent team. This opens opportunity to explore other different models to get the best of the match." W1FC7

5.5.4 Synergetic Modelling

Synergetic modelling is a technique used to identify the correlation in a player performance with others in the team. It is called synergetic because synergy is defined as one plus one is more than two. I.e. collaboration of different actors could improve the outcomes if each of them is working alone. Football as a sport focuses on the collaboration of the players in the team. If there is not such collaboration between team members, the performance is expected to go down. The team members, if they work collaboratively, will be able to strength each other and improve their performance as one cohesive team.

"Players are not machine. The psychological and fitness are inseparable. Sometimes even you can see psychological relations between players. Some players' performance is highly correlated with others' performance. These factors are important, but I am not sure how knowledge discovery or data analysis can help here". W1FC7

"Fitness, technical skills and other abilities are important, but working as a team is a different story. As a team they can strengthen each other." W1P7

Several participants noted that player performance is affected by other players, rising or falling in response to the 'chemistry' between them.

"When X, Y, and Z players play together in any team, the performance of the match changes radically. All of the KPIs of the players such as running, passes rates, and scoring, change to better if they play together." W1FC7

It has not been noted any systematic approach to find such synergetic impacts. What is suggested in this research is to use correlational analysis. But what is noted by the interviewees is using the context-based analysis. I.e. the impacts on performance if some players missing and some players in the match.

"I tell you about one player called N, last year he was playing back to player L. If player L absent in any match, you can see player N performance goes down significantly. There is a chemistry between these players. But the same player does not have such chemistry with others in the team. This analysis if found by the context analysis when we noticed the player performance goes down without a clear reason." W1FC8

The drawback to this approach is the influence of chance, because it can be difficult to identify such factors on a certain player given that 10 scenarios for other 10 players will also be taken into consideration, which can make the analysis overwhelming. Thus, correlational analysis is recommended as a way to examine the different KPIs of players. Significant correlations can be signs of synergetic impact, based on the assumption that chemistry between the players with synergetic impact will have a consistent, measurable correlation as they influence each other.

"The Chemistry depends, on adding the weakness of the other" W1TD

The synergetic impact can be on tactical and physical KPIs, but do not typically support arguments for technical KPIs. Regarding the synergetic impact on tactical abilities, one interviewee said:

> *“Z" and “X”, one is offensive, and one is defensive. IF you have both of them defensive then you will never have a goal chance, because the two players are too similar” W1TD*

Whereas, the same participated said the following about synergetic impact on the technical abilities of players:

> *So “Z” defensively is not but “X” is good, and it depends on their foot as well, “P1” is left footed “P2” is right footed, it brings balance in the team. One is good in the air one is good in the ground.” W1TD*

5.6 Knowledge Discovery Value Co-Creation Framework for Football Data Analytics (KDVCCFFDA)

This underpinning framework to understand the value creation from the adoption of the KD technologies is the resource based view, adopted from Melville and Kraemer (2004). Besides, the benefits map as a structural framework, adopted from Ward and Daniel (2012), to break down the value creation process into outputs, capabilities, outcomes, and benefits (i.e. value). Moreover, the value creation process is not waterfall due to the fuzziness nature of knowledge. Accordingly the Agile methodology is adopted (Beck et al., 2001; APM, 2015) to ensure the process is Agile and both parties (head coach and data analysts) are taking active role in discovering knowledge.

First, according to Melville framework, the resources are broken down into technological and complementary (or human resources). This research contributes to the knowledge by defining and taxomising the KD technological resources in the football industry. The Information Technology resources that aid in improving the understanding of the data available to the coaches and data analysts. These are Data capturing technologies, software applications for annotation and coding and lastly, databases, datasets and their interface to process and query the data available.

Also, this research contributes by detailing the human resources required for creating value from the KD technologies in the football industry. The Human Resources in this research are as followed. The Data Analyst Competences found in this research are planning football, statistical, technological and communication. They are to clarify and improve the competences in which knowledge can be built, processed and used. The knowledge in football competence of the data analyst are there to aid in identifying the suitable and best technologies in capturing and analysing match events. Additionally, that as well help in improving the communication and collaboration between data analysts and coaches and improving in processing the tasks required. Thus, improving the analytical models that address the several issues that are required by the data analysts. The competences of the various technological resources available in football will aid the data analysts to investigate suitable data capturing technologies, look for specific and databases or datasets that support and optimise the data processing and analysis needs. Thus, improves the KD analytical models developed.

Next coaches' competences are found to be the statistical and software application competences. The coaching statistical competence in this research is to reflect on the trust, motivation and courage of the coach in using statistical data within the coaching team. It is very important for assisting in the data planning, proposing new statistical analysis and develop custom fit coaching models for the coaching team. Alongside of that is the coach capability of using different software application in his coaching activates and how that is reflect in his positive and negative coaching practices due to the awareness of limitation and allowances of software technologies. The outputs of using these resources effectively are discovering new KPIs and developing their analytical models (i.e. discovering relationships between their own sets of KPIs (e.g. relationships between physical and technical KPIs).

Because the knowledge is fuzzy in its nature, waterfall approach to discover knowledge is not a valid option. This research contributes to the Agile project management literature by underlining the role of the co-creation process in discovering new knowledge as project. The co-creation approach using Agile tools are found successful with the teams using them. Based on that, Value Co-creation tools are proposed. They are User Stories, Story Cards, Story Mapping Sprints, and Retrospectives.

The use of benefits map structural framework is found to be useful here in breaking down the value creation process into set of connected boxes as illustrated in Figure 5-6. The capabilities would be in the coaching team abilities in determining and understanding players' performance, identity the opponent's strength and weaknesses as well the opportunities and threats of next match. That as well with aid in understanding more about the opponent's teams' players' performance. The main outcomes that area highlighted by this research are the strategies in which the coaching team can reflect upon their practices. To elaborate more, developing effective training strategy are one result of the resources outputs and the coaching team capabilities. Based on the discovered KPIs and custom fit analytical models, the coaching team would be able to understand more about their training needs, area of weakness or strength, strength to utilise and optimise, weaknesses to avoid, work on and prepare for. By developing effective training strategy, match strategies can be improved. Having improved understanding about training needs and players capabilities (e.g. speed, sprints and passes and synergy between players) should aid in developing matches strategies. Also, reflecting in match training scenarios should reflect on improved match strategies. As a result of improved training and match strategies, understanding players and teams needs would be improved. Hence, assisting in developing effective recruitment and transfer strategies based on better understanding and reading of training and match strategies.

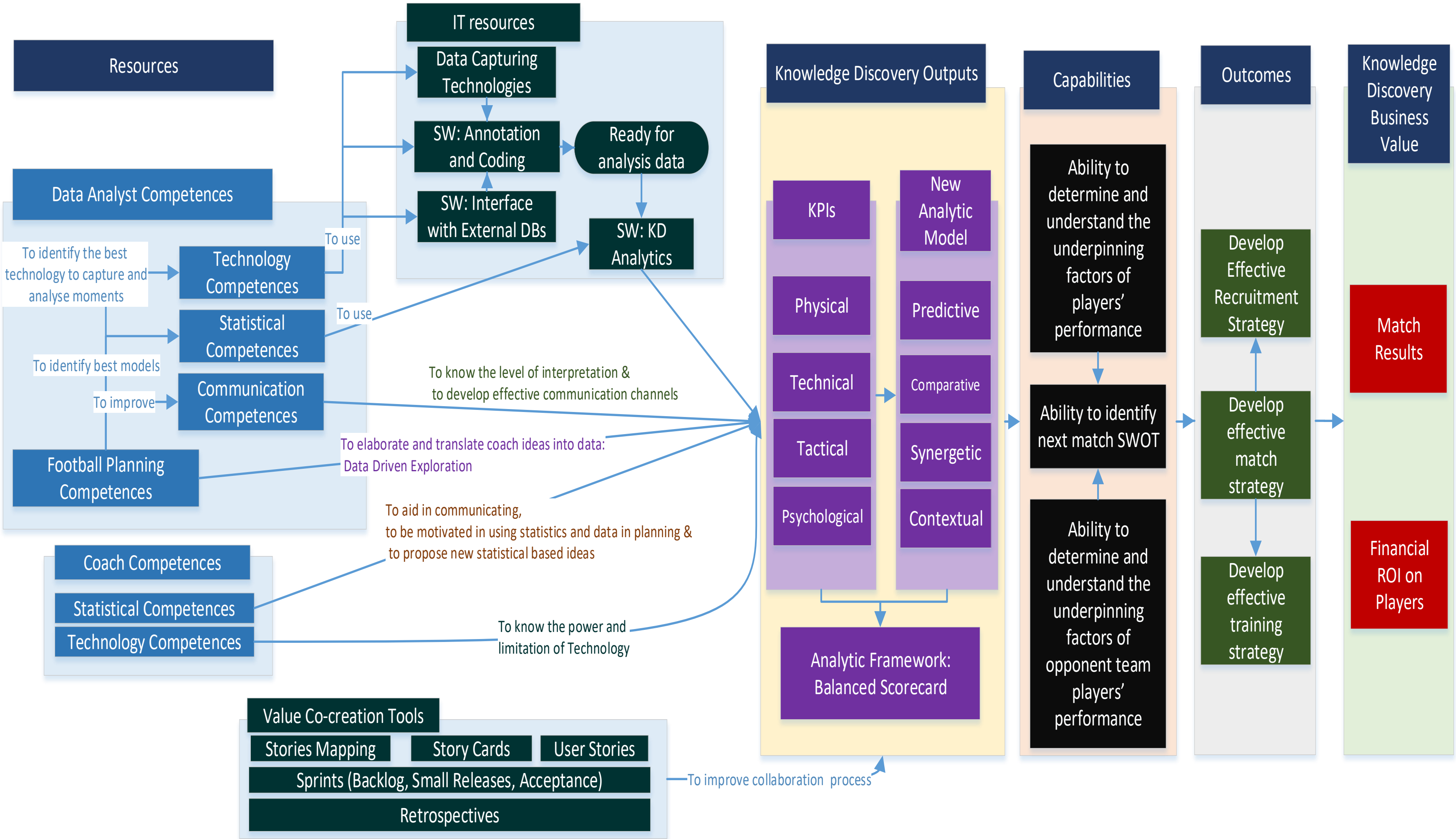

Figure 5-6: KD Value Co-creation Framework for football Data Analytics - © by the researcher

5.7 Knowledge Discovery Maturity Model for Football Data Analytics (KDMMFDA)

Knowledge Discovery Maturity Model for Football Analytics (**KDMMFA**) is developed to summarise the research findings and provide a useful tool for teams to assess their maturity in adopting knowledge discovery in their policies. The maturity model consists of four levels: Ad hoc, defined, managed, and optimised as will be detailed next.

5.7.1 Ad hoc

The first level, the ad-hoc, is unawareness or weak awareness of the KPIs, how to use them and how to put them into meaningful meaning. This level shows the coach is not interested and he does not care to consider KPIs in his training or match strategies. I.e. he might use videos and relying on qualitative analysis and experience to formulate strategies. This level assumes there is no existence of a data analyst. If existed, he has a minimal role in developing training and match strategies.

5.7.1.1 IT Resources

This level assumes that the team do not use or minimal use of technologies to capture the players' KPIs and so no use of any software for discovering correlations or classification (e.g. clustering analysis) analysis. I.e. to operationalise the Ad Hoc IT resources levels, the criteria are

- No existence of any technology that could code the players performance
- No existence of any technology that could track the players' performance (e.g. cameras)
- No existence of any technology that could do analysis or correlations
- No existence of database for the players performance

5.7.1.2 Human Resources

Human resources at the ad hoc level are minimal in terms of the required knowledge discovery competences for both

- No data analyst employed
- If a data analyst is employed, then is not aware of statistical tools
- Data analyst is not aware of the software applications that could help in analysis
- Data analyst is not aware of the football terms and concepts
- Data analyst communication skills are limited or weak

- Coach not aware of the value of knowledge discovery in the planning process
- Coach does not have specific attitude towards the use of data analytics in improving his strategies
- Coach is not aware how KPIs and use of KPIs could improve the planning process.
- Coach is not aware of software applications that could help in discovering knowledge in football.

5.7.1.3 Agile Based Practices Resources

Agile based practices resources are assumed to be minimal here with few use of them and with weak evidence of collaboration, communication, and/or trust between knowledge discovery actors (i.e. data analysts and coach). The items to be recorded as weakness at this level are:

i. No use of stories in articulating problems
ii. No clear vision of the full insight needed in the analysis
iii. Lack of ability to of comprehensive analysis (partial task not the whole Inconsistency in the analysis outcomes
iv. The tasks are not clearly identified for data analyst
v. No clear timing of the meetings and production of reports
vi. No lessons learned from the analysis process is documented
vii. Lack of communication between the teams and/or stakeholders.
viii. Limited contributions/collaboration by the stakeholders for developing the questions

5.7.2 Defined

In the "Defined" level, the team manager is aware of the different KPIs, analytics models, and how to use their results in the strategy development. This case could happen for new coach coming from abroad, but the club does not have sufficient resources to fund for the data analyst or technologies to have knowledge discover IT infrastructure. This is common in Olympic league and League 2.

5.7.2.1 IT Resources

In the defined level, the minimum IT resources required for getting players' performance are identified and used. At this level, the secondary data is only available from the third party but without access to any technology to track player performance.

- The use of secondary database provided from third party.
- No existence of any technology that could code the players performance.
- No existence of any devices that could track the players' performance (e.g. cameras/GPS).
- No existence of any technology that could do analysis or correlations.

5.7.2.2 Human Resources

In the defined level of human resources, the data analyst is available but with minimum knowledge of the statistics in terms of measuring the KPIs but not necessary being able to find correlational or clustering analysis. Also, at the defined level human resource manager knowledge in football is basic with basic communication skills. At this level of coach is aware of the importance of using statistics without having in-depth knowledge of statistics or use of the statistics in planning.

- There is a data analyst but with minimal understanding of statistic terms (i.e. limited to comparison in figures).
- The role of data analyst is limited to importing data from websites to write a report for the team manager.
- Knowledge of football is limited to reports produced.
- Communication skills are adequate. The communication is one way.
- Coach is aware of the availability of different tools and applications that could help in the knowledge discovery.
- Coach is aware that there are statistical models that can be used to improve the planning.

5.7.2.3 Agile Based Practices Resources

Coach and data analyst are using basic agile methods to improve the constructive communication between members. The basic methods here is operationalised in terms having scheduled meetings with defined acceptance criteria for the reports and outputs. The defined level is operationalised into

- The coach and stakeholders having well established Insights and vision regarding the analysis needs
- Meetings are done according to the sprints scheduling
- Defined acceptance criteria for each sprint regarding the discovery
- Encourage the knowledge discovery process by having set of stories/questions to work on in order to reach insights and vision of each sprints.

5.7.3 Managed

In the managed level, the team manager knows and utilises the basic features of data analytics. There are some coding applications that could quantify and measure the players performance such as SportsCode. Basic analyses are done such as comparisons between players. The focus is mainly on the physical KPIs because technical KPIs are more difficult to be captured through basic tools. Correlational, multivariate or other knowledge discovery analytic models are missing. The knowledge discovery practices are limited to what can be known from comparison of the physical KPIs.

5.7.3.1 IT Resources

At the managed level, the team has access to different tracking technologies besides the availability of the secondary data. Besides the use of coding applications to track and monitor different events in the match. But at this level there is access to advanced analytic applications

- Data analyst measures and uses coding application to get primary data of the players' performance
- GPS and other tracking devices are used
- No advanced analytic software application

5.7.3.2 Human Resources

The data analyst at the managed level are able to use tracking technologies and use of excel in sorting, coding, saving, processing, and retrieving basic KPIs. The level of statistics use is average, mode, and median with no use of variations analysis. Also, the data analyst could have a constructive communication with the coach since the knowledge in the football is profound to absorb the match strategies. Also, the communication is improved because the coach have accepted level of knowledge in understanding the capabilities of coding application and awareness of the possibilities of using KPIs statistics in creating new match and training strategies.

- Team of data analysts are coding the match performance and proposed opponent teams
- Use Excel in comparing players and teams
- Ability to use statistical modelling is limited
- communication is two-way
- There is awareness of the use of advanced statistical models.
- Coach knows and uses the possible features of the coding applications
- Coach is interested in different tools and applications that could help in the knowledge discovery.
- Coach is interested in statistical models that can be used to improve the planning.

5.7.3.3 Agile Based Practices Resources

The communication is more structured so that the lessons learned can be documented constructively. The use of story cards, sprints and other agile techniques but the knowledge management in documenting and using the communications are not optimised and not used effectively.

- Set up a tool for manging the KD process in terms of ***problem identification***, ***user stories***/***questions generation***,
- Having and working on clear ***research*** framework to reach the vison and insights of each sprints.
- Enforce learning from the reached results
- Enforce modelling practices addressing the similarities in the analytical questions/stories in order for enhancement
- Set up a clear KD analysis process based on the above and reflecting on them at the end of each sprints.

5.7.4 Optimised

The coach and data analyst are using advanced statistical models to do data mining and exploring new patterns in the data. This case can happen if the data analyst is well trained on advanced analytic models that can do contextual, predictive and simulations. These requires existence of advanced specialised analytic software applications. Also, it requires strong communications between the data analyst and beneficiaries of the knowledge.

5.7.4.1 IT Resources

IT resources at the optimized level refers to the using the full potentials of the technological resources available for the knowledge discovery. This does not only include data capturing technologies but also data analytics technologies. I.e. the IT at the optimised level is operationalised into the following statements.

- Besides the data coding system, there is a software that can correlate and differentiate concepts under investigation
- Besides the tracking technologies, body sensors are used
- Database is well structured, and data is clean
- database includes the performance of the other teams in the league with the same level of details of the team

5.7.4.2 Human Resources

Data analyst and coach competences in the knowledge discovery at the optimised level is the highest. At the optimised level, the communication is highly structured and constructive. The competences of data analyst to inform new data lead strategies is profound. Also, the coach is able to translate the problems into clear stories can be translated into set of clear hypothesis or data inquiries. The data analyst has high level of competences on using analytic applications and artificial intelligence applications. Also, the coach has high data curiosity to understand planning and training problems better.

- Data analyst is familiar and able to use the data analytic applications (Such as R and MATLAB)
- Data analyst have good knowledge of different analytic models (such as Artificial Intelligence Algorithms, Multivariate analysis, and structured modelling)
- Data Analysis has profound experience in football strategies (Training, transferring, and match strategies)
- Communication is solid and constructive between team manager and data analyst
- Coach has good knowledge and understanding of the statistical concepts and models (e.g. artificial intelligence algorithms)
- Coach has good understanding of how different statistical applications and models can help in improving his strategy
- Coach is a fan of data in planning

5.7.4.3 Agile Based Practices Resources

Agile based practices at the optimised level aim to fully adopt Agile methods and techniques to improve the quality of the constructive communications that can lead to discovering new useful and insightful knowledge. The use of retrospective and lessons learned is competent enough to allow effective continuous improvement in the value co-creation process through constructive communications.

- Monitor and measure the KD analysis process quality (against, user questions, stories, stories/question mapping, acceptance criteria)
- Enforce documentations, recording, and tracking process, model development in order to develop and tell informative and relative analysis stories
- Enforce retrospective meetings to improve and issues in current sprint and improve future sprints.

The next section will present the knowledge discovery maturity model for football analytics in a table format for the ease of visualisation and use.

5.8 KDMMFDA – Table Overview

This section represents the KDMM for Football Analytics in a table formats for improving the visualisation of it. Please see table

Table 5-7: KDMMFDA - © by the researcher

	Ad hoc	***Defined***	***Managed***	***Optimised***
HR Resources	• No data analyst employed • Data analyst is not aware of statistical tools • Data analyst is not aware of the software applications that could help in analysis • Data analyst is not aware of the football terms and concepts • Data analyst communication skills are weak • coach Manager not aware of the value of knowledge discovery in the planning process • coach manager does not have specific attitude towards the use of data analytics in improving his strategies	• Team of data analysts are coding the match performance and proposed opponent teams • Use Excel in comparing players and teams • Ability to use statistical modelling is limited • communication is two-way • team manager knows and uses the possible features of the coding application • There is awareness of the use of advanced statistical models.	• Team of data analysts are coding the match performance and proposed opponent teams • Use Excel in comparing players and teams • Ability to use statistical modelling is limited • communication is two-way • team manager knows and uses the possible features of the coding application • there is awareness of the use of advanced statistical models.	• Data analyst is familiar and able to use the data analytic applications (Such as R and MATLAB) • Data analyst have good knowledge of different analytic models (such as Artificial Intelligence Algorithms, Multivariate analysis, and structured modelling) • Data Analysis has profound experience in football strategies (Training, transferring, and match strategies) • Communication is solid and

	• Coach manager is not aware how KPIs and use of KPIs could improve the planning process. • Coach manager is not aware of software applications that could help in discovering knowledge in the football.			constructive between team manager and data analyst • Team manager has good knowledge and understanding of the statistical concepts and models • Team manager has good understanding of how different statistical applications and models can help in improving his strategy
IT Resources	• No existence of any technology that could code the players performance • No existence of any technology that could track the players' performance (e.g. cameras) • No existence of any technology that could do analysis or correlations	• The use of secondary database provided from third party • No existence of any technology that could code the players performance • No existence of any devices that could track the players' performance (e.g. cameras/GPS)	• Data analyst measures and uses coding application to get primary data of the players' performance • GPS and other tracking devices are used • No advanced analytic software application	• Besides the data coding system, there is a software that can correlates and differentiate concepts under investigation • Besides the tracking technologies, body sensors are used • Database is well structured, and data is clean

	• No existence of database for the players performance	• No existence of any technology that could do analysis or correlations.		• database includes the performance of the other teams in the league with the same
Value Co-Creation Activities	• No use of stories in articulating problems • No clear vision of the full insight needed in the analysis • Lack of ability to of comprehensive analysis (partial task not the whole Inconsistency in the analysis outcomes • The tasks are not clearly identified for data analyst • No clear timing of the meetings and production of reports • No lessons learned from the analysis process is documented • Lack of communication between the teams and/or stakeholders. • Limited contributions/collaboration by the stakeholders for developing the questions	• The team and stakeholders having well established Insights and vision regarding the analysis needs • Meetings are done according to the sprints scheduling • Defined acceptance criteria for each sprint regarding the discovery • Encourage the knowledge discovery process by having set of stories/questions to work on in order to reach insights and vision of each sprints.	• Set up a tool for manging the KD process in terms of *problem identification*, *user stories*/*questions generation*, • Having and working on clear *research* framework to reach the vison and insights of each sprints. • Enforce learning from the reached *results* from the previous steps i and ii and reflect of that based on the acceptance criteria and the intended vision and insights. • Enforce modelling practices addressing the	• Monitor and measure the KD analysis process quality (against, user questions, stories, stories/question mapping, acceptance criteria) • Enforce documentations, recording, and tracking process, model development in order to develop and tell informative and relative analysis stories • Enforce retrospective meetings to improve and issues in current sprint and improve future sprints.

			similarities in the analytical questions/stories in order for enhancement • Set up a clear KD analysis process based on the above and reflecting on them at the end of each sprints.	
Analytics Practices	• Team Manager does not worry much about the KPIs • Strategies are developed based on videos Sloley • Team manager relies on his coaching team opinions in developing strategies	• Team manager is aware of the KPIs, but he cannot utilise them • Team manager is aware of different analytic models, but he is limited in the ability to utilise them • Team manager uses secondary data reports for planning	• The comparative models (such as t test, u test) are used to compare teams, and players • The use of physical and technical KPIs are common but tactical KPIs are less • there is no use of advanced analytic models	• Use of contextual analysis • use of predictive analysis • use simulations models • use most of KPIs • use advanced structured KPIs relations such as Structured Equation Modelling

5.9 Summary

The aim of this chapter was to investigate the potential value from adopting knowledge discovery technologies in teams and to develop a maturity model for realising this potential value. The knowledge discovery framework is developed and operationalised into maturity model in this chapter. To realise the knowledge discovery potential value, it is required to have the technological and human resources. When technological and human resources are orchestrated effectively using agile approach, new KPIs and analytic models can be developed which should inform useful and insightful planning and training practices so that the match results are improved. The maturity model assesses the existence of technological, competences of human resources and the adoption of agile based practices so that new KPIs and new analytic models can be developed to create useful knowledge for the coach.

Chapter 6 Knowledge Discovery Maturity Model – Analysis, Evaluation and Verification

6.1 Introduction

The aim of this chapter is to verify and validate the maturity model developed in the previous chapter. This validation and verification will also improve the validity of the framework as a whole. The chapter begins by describing the methodology used for the evaluation process, after which a background of the cases is introduced. The validation and verification process first focus on the maturity model, and then reflects on the use of the KPIs and analytic models in the development of strategies. Finally, this chapter presents the landmark feedback obtained from the participants in the current study.

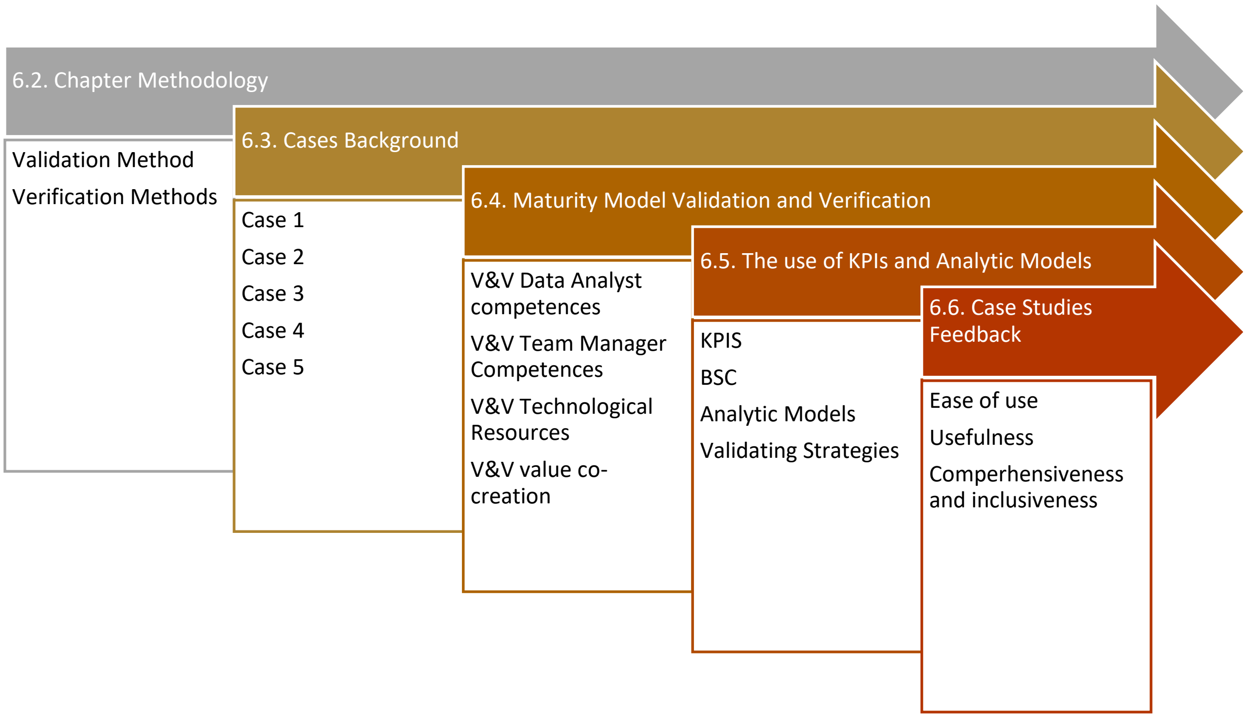

Figure 6-1: Chapter Structure

6.2 Chapter Methodology

Validation and verification are considerations involved in ensuring the quality of the research. Validation serves to ensure that experts agree with the framework and tools developed in this research; verification pertains to the use of the maturity model that operationalises the research findings and then a discussion of the results with cases.

Validation involved face-to-face interviews conducted with nine experts, who gave opinions and insights on the framework, models, and tools. The details of these experts are in Chapter 3. Their insights into the research elements were integrated to improve the weaknesses identified. Verification was conducted through five case studies (five football teams in Saudi Arabia).

6.3 Cases Background

Five teams were selected for involvement in this phase of the research. These teams were different from cases used in developing the maturity model and had different resources available for KD processes. The selection process sought to ensure that different teams with different resources were selected, to ensure that the verification would be meaningful. Two national teams are selected and three teams from the league (two of which held top records in the professional league and the third is an average team). One or two interviews were held with members of each team, in order to gain a deeper understanding and to ensure the validity of the responses for the model questions.

The maturity model was operationalised into a set of questions with a score of five on a Likert scale (from strongly agree to strongly disagree). The questionnaire is in appendix A. The interviews were carried out face-to-face and took an average of 90 minutes. The results of the assessment were discussed back with the respondents, in order to obtain their feedback, as defined in the verification process.

All teams' data, backgrounds and records were obtained from the official Saudi Football Federation website: www.saff.com.sa, Saudi Professional League website: www.spl.com.sa, and from the official broadcasting sponsor: www.dawriplus.com. The main reason for the limited background introduction of the team is to maintain the ethical anonymity practice and policies of the research. It is just to highlight the major achievements of the teams and their contributions. The summary of the findings of the teams' assessments is in Table 6-1.

Table 6-1: Summary of Cases Strength vs Weaknesses points

Case	Team	Main strength points	Main Weaknesses
Case1	CT1	Resources – Data analyst background is professional football coaching. Existence of secondary data sets and use of video.	Data analyst is called video analyst. There is no any role/position for analysing performance data.
Case 2	CT2	Resources Bachelor's Degree in Computer Science Training in football analytics and Coaching.	Use of advanced analytic models
Case 3	CT3	Resources Master's Degree in football performance analysis (Portugal) Coach Experience in the SPL	Communications/ use of advanced analytic models
Case 4	CT4	Serbian Coach – Passionate of data analyst and know about statistics, the use of analytic software.- Existence of Electronic Performance Tracking System (EPTS)	Agile – communication
Case 5	CT5	Team manager strong attitude to use statistical. Great coaching experience	Low resources. No dedicated full-time data analyst.

6.3.1 Case 1: CT1 – Background

CT1 Saudi Football Club is a Saudi Arabian professional football club based in the western region. It competes in the Saudi Professional League (SPL) and is one of the top teams in Saudi Arabian football.

Domestically, CT1 have won many titles including the professional league, King Cups, 6 Crown Prince Cups, Prince Faisal bin Fahd Cups and Super Cup. In terms of international club football, CT1 were the winter of several GCC Champions League titles and an Arab Club Championship, as well as reaching two AFC Champions League finals. Along with top Saudi Arabian football teams, CT1 is one of the four founding members of the SPL and have never been relegated from the top flight.

Team manager / Head coach

Since 2014, CT1 have great coaching teams that aid and lead to significant performance improvement. Coaches from different countries such as Switzerland, Portugal, Ukraine and Argentina are the latest coaching expertise joined this team.

Data analyst

The club has one data analyst who does video analysis and develops reports from STATS (formally ProZone) data about the players, lines, team performance and evaluates competitors. The background of the analyst was professional football coaching and training courses in football performance analysis.

Technologies available

The technologies available were video clips, and primary and secondary datasets. There was no clear evidence that the analyst used training datasets collected using EPTS resources or used training data produced in the report.

Models used

Descriptive analysis (i.e. speed, distance, % of success)

6.3.2 Case 2: CT2 – Background

In 2016, this team qualified for the final against Japan, the winner of 2016 U19 Asian Federation Championship (AFC). Proceeding to the 2018 AFC U19, T2 have not lost any game in Qualifiers Group D. CT2 qualified to the Group Stage and will compete against, Malaysia, China P.R. and Tajikistan in October 2018.

Head coach / Team Manager

The head coach of CT2 is a Saudi Arabian coach.

Data Analyst

One full-time data analyst/video analyst (term used interchangeably). This expert has a bachelor's Degree in Computer Science. Based on the interview with him, he started his analysis in football as a fan and developed by taking football analytics courses and football coaching training. The coaching team feel that the data analyst understands the training and coaching strategies and that he is delivering the required reports. The analyst understands that there are differences in statistical interpretations of the data and tries to develop these in a meaningful way.

Technologies

The coaching team uses video clips, EPTS (polar belts and watch) and primary and secondary data.

Value co-creation aspects

There is a good culture within the coaching team, which was evident from the interviews, questions, and overall performance of the team. The communication, meetings and trust within the coaching team seems to have developed positive collaboration towards coaching and analysis queries. The team manager, coach and data analyst have worked together for more than a year.

Models used

Descriptive analysis

6.3.3 Case 3: CT3 – Background

CT3 has not qualified for the Olympics since 2000, however they were the Champions of the Arabian Gulf Cup in 2008. In 2017, the CT3 performed well in the qualifiers and qualified to the Group Stage. In November 2017, a new Argentinian coach was assigned to the team, but the team did not qualify from the Group Stage. The current coach nationality is Saudi Arabian and is a successful head coach of a professional Saudi Arabian football team.

Head coach / Team Manager

The current coach of CT3, led the one his football team to the top four teams in the Saudi Arabian Professional League (SPL), which is a significant improvement from their poor performance from 2013. As a consequence, he was offered the role of head coach of the CT3 after last season. His coaching team are formed of 7 members: the team manager, 2 assistant coaches, a manager, a physical coach, a goal keeper coach, and one data/video analyst.

Data Analyst

The video analyst of the CT3 have master's qualifications in football analysis. The current resources used now are video clips, primary and secondary data.

Technologies

Video clips, and primary and secondary data. There is no use of purchased primary and secondary data.

Models used

Descriptive, and contextual analysis model is developed.

6.3.4 Case 4: CT4 – Background

After qualifying for the SPL, the management of CT4 invested heavily in developing and improving the coaching culture within the team. At an Olympic level, the CT4 Olympic team won the Saudi Arabian Olympic League in 2018.

Head coach / Team Manager

Great coaches have joined CT4 and it tends to develop good and strong team outcomes. One of their coaches was one of the great coaches that performed very well in the FIFA World Cup 2018. The CT4 team seems to seek specific coaching competences that fits their football team strategies from their approach of selecting coaches.

Data Analyst

The team data analyst in seems to perform the duties expected by the coaching team, including statistical interoperations of players, lines and overall team performance.

Technologies

The resources used for players team performance analysis are video analysis, primary and secondary data. Additional analysis using sophisticated tools were stated but not clarified. There is no clear evidence that there are use of various Electronic Performance Tracking System (EPTS) devices.

Models used

The mostly developed analytical models were comparative and descriptive models, with an unusual focus on contextual analysis.

6.3.5 Case 5: CT5– Background

CT5 is one of the top classic football teams Saudi Arabian. It has been one of the top 5 teams in the SPL during the last 10 years. The team competes across all different league competitions, maintaining a top ranking in the league, and are recognised for their excellent football academy.

Head coach / Team Manager

For the most of his professional career, the coach, was a former player of one of the top Saudi Arabian football clubs. He resigned as player in 2014 and started as a coach while undertaking his professional training. In 2016, he was recognised as one of top three young coaches in Saudi Arabia. He is one of few Saudi Arabian coaches to holds an Asian Federation Professional Coaching License, in recognition of the national shift towards the development of professional coaches to improve coaching and training standards.

Data Analyst

No dedicated performance analysts, but one is available part-time. That may have been influenced the collaboration between the coach and the analyst.

Technologies

Basic technological resources, such as video analysis from videos and observation.

Models used

The focus in the analysis model tends to be comparative, descriptive and simple statistics.

6.4 Maturity Model Validation and Verification

This section is structured according to the elements of the framework. The model consists of four main elements: data analyst competences, team manager competences, value co-creation process, and technological resources.

6.4.1 Data Analyst Competences

The key competences for data analysts are technology, statistics, football planning, and communications. The validation sought to ensure expert agreement with these elements. This followed by a verification through applying the tool on five cases.

6.4.1.1 Validating the Human Resources Required

There was acceptance of the model and results, with some comments supporting this position. All participants perceived football knowledge to be the most important factor, given its importance for discovering new knowledge from data, presenting the analysis in a useful and easy to understand way, and effectively understanding the needs of the coach.

> *"I faced a problem with the data analyst in the youth team. Frankly speaking, I failed to work with him. As you have shown me, the data analyst needs the sense, the feeling and knowledge of football. Some analysts have strong knowledge about statistics and analysis, but no idea about football. I can confirm what you have said. I sometimes think that analysts should have at least minimal experience in coaching or has played football for a while. This can help building ideas and giving a better understanding." W2FC4*

> *"It is crucial that the data analyst be able to understand the coach approach and his style so that can give insightful recommendations based on the data. I struggled a lot with my previous data analyst who were lacking sufficient football knowledge" W2EM2*

As mentioned by other experts, it is critical that mutual understanding and communication are constructed between stakeholders.

> *"There has to be clear understanding in how you see the game. This only comes with time and by working together for a long time. The analyst understands when an attack starts and when it finishes – does it start in a building attack phase – does it start in creating an attack phase – so you need to have a clear understanding. If you have that, you can go a long way." W2FTM8*

One of the participants addressed the effort and time spent to convey message to those data analysts who does not have sufficient experience in coaching and sports.

> *"I can give you an example. I told my analyst to analyse a certain corner in different scenarios for the defenders. He did not give me the full picture. He did not give me what I expected. The communication was not great because of his lack of knowledge in football. Sometimes I spent more than 2 hours to convey my requirements to him. It was a waste of time." W2FC4*

Football knowledge was a key factor in improving the ability of analysts to augment the work done by coaches.

> *"Our Analyst who have worked with in the world cup is a very intelligent football guy who knew "what is what", and what I was looking for - so when he came to say I asked I want to know how many times our central midfielders got into the right – he knew exactly what I meant by that." W2FTM8*

> *"The analysts are doing a lot of statistics on, basically, how many transitions from attacking to defending and from defending to attacking but again there should be a clear understanding between the coach is when does it starts and when does it finish – it's just had a clear and good understanding between the two people." W2FTM8*

Another perspective here is the diversity of the data analysts and coaches that are working together to collaborate in improving the KD process. W2FM8 stated that his team has two different coaches; one for in possession and one for out of possession. Both coaches work closely with the analyst to explore issues and formulate team strategy for different positions.

> *"The analyst needs to understand how the coaches work. If you got a head coach, an assistant coach, and whatever coach – we have three coaches, a head coach, in possession coach, out of possession coach and we have to be in one room together for all three of us to come up with the right sort of information, because my view as head coach is different than the in-possession and out of possession coach – so we got to have a joint thinking between everybody and it takes time." W2FM8*

6.4.1.2 Verification of the Data Analyst Competences

According to the proposed framework, there are four competences required for effective KD processes: technology, statistics, football planning, and communications. All participants from the five cases agreed that these competences are the most required for the data analyst, evaluating them five out of five (with the average score for each competence/per team is plotted on a radar chart). Nevertheless, certain differences were identified, with the highest average being case 3 and the lowest case 5.

> *"It's important for the team analyst to know his role and boundaries like any other employee, and what data is required by the Team Manager/Head Coach. Knowing that it makes his/her job easier and more efficient, helping them to build a connection and trust with the Team Manager/Head Coach." C1DA1*

> *"It's important for a team analysis to know what data he is required and what software/tools that can provide him/her with the information and not go wasting his/her time in looking in other data sources and is not relevant." C1DA1*

> *"The data analyst in our team is useful and productive" C2AC1*

Case 5 has a relatively low match performance. This case scored lower on all aspects than the other teams, perhaps because of a lack of resources and a part-time analyst with limited access to technologies. In contrast, the data analyst in case 3 has a master's degree in data analysis and access to specialised software applications. The data analyst is full dedicated to the team.

Case 1 and 2 are interesting because they demonstrate high technology competences, but relatively low average statistical competences. This may be because the data analysts are highly technology led, which gives access to descriptive statistics, but without training in sophisticated data analytics courses that have provided advanced statistical modelling techniques. Indeed, the data analyst in case 1 is called 'video analyst', which reflects that his duties involve analysing videos without focusing in data modelling for technologies. The budget of these two teams are much higher from others, enabling them to outperform others in buying new technologies. These teams have good results in using different KPIs, but not the highest, perhaps due to insufficient statistical competence. This performance could be due to the communication, football and technological competences of the data analyst. The participants agreed with this analysis.

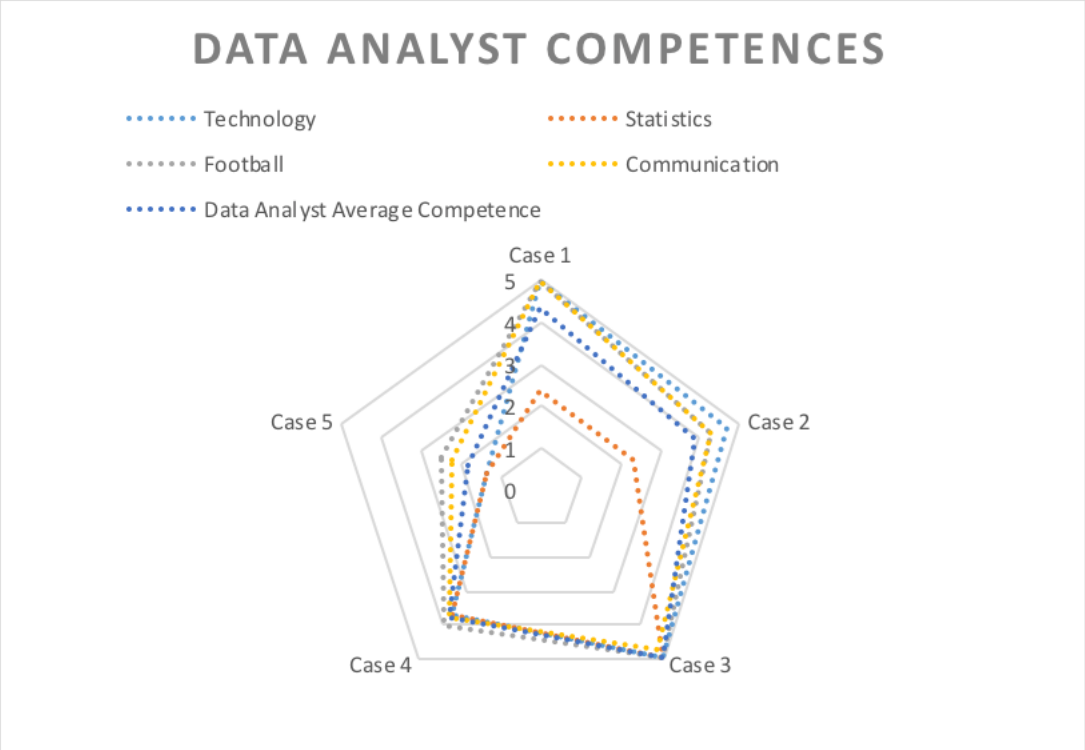

Figure 6-2: Data Analysis Competences

6.4.2 Coach Competences

Two coach competences proposed in this research as requirements for knowledge discovery. They are awareness of benefits of using data in planning (i.e. how to use KPIs in planning) and attitude towards using these KPIs in planning.

6.4.2.1 Validation of Coach Competences

Experts agreed on these two factors. The main confirmed points are the awareness and knowledge of the use and the usefulness of knowledge discovery technologies.

> *"Yes, I completely agree with you! I have seen many coaches who do not have any idea about the data analytics that could help them in managing and discovering knowledge from team performances. They got nothing from such technology because they do not know what they can get from them."* W2EM2

> *"Currently, what you need is awareness. Only 5 or 6 teams are using data analytics in the football. This is even very recently starting from two years ago only. In this year, they become 8 teams only using data analytics. Out of 170 teams, 162 team do not have data analysts and there is no use of any analytic tools. Do you want the reason? It is not because*

of the budget; but there is lack of awareness of the usefulness of the power of data analytics. we need to spread such culture of using data analytics in football sports" W2TCM1

6.4.2.2 Verification of Coach Competences

In this research, two factors are proposed as being critical for team managers in order for them to realise the value from the knowledge discovery: attitude towards statistics and use of statistics in the analysis, and the knowledge and awareness of different analytic approaches. All cases agreed that these factors are vital, scoring five out of five, for translating the data analyst reports and analysis into strategies and performance. Regarding the current self-assessment, team managers for case 1 and case 3 have the most passion for the use of data in analysis, although their knowledge and awareness are less than case 4. Case 5 has the lowest knowledge and awareness of the data analysis models, but relatively high (4/5) awareness. The differences between awareness and attitude could be seen as a factor for learning and adopting new analytic models in the near future. This could be also explained in terms of the need for competent data analysis. Based on the average score of attitude and awareness, case 4 is the highest with a score of four and case 5 is the lowest (2.88). The differences here are reflected in the budget allocated to data analysis technologies and resources. Case 5 has the lowest attitude towards the use of numbers in planning and the lowest knowledge about data analytics, possibly because the team is still relatively new and does not have access to resources. The coach is local, with no access to formal training on the use of data analytics on planning. Additionally, the management of case 5 has not invested in such technologies because there is limited belief in these technologies, whereas case 4 has a significant budget in these technologies.

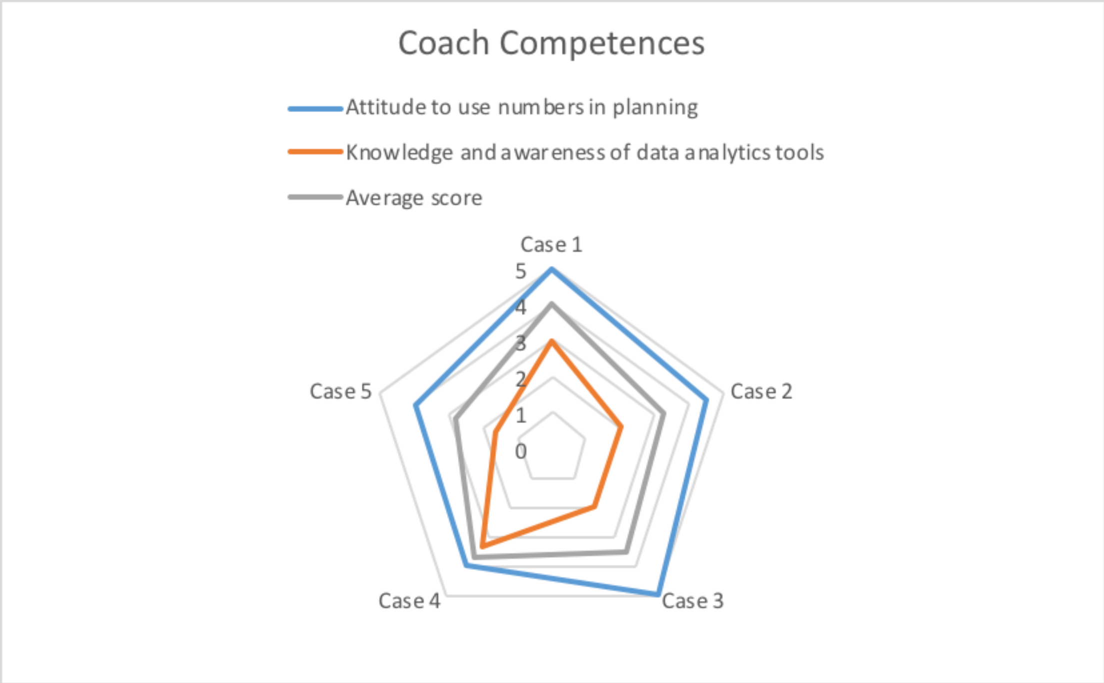

Figure 6-3: Coach Competences

6.4.3 Technological Resources

The technological resources proposed are videos, databases, sensors and software applications. The following sections validate and verify these factors.

6.4.3.1 Validating IT Resources Model

In validation, the technological model proposed in the previous chapter was accepted by all nine interviewees. A comment was raised about the database and about the sufficiency of the model. The first uses FIFA videos and analysis, which provides a database of players.

> *"We use also FIFA videos and its analysis. It issues CD contains analysis of the world cup matches. It provides insightful analysis. We use these CDs to create benchmarks for our team performance. We use some videos as to improve our player and coaches' competences"* W2FC6

The limitations of using FIFA CDs is that data are limited to only world cup matches, which is less useful for teams in the premier league. It is interesting that videos are being used to set new international benchmarks for the players. The other comment was on the sufficiency of the model, with criticisms being targeted at the weakness of the model without support by experienced data analysts with different specialities.

> *"I lead a national team for 4 years as a first coach. In the last season, we used different devices to track speed, distance, sprints, recovery rate, breath, and maximum distance in sprints. We get best use of it once we hired physical specialist who take control of the analytic process. He led the analysis process and present the reports weekly and disseminate relevant information to players. Also, he helped us in identifying new targets for players and investigating potential reasons for any gaps in the performance" W2FC4*

This point is addressed in greater depth in the human resources section, although the model framework clearly relies on both human and technical resources. Others supported the efficacy and appropriateness of the model.

> *"InStat, Camtasia, and Dartfish are used. Also, we use PowerPoint presentation to present the ideas and statistics to the coach. We present information about effective attacks, number of correct passes. We use videos to support the presentation of KPIs and some videos to clarify unique behaviours" W2FC5*

6.4.3.2 Verifying the IT Resources Model

Teams have different evaluations of the importance of each technology. While the premium league teams (case 1, 4 and 5) evaluate the use of databases as the most important, with scores of 5 for all teams, the national teams (case 2 and 3) perceive these as less important, with scores of 3 for both teams. This may be due to the availability and reliability of the information for different teams. While the professional league teams can play more than 70 matches per year, the national team plays six or more friendly matches per year. Accordingly, national teams (case 2 and 3) are perceiving the use of videos and tracking sensors as more important during the training sessions, to give them more accurate, reliable measures than secondary reports produced for matches at relatively low intervals.

> *"For Information Technology (IT) and the tools to use, it's important to connect training sessions data with real life game data in order to get connected data of the player to improve his/her performance and to get the best outcome." C1DA1*

Accordingly, the level of usage follows the same pattern: case 2 and 3 use more sensors than other teams in tracking player performance during training, whereas case 1, 4 and 5 rely more heavily on databases than national teams.

The use of software applications seems to be associated with the level of data analyst competences, as case 1 and 3 have higher competences than the average (see Data Analyst

Competences) and are also using more software applications than normal in the KD process.

When comparing national teams, case 3 is doing slightly (0.6) better than case 2, perhaps because they have a more qualified data analyst, who has a master's degree in football data analytics. This expertise might give the team an edge over case 2, whose data analyst bases insights on football experience, rather than formal education in quantitative analysis.

> *"Sometimes you want to explore or use a new tech, but you can't because of financial matters" C2DA2*

Comparison of professional league teams averages, case 1 is the best while case 4 is the worst, with a difference of 1.2 in a scale of 5. This difference could be explained in terms of the greater resources available for KD in case 1. This variation can also be understood in terms of head coach/team manager passion and attitude towards the use of data in planning. Hence, case 1 is the highest in the head coach attitude, while 4 and 5 are the lowest on the same scale, as detailed in coach competences section.

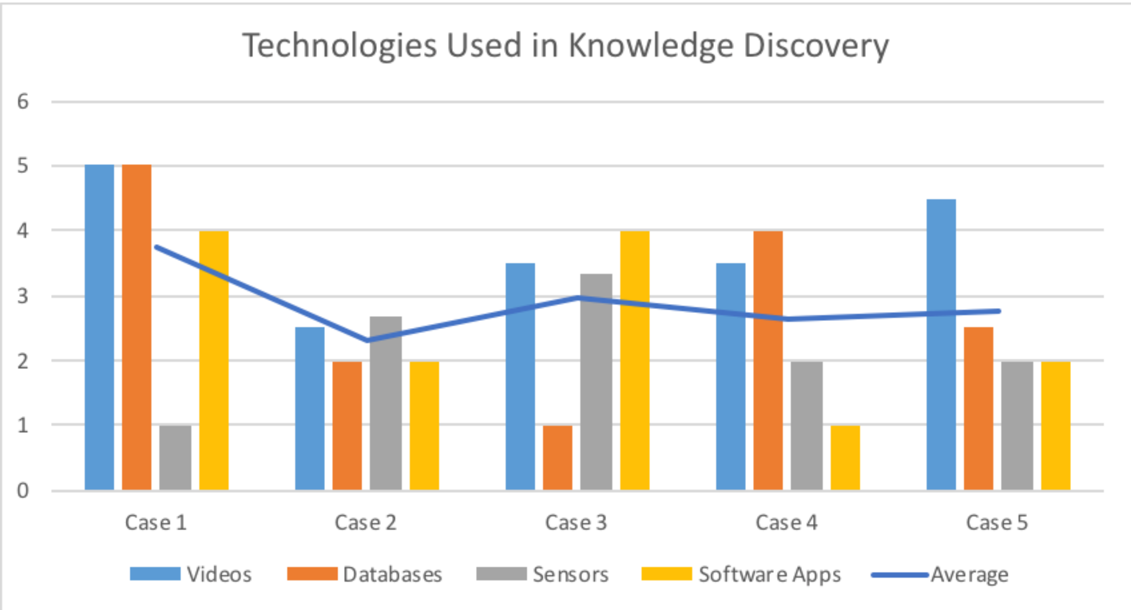

Figure 6-4: Technologies Used in Knowledge Discovery in Football

6.4.4 Value Co-creation

Value co-creation activities are built upon three main factors: structured communication channels, use of storytelling, and sprints. The following sections seek to validate and verify these aspects.

6.4.4.1 Validating the Value co-creation model

In general, all participants in the validation process were engaged and interested in the tools proposed during the value co-creation model. Three had not adopted any of these tools, but they were interested and expressed a belief there is a need to apply them, while others already use some of these tools but not in a systematic way. The conclusion is the tools are validated as being useful for coaches and data analysts. The main comments are documented below serve as evidence for such validation.

> *"I completely agree with this framework. It makes sense in terms of the iterative and continuous work and meeting between the coach and data analyst. I believe the analyst is a member of the coaching team" W2FC6*

Similar feedback was received from another expert. However, he added the routinisation and documentation of such process would provide valuable lessons for learning for helping new members.

> *"Yes, I agree with having a systematic and lean approach in discovering knowledge. Also, documenting requirements and analysis to be as lessons learned. it will be very helpful in supporting new member joining our analysts' team" W2FC5*

Tools were also validated by experts. Some teams use such tools without giving them to similar terms, whereas others found they are innovative and useful ideas. Starting with an examination of user stories/user questions:

> *"In the analysis process, we (coaching team) have around 35 questions about our team and opponent team. Questions such as speed, crossovers, and maximum sprints. By answering these questions, the picture becomes clear enough and from this point we can decide the direction of the knowledge discovery process" W2FC4*

Likewise, story cards were perceived as an innovative method that made sense to the participants. Some teams already use this artefact without calling it "story cards".

> *"We sometimes have things similar to those cards. In questions, we ask about "areas of intensity and pressure of the attack from the opponent, players performance, the*

performance in the wings, the main strength pitch areas of the opponents, recovery time of the players after sprints, distance between lines, the dispersion of players in the pitch, the timing of closing the gaps between the lines and time of increasing the gaps between the lines" W2TD1

Similarly, 'sprint' was perceived as a convincing and useful tool that some teams were already using.

> *"Some analysts give you the analysis on small batches. You as coach give them the highlights and directions and the role of the analyst is to go in-depth and go for details. Analysts are able to develop new insightful ideas, all what they need is the direction and guidance" W2TD1*

> *"Each week the analysis is improved and updated. It is not the same thing. Each match needs new knowledge, new insights, and new strategies. It is not copy and paste. It is an iterative and evolving process" W2FC4*

> *"Yes, this is similar to what we do! Each period of time, data analysts update us with new fresh insights. We (the coaching team) sets the directions and they feed us from time to time" W2FC6*

6.4.4.2 Verifying value co-creation

All teams agreed on the importance of structured communication between stakeholders. They also unanimously perceived the ideas of storytelling and sprints as being critical to ensure that team managers and data analysts understood one another and were working towards the same goal. In terms of self-evaluation of the performance on each aspect, case 3 rated itself as 5 out of 5 in structured communication, while case 2 was the lowest with score of 3.8. The reason here in that these variations could be understood in terms of the time working as one team, while the team manager and data analyst of case 2 and 4 have only started working together recently (4 months and 2 months respectively), while case 3 has a relationship that was established more than a year ago, enabling creation of a structured communication channel. The use of sprints was roughly identical for all teams, with score of 4.5, except for case 3, which scored 4.75. This gives an indication that teams are consistent in their perception of the importance and usage of these tools for collaboration in the production of meaningful knowledge.

Finally, storytelling was used most often in case 5 (4) and least often in case 3 (3.4). There is no evident reason for this variation. It may simply be an expression of the preferences of the coach and data analyst, who prefer to rely on sprints than storytelling.

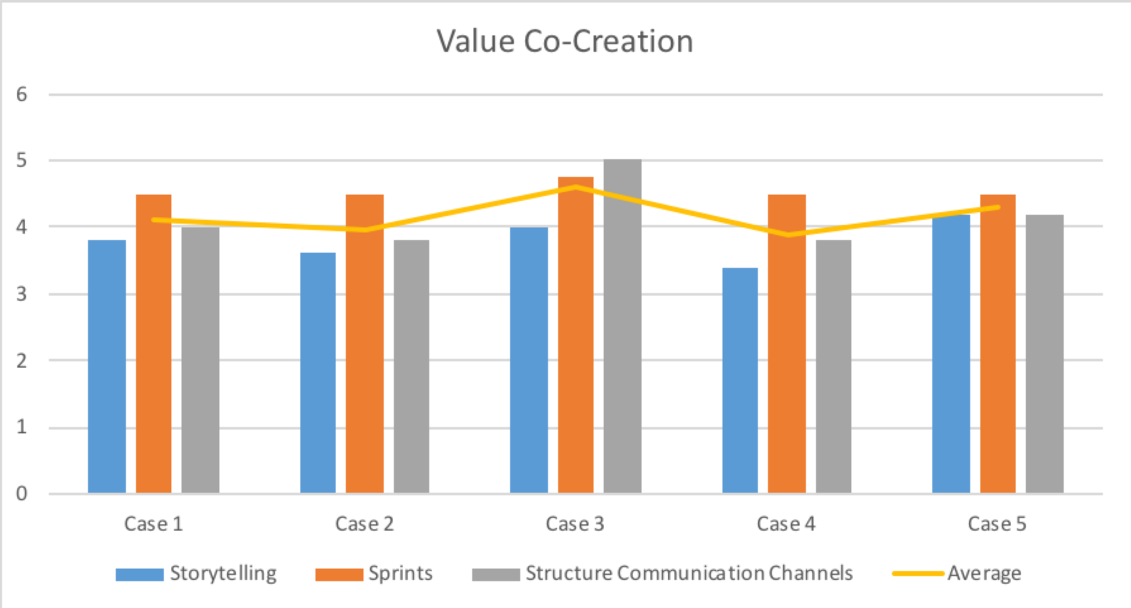

Figure 6-5: Use of Value Co-Creation Tools

6.5 The use of KPIs in the Cases

The validation of KPIs occurs in four levels: the definition, importance, usage, and relations (for KPIs BSC). The structure of this section examines these issues with respect to the four main KPIs: physical, technical, tactical and psychological KPIs.

6.5.1 Physical Indicators

In this research, physical KPIs denote physiological and fitness measures for players. Some are traits that cannot be changed, such as height, while others can be improved by training such as speed or recovery rate. Physical KPIs are classified into speed, movement and distance. All the cases besides the experts interviewed, agreed on this definition, with all criteria given scores of 4 or more. Only two comments are proposed. Case 1 suggested adding an additional KPI to measure the 'agility' of players saying

> *"I connect "distance", but endurance & stamina. And movement can be defined as change of direction & jump. And I would add "agility" as a physical." C1TD*

The second added the need for the use of intelligent technologies in measuring the tracking these physical KPIs.

> *"It is important to reflect the use of intelligent system in measuring and tracking physical KPIs" C3P1*

All teams agreed on the importance of using physical indicators in planning, with all participants grading this as 5, apart from case 4 and case 5, who graded it 4. This lower score may reflect their perception that using numbers in planning is less important. This is reflected in usage levels for these indicators, with case 1, 2 and 3 scoring usage as five, in contrast to case 4 and 5, who scored usage as 3.5 and 3. The lowest was case, not only because of low interest in statistics, but also a lack of KD resources and limited access to a part-time data analyst, software applications and access to different databases.

I think I might need to code the cases team with other codding names just to avoid confusion and be clear when discussing results not to get mixed with other teams in the framework.

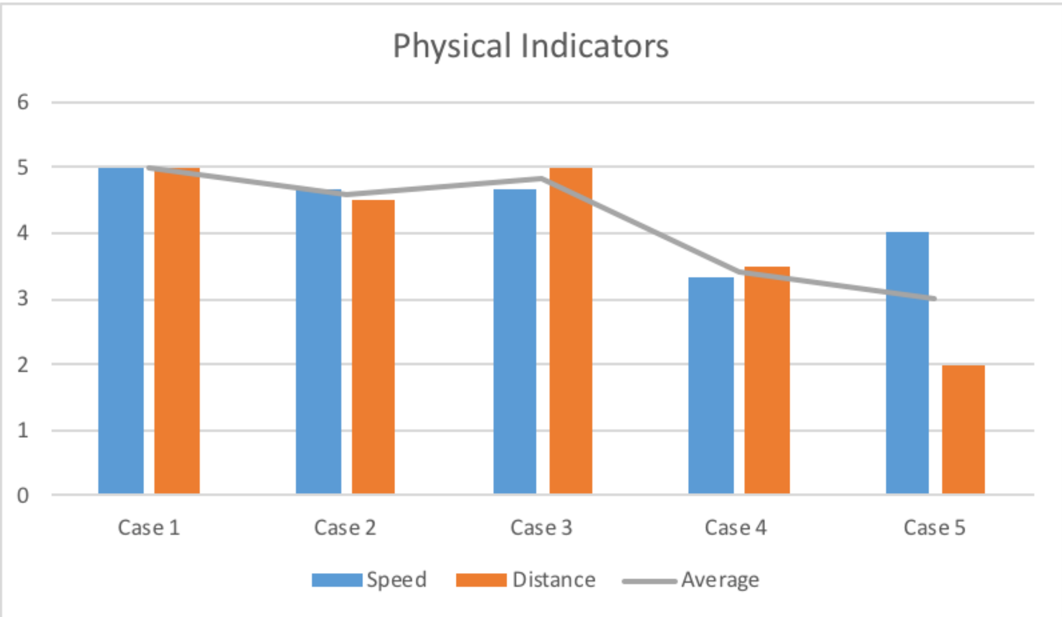

Figure 6-6: Use of Physical KPI

6.5.2 Technical KPIs

Technical KPIs are defined by this research as "different individual football physical competencies required to control or to regain the control, to direct the ball, and to build constructive movements during the match". They are classified into off the ball competences (ability to regain the control) and on the ball competences (ability to direct the ball towards a constructive movement)”. There is a strong agreement on this definition across the respondents.

> *“Technical define as the level of player with the ball in controlling, passing, shooting, tackles, dribbling, and header.”* Case 1

> *“You should also add accuracy of long passes”* Case 2

Both comments are not contradictory with the definition or objective of this research. Accordingly, the definition is validated in this research. Case 1 adopts all indicators mentioned in this research while case 5 is the lowest. This finding is aligned with the research proposition that the factors mentioned in the maturity model can function as predictors for the level to which the indicators are used in planning.

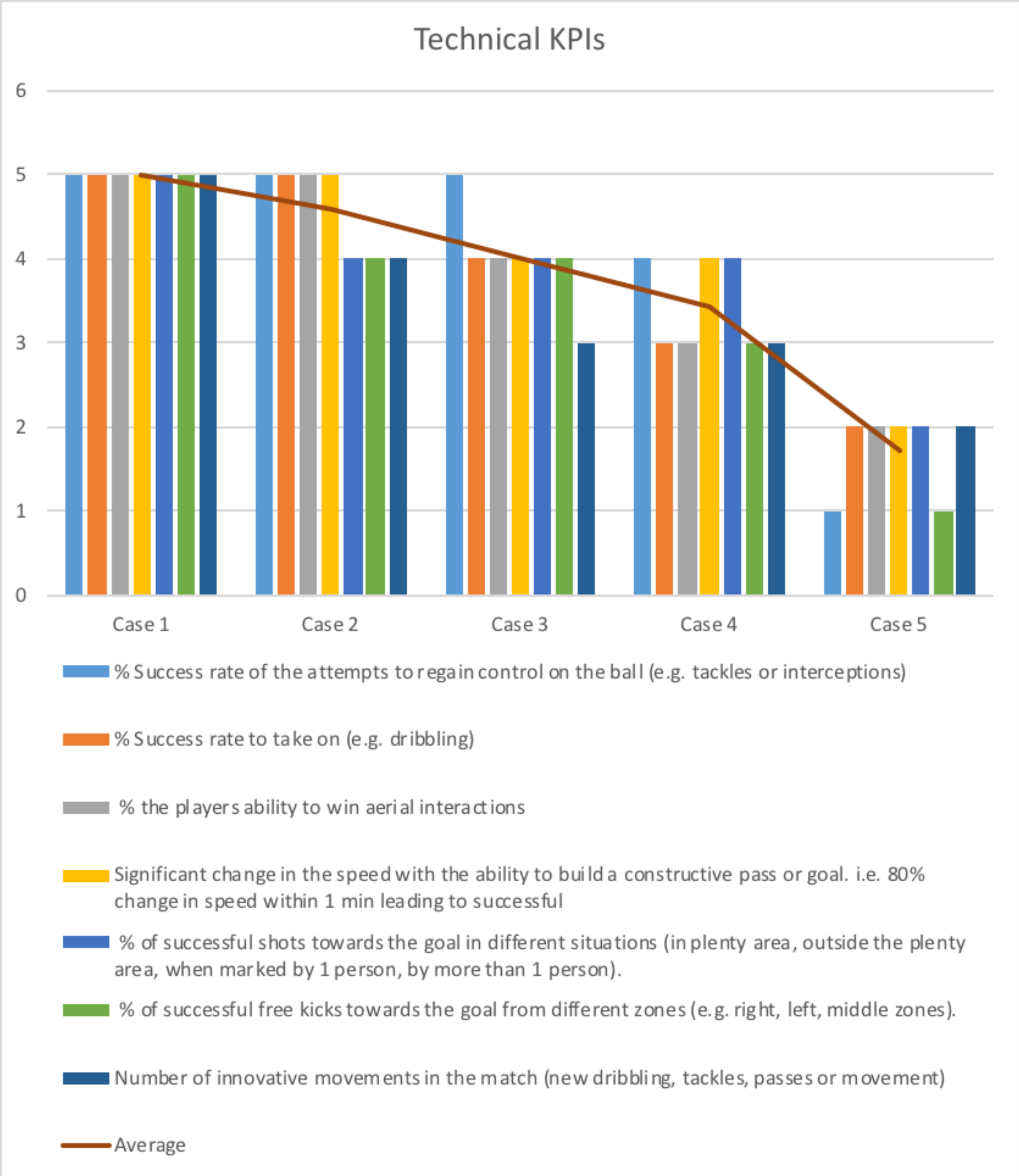

Figure 6-7: Use of Technical KPIs

6.5.3 Tactical KPIs

Tactical KPIs are defined by this research as "as metrics to measure the players' ability to position himself in the pitch effectively and efficiently in such a way the probability of passing, possessing, scoring and intercepting are improved". The tactical KPIs are measured by player, unit of play (set of players), tactical lines (e.g. attacking, defending, or midfield line), or by the team. They are classified into passes, possession, and playing style." There is only comment received on this definition.

"Tactical is define as ball in possession "attacking", ball out of possession "defending", transition from attacking to defending, transition from defending to attacking. And may add individual player intelligent and insight." C1DA1

This comment supports the current definition rather than being contradictory. Accordingly, this definition is validated. The usage level is associated positively with the level of resources identified in the maturity framework. In other words, case 1 has the highest level of usage, whereas case 5 is the lowest. This finding verifies the arguments of the research that the factors identified enables teams to identify new knowledge by applying and innovating different KPIs.

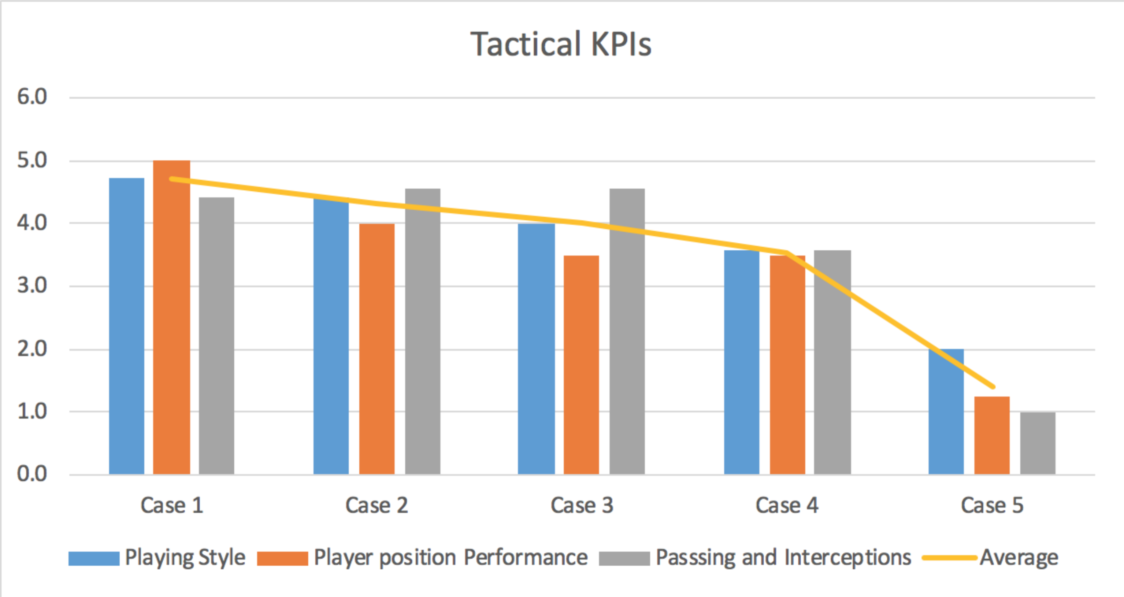

Figure 6-8: Use of Tactical KPIs

6.5.4 Psychological KPIs

This research defines psychological KPIs as the ability to play in the standard performance under different psychological pressures. I.e. psychological resilience indicator. All participants agreed on this without adding comment except for case 1

"Psychological can be defined as playing under pressure, leadership, composure, anger, and motivation." C1P1

This definition is consistent with the definition in this research. Accordingly, this research definition of psychological KPIs is valid. The level of usage for this KPIs is the highest in case 1 (5) and lowest in case 5 (3). This resonates with to the coach management style and data analyst competences. These indicators are not normally incorporated into the software packages available on the market, instead requiring special coding for resilience indicators and discipline indicators. Accordingly, its extensive KD resources enable case 1 to adopt these indicators more effectively than case 5, which has very little investment in KD resources.

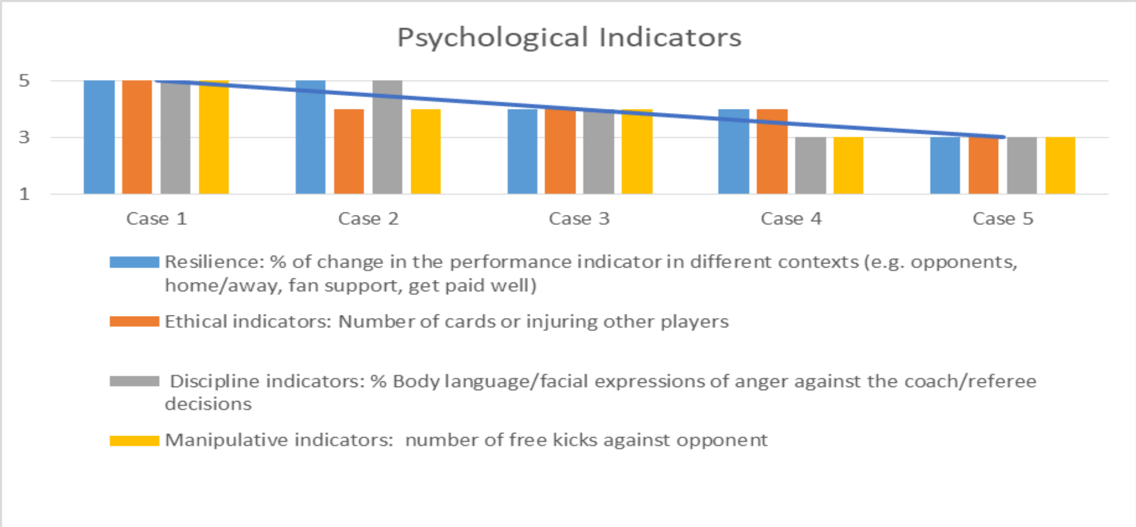

Figure 6-9: Psychological Indicators

6.5.5 KPI Balanced Scorecard

The balanced scorecard metric was validated by asking the experts and cases under investigation about the level of their agreement with each of the statements. A presentation briefing was given on the scorecard. The respondents appraised the framework and unanimously agreed that it was accurate. The KPI balanced scorecard framework was revisited and positively reviewed by experts. The validation examined the importance of understanding the relationships between KPIs, the existence of such relations as proposed in the framework, and the acceptance on the categorisation of the KPIs.

First, the importance of understanding the relationship between KPIs as an approach for knowledge discovery has been verified with all interviewees. The feedback addressed the role of such a model in KD.

> *"Statistics in itself add so little to an experienced coach. It is useful only if it is used to test such relations. It provides a concise and persuasive evidence for relationships between KPIs. This is the way the knowledge can be discovered" W2TD1*

> *"This is really good, you got really good information here" W2FM8*

The other feedback addresses the importance of having knowledge discovery technological resources. This framework can work only if such technological resources are available.

> *"This is very insightful and a rigours model. It is critical for discovering the knowledge and empowering the coach to discover the right knowledge for the game. But the main thing stopping me is the data. How can I get all of these data without having strong IT platform and centralised database? If I have such detailed information about the player performance in different contexts, I would say this framework will be useful. Also, I would like to add something here, the physical performance is monitored by a specialist who gives a detailed report about the player fitness. But it makes sense to connect that with other performance areas as you show here. I would be happy if you write this framework in a detailed book to be reference for discovering knowledge in football. I would say if this framework supported by videos and pictures, this could help a lot" W2FC5*

Second, the existence of these kinds of relationships has been verified and confirmed by participants.

> *"I agree with you. This makes sense to me. I see the most important things affect the match result and tactical skills are the physical and psychological performance. Most of big teams now have specialists in psychological and physical performance. The teams that can understand and manage these factors of the players, they are the winner" W2EM2*

In addition, there was broad agreement that tactical performance is primarily dependent on the ability of a player to understand the tactics of the game and match that understanding with high performance.

> *"The good attacker who has a good vision. He makes the play maker. Also, the good defender who can understand the opponent attackers' tactics" W2TD1*

Tactical skills are confirmed as being critical for match success.

> *"a 90 min match I might not need all the player successful passes or shots however I will need the player critical passes that leads to a goal, created a chance/opportunity to attack and score that what will benefit me as a coach – not only 80% successful or 20% unsuccessful passes this reading does not help me a lot. This is very simple from 3/5 and a maximum of 6 if the player is a super star - He can create 6 attacking opportunists." W1TD*

Also, the influence of the psychological indicators on the physical, technical and tactical performance of players was recognised as being extremely significant.

> *"Yes, psychological factors play an important role in performance. You can see a player feel tired after 20 minutes. Even if his normal physical performance is far beyond that, he can get tired because of the stress. Stress pushes cortisone into the blood, which makes the body dysfunctional. This can influence the player performance in all aspects." W2EM2*

> *"Yes, psychological factors influence the other aspects of a performance. If the mood is negative, the physical and technical performance will generally be weaker than expected. Even the ability to pass and or understand movements will be weakened. You are right, you connected these different elements together in a good way." W2FC4*

A different review of the proposed framework focused on the belief that tactical performance can influence technical and physical performance. When opponents have stronger tactical skills, this can have a negative impact on the value of physical and technical skills in a team.

> *"Yes, but there are other factors not noted here. Something out of the framework; it is not connected with physical or tactical skills. The opponent ability to read my tactics and ability to control the game though the superior tactical performance. In this case, technical and physical performance could do nothing against such team" W2TD1*

In general terms, however, there was general acceptance of the categorisation, with unanimous acceptance of the definition and classification.

> *"If my defender is not able to catch the attacker, the attacker is far faster than the defender, this of course will be analysed by physical measures and forward to physical specialist. If the attacker of the opponent team is clever enough in dribbling any my defender is not able to do proper interception, this will be covered in the technical training. Technical and physical indicators are different, but they are linked" W2FC5*

Physical and technical skills are mainly gifted skills which cannot be changed easily. In addition, they are most often used to compare the players in opponent positions (i.e. defenders and attackers) to explore area of weakness in the team and in the opponent one.

> *"Technical skills and physical performance are something gifted to the player. Training can do few here" W2TD1*

Experts agree on the importance of tactical skills and importance of training on them

> *"Yes, tactical skills are the one. For instance, penetrating the defence lines need tactical skills. As a coach, with help of data analyst, identify the weaknesses in the opponent team. Here you can train player on specific key passes or throw passes that could penetrate weak areas in the opponent team. Here we present videos for the team players visualizing the tactics of the match to penetrate such lines in a specific time" W2FC6*

In addition, the framework was verified by asking respondents to evaluate the impact of each type of KPI (physical, technical, tactical, and psychological) using a continuous itemised (5-point Likert) scale to give more freedom for the evaluation. The summary of the verification process is tabulated below (see Table 6-2). According to the table, the ranking of the factors affecting the match performance is technical, tactical, physical and psychological factors. The framework rank order of the direct impacts is tactical, technical, physical and psychological factors. The difference between the verification result and the proposed framework is the order of technical and tactical. Three of respondents evaluate the tactical is more important while only two said the technical is more important than tactical. Furthermore, two participants evaluated the impacts as identical. Bearing in mind, the framework stating the tactical has only a direct effect while the technical has a direct effect and indirect effect (through tactical indicators), this can be a reason for the two respondents who evaluated the impact of technical KPIs is higher than the impact of tactical KPIs on the match performance. The role of psychological KPIs on technical, tactical, and physical performance is very close without significant differences among them. This also verifies the original framework. But the framework proposes psychological factors can influence the physical slightly more than technical KPIs however the verification showed something else. But because the difference in the score is only 1.1 out of 100, it cannot be argued the psychological impact on the technical is higher than the physical. But both the framework and verifications show the least impact of the psychological is on the tactical impact.

The proposed framework is similar to the verification results in terms of identifying the factors affecting tactical performance. In order, they are technical, physical, and psychological. This research aims to develop this KPI BSC in order to illustrate how the interactions between KPIs shall be investigated to discover new knowledge and serve as a road map for the discovery of new knowledge. Indeed, the participants in this study were pleased to adopt this framework in their daily data analysis

> *"Very comprehensive and useful! I will be happy if you write a book about that. This can be a useful encyclopaedia for us in football knowledge discovery. This will help us in doing what we do"* C2DA1

Table 6-2: Experts Evaluations regarding KPIs BSC

BSC KPI	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Average	Rank on Match	Rank on Tactical	Psycho Impacts
1- The role of physical/fitness indicators on the tactical indicators	100	100	100	60	60	100	63	83.3		2	
2- The role of physical/Fitness indicators on the technical indicators	100	82	100	70	50	100	66	81.1			
3- The role of physical/fitness indicators on match performance	100	100	100	65	50	100	76	84.43	3		
4- The role of technical indicators on tactical indicator	100	87	100	80	90	100	92	92.7		1	
5-The role of technical indicators on match performance	100	95	100	75	90	100	93	93.3	1		
6- The role of match tactical indicators on match result	100	100	80	76	80	100	84	88.571	2		
7- The role of psychological indicators on physical indicators	100	85	30	70	40	100	39	66.3			2
8- The role of psychological indicators on technical indicators	100	90	40	70	40	100	32	67.43			1
9- The role of psychological indicators on tactical indicators	100	64	20	64	40	100	68	65.14		3	3
10- The role of psychological indicators on match performance	100	100	50	64	50	100	61	75	4		
Average	100	90.3	72	69.4	59	100	67.4	79.73			

6.6 Use of Analytical Models

Validating the analytic models was challenging because interviewees were unfamiliar with statistical analysis, many using visual built-in tools. Many of the data analysts were not even familiar with custom made data solutions. However, they are involved in trials demonstrating the importance of such tools, even if they are not currently using them.

> *"this makes sense here. I can give you example to support your research.* ***P7*** *and Rivas are two players. we spent lots of time understanding their performance. It was not clear for us the reasons for having different performances for each. After time, we have discovered that their performance affects each other. They are working closely as twins, if any of them is not playing, the other performance influenced negatively" W2EM2*

Participants acknowledged the importance of analytic tools, but with a relatively low level of usage or adoption. The highest level of adoption was team 4, while the lowest was case 5. This variation can be explained by looking at the level of attitude and awareness of the coaches. The coach of team 4 is passionate about statistics, while the coach of team 5 has the least interest in data usage. All cases were below average on other scales, showing that there may still be a large scope for improvement if these teams utilise the power of KD.

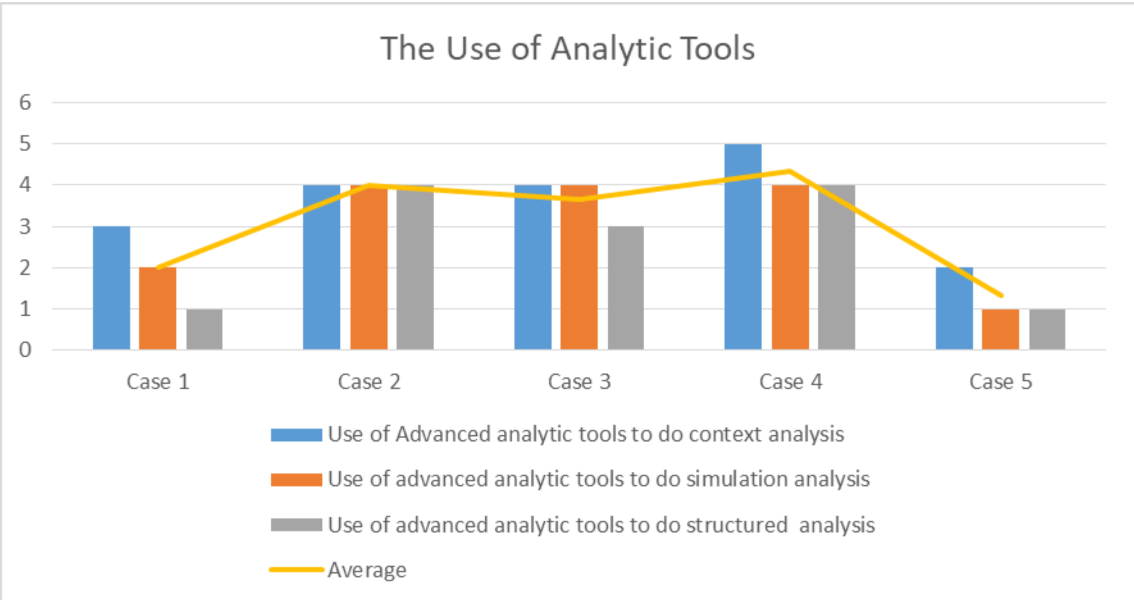

Figure 6-10:The Use of Analytic Tools

6.7 Validating the role of KD in creating effective strategies

The participants agreed with the role of KD in the strategic models of team managers, with explicit comments addressing and magnifying the value of this model.

6.7.1 Transferring Strategies

All participants agreed that KPIs can play a significant role in the selection of players. However, one issue raised is that the current use of KPIs is insufficient on its own to obtain access to the best players. Accordingly, observation is necessary before taking decision, because of the weaknesses in terms of current KD practices.

> *"Yes, we do that, when we search for new players, we look at indicators about physical and technical performance. These figures are fixed and updated every 10 years. From age of 6 to age of 16, the performance is standardised. After 16, the physical performance of players changes significantly, here you can know whose performance is the 'standard' or above 'standard'. Bu our current set of KPIs, to be honest, are not sufficient to taking decision of transferring. It is just a starting point. I need to see the player by myself to see his personal interaction with others. Also, my coach team comes to assess different aspects which we do not know how to quantify using technologies. May be knowledge discovery science could play a role here! Who knows?" W2TD1.*

Similar perception perceived and noted by the youth team manager

> *"Some coaches do skills/technical test for young player, evaluate and record it, this renewed every 10 years (based on the age categories (under 12 under 18 over 19). We observe Players performance in the match besides using tracking devices and recording player performance." W2FC5*

Also, that was highlighted by a Team Manager,

> *"But again, if you work as an analysis and you know what I like in a footballer, what roles I expect a central midfielder to play and if the analyst know that then you could do your recruitment around that" W2FTM8*

6.7.2 Training Strategies

Participants agreed that KPIs can play a significant role in training players. However, one point is raised here which is the effectiveness of training in improving players KPIs. The current use of KPIs do not show the maximum player performance can be achieved by training.

"I agree with you! Not all skills can be trained. There are special skills that are gifted, such as playing by right and left legs. These are not trainable skills. Also, the ability to change performance is limited. You have to know the limits of your player. This can help you when deciding to train or transfer." W2TD1

"Some skills are not trainable at all. Each position needs some skills that some of them, especially technical and tactical skills, are not gained by training" W2EM2

6.7.3 Match Strategies

The main use for KPIs is the development of match strategy through comparison of dynamic team performance with opponent teams to discover areas for improvement and potential remedies for ongoing issues.

"This is what I want from the data analytics. I want to collect all useful and insightful information about the players in my team and the opponent team. Measuring everything whatever can be measured from technical and physical performance. Based on such comparisons, I define the game strategy and match tactics" W2FC5

6.8 Case Studies Feedback

The participants from the case studies stated that they were extremely happy with the analysis and the assessment. Overall, the feedback was extremely positive.

"This is very insightful, thorough, and comprehensive. I believe it covers all aspects of KD." C2DA1**.**

"I hope that you can put all of these things together in one book to be a reference for coaches and data analysts for improving our performance" C2DA

"Interesting research, useful and doable." C3DA1

"I agree with these findings! All good! I cannot agree more." C4AC1

6.9 Summary

In order to validate and verify the research findings, a Knowledge Discovery Maturity Model (KDMM) was proposed in the previous chapter. In this chapter the maturity model was validated by experts and validated by 5 case studies. This step aided and supported in operationalising the research findings. The aim was to target heterogenous sample that should reflect variations of competences. That variations should be reflected on the outcomes of KDMM across the different participants. Additionally, that will aid in spotlighting any weakness in the KDMM and aid in improving it.

The KDMM considered the following competences. Human Resources Competences (i.e. data analyst competences, coach competences), Technological Resources Competences and Agile Value Co-creation Competencies. It inspected the use of different KPIs by the different cases. Furthermore, The KDMM investigated the participants understanding of the relationships between the different sets of KPIs to identify potential areas of improvements.

Revisiting the outcomes of the KDMM, it is noticeable that there are variations between the data analyst competences across the five cases. The key highlighted by this chapter is that the improved realisation of the team's available resources is derived from the human resources competences of the team. The key point is that even if some teams have exceptional technologies that does not mean they are exceptional in understanding their players' performance than their opponents. It is an integrated cycle that require orchestrated utilisation of resources, competences and collaboration (i.e. Agile value co-creation). That should aid in improving the KD process of the coaching team allowing them to better understand their team performance. For example, if the coach has low attitude in using data to build on the team strategies that wouldn't assist him in realising the value of it. Additionally, it is noticeable that the data analyst knowledge of football is influencing the level of communications within the coaching team as seen in Figure 6-2. The could be perceived as a key in improving the value co-creation between the coach(s) and the data analyst. Finally, proposing the KPIs BSC was received positively by the experts. The visualisation of the sets of KPIs delivered improved and informative understanding of the possible relationship between them. That led into encouraging valuable discussions during one of the interviews. As an example, most of the experts agreed that tactical KPIs have a direct effect to match strategies. However, some experts emphasised that technical KPIs sets may have stronger effects on match outcomes. That does not contradict the research proposition, in fact, it supports that since technical KPIs sets have direct effect on tactical KPIs set directly and indirectly (see Figure 5-5). Due to the participants availability I was able to obtain limited feedback of the case studies. The feedbacks were positively encouraging and supporting future research collaboration in this area. The research findings were able to address professional concerns regarding their team performance. Additionally, that aid them conceptually to spot out area of weakness and strength in their team and match analysis practices and activities (see 6.8 Case Studies Feedback).

Chapter 7 Discussion and Conclusion

7.1 Introduction

Knowledge Discovery (KD) is a new science that emerged concurrent with the concept of data mining and big data. The main difference between KD and other concepts is the focus on creation of knowledge through data analysis. In other words, KD is primarily concerned with complementing data reports with the observation of practices, as well as using experiences to create knowledge to enable organisations to outperform their competitors. This area is rapidly growing in the world of football, with investment in such technologies in the football industry exceeding $1 billion by 2015. However, as such investment only started in Saudi Arabia in 2016, this study has examined the question of why some teams can outperform others through these technologies.

The Saudi Arabian sport context has yet to adapt to modern data analytics, meaning that a dedicated study that created one algorithm for a specific case would be likely to be undervalued. Therefore, the aim of this thesis has been to create a platform and a road map to unlock value from KD technology in a functional context. Thus, this research has attempted to develop a framework for understanding the value co-creation process between data analysts and head coaches using KD technologies. The development of such a framework enabled a maturity assessment tool to be created that was able to map the strengths and areas of improvement for teams, enabling them to gain value from KD technologies. Therefore, this research developed a taxonomy of KD technologies in football, identified required competences to utilise such technologies, the required KPIs and analytical models that could be a roadmap for data analytics and coaches for discovering knowledge, and identify the potential values that can be realised from them.

This chapter begins by revisiting the research question, aim and objectives, then highlights the contributions of this study to the literature in this area. The implications of the research are then discussed. Finally, after identifying the challenges, this chapter outlines the limitations of the current study.

7.2 Revisiting the Research Question, Aim and Objectives

7.2.1 Research Question

This research starts by this question “Why are some teams better able to gain value from investment in knowledge discovery technologies than others in the football industry?”

The reasons for this variance can be explained by the resource-based theory, with the core reason for different levels of value being the different availability of technical and human resources among teams. In other words, not all teams have the same access to technologies and not are equally in terms of their human resources competences. The value is only perceived if the KD technologies are used to improve the decision making process of coaches through improvising the abstraction and visualisation of the contexts in terms of using new KPIs and new analytic models. Through this better understanding of the contexts than competitors in terms of using these new KPIs and analytical models, effective changes can be made to the coaching and training practices. Otherwise, if they are not reflected in changes in coaching practices, the existence of these KD technologies could be valued as virtually negligible.

7.2.2 Research Aim

This study sought to develop a framework for understanding the variation in the value co-creation process from the knowledge discovery systems in the football industry.

This study has fulfilled its research aim. Value is only created when coaching practices are altered due to the existence of new knowledge. This knowledge can be operationalised into new sets of indicators, or alternatively into mathematical or visual models that can help coaches to see something that they could not have seen before. Additionally, the value is constructively co-created among stakeholders through dialectics and communications. These communications and interaction between different stakeholders then provide questions and inquiries that ultimately create the requisite knowledge. The ability to scope and address questions requires certain competences from the actors involved in the value creation process, however. Additionally, technological resources can enable and enhance the ability of actors to create new substantive inquiries. In terms of the findings of this study, technology is an enabler and a delivery mechanism, but not the sole reason for performance variation.

The framework in this study consists of four main models: the technological resources model, the human resources model, the value co-creation model, and key performance indicators model, which creates a Balance Scored Card. This framework is mapped over the benefits map to show the interactions between different elements and to prescribe the journey from having the resources to realising the value from investing in this resources. The resources come together to build outputs which are new KPIs and new analytic models. These outputs create explorative and exploitative capabilities in terms of ability to understand the team players' and opponent team players' performance so that the SWOT analysis for the matches can be created effectively. Through such understandings new outcomes come up in terms of the new insightful and knowledge-based training, transferring, and coaching strategies so that the performance results can be improved. All of these models are integral components of the framework, enabling comprehensive understanding of the value co-creation process for KD systems.

7.2.3 Research Objectives

1- To operationalise the expected value of the KD to the coaching team

The value of the KD process comes from the changes in coaching, training, and player transfer practices. This comes from the access to well-informed, evidence-based, verifiable knowledge, augments the decision-making process. However, KD refers to not only the use of indicators or visual analysis, but also the creation, association, correlation, and integration in analytic models of these indicators or visuals. Each new indicator can be seen as a potentially valuable perspective with which to better understand the performance of team players and their opponents, which creates new opportunities for the coach. Each new relationship between indicators can also be understood as new knowledge that could empower the coach to create robust plans relative to those opponents who do not have access to such knowledge.

Value depends on the level of change made to practices and improvements made to performance. The level of change in practices is assumed to be reflected in terms of levels of new knowledge generated through KD activities.

2- To identify and taxonomies the KD resources and depicts a model to understand the role of each class of football technologies in improving the coach performance.

The term technological resources refer to hardware and software devices or systems. Technologies include data capturing technologies (tracking, body sensors), database interfaces, annotations software, and KD analytics. Data capturing technologies allow the coaching team to record data for further processing. Database interfaces support the coaching team with statistical datasets concerning players and teams. Some also come with visualisations and team specific reports (not customised based on the coaching team preferences). Annotation software helps to process, and code pre-set, or specified, events or football actions. Lastly, KD analytics applications help coaching teams to analyse data for deeper insights through the development of customised models based on specific interests. The capabilities in using these technologies, adapting them to serve specific needs and coaching vison, and developing related analytical models are based on the coaching team needs.

3- To identify and frame the role of different knowledge, skills and competences required from producer (i.e. data analyst) and consumer of the knowledge (i.e. coach) so that the expected value from the KD can be realised.

The roles that need to be understood in terms of gaining value are consumer and producer. A producer needs to be competent in using statistical analysis, software applications, communications, and football planning competences. The more competences that a producer has, the more he will be able to contribute to the KD process and help the consumer digest and absorb knowledge, thereby enabling it to be reflected in practice. A consumer needs to have a strong attitude for quantitative analysis and reporting to be able to contribute to this process.

4- To frame the value co-creation process and augmenting it with different tools to improve its value.

As an approach for the improvement and encouragement of effective, efficient communications, this study proposes the use of agile approach tools and techniques. These should enable the formulation of superior communication processes and practices between the producer and consumer of knowledge, potentially helping the optimal benefits to be created and accepted. The key tools proposed for understanding analysis requirements and delivering solutions based on accepted criteria are Use Stories, Agile Release Planning and Story Mapping. Iterative validation and evaluation techniques for these deliverables (i.e. analysis, tasks, reports and stakeholders' agreements) should be undertaken using Sprint and Retrospective approaches.

5- To develop resource-based maturity model to identify the weaknesses and strengths in the augmentation of the resources to get value from knowledge discovery activities.

The KD Maturity Model in Football Performance Analysis was developed to verify and apply the research findings. Because the research is proposing that clear criteria for KD processes and practices results in more effective and efficient KD outcomes, the levels of processes and practices need to differentiate between applicant maturity levels. This research proposes the use of four levels: Ad-hoc, Defined, Managed and Optimised. These levels differentiate the capabilities to analyse football performance data with respect to people, namely the coaches, the data/video analyst(s), the coaching team and any other related stakeholder(s). Additionally, the levels are gradated with respect to the following Key Process Areas (KPA); Human Resources Competences, IT Resources Competences, Knowledge Co-Creating Practices, Use of KPI Competences and Analytical Modelling Competences.

7.3 Contribution to Knowledge

This study provides six main contributions to knowledge, as follows:

1- A novel adoption and customisation of the framework proposed by Melville *et al.* (2004). It is the first research to use it for developing a framework for understanding the value co-creation process from the KD technological resources.

2- A novel proposal and verification of Agile methods, as borrowed from software engineering literature (Beck *et al.*, 2001; APM, 2015). This provides valuable ways in which to improve the value co-creation process between coaches and data analysts for effective use of KD technologies.

3- The novel development of a taxonomy of KD technologies in the football industry.

4- The novel use of a KD maturity model utilising the resources approach.

5- Clearly articulating the required competences from data analysts and team managers for the value co-creation process in KD in the football industry.

6- The development of a novel KPI balanced scorecard, borrowed from organisational strategies literature (Kaplan and Norton, 1996) and its adaptation as a road map for the KD process in the football industry.

7.4 Academic Implications

This research in novel in integrating two complementary frameworks. The first framework was originally developed by Ward and Daniel (2012) and subsequently extended in other studies (e.g. Serra and Kunc, (2015); Badewi, (2016)). This framework demonstrates how project outputs lead to outcomes that can be translated into capabilities and changes in performance (benefits). This research is the first to borrow these concepts from IT project management literature. The current study has approached the data analysis process as a value co-creation project that leads to benefits when the team strategy development is improved by superior understanding of the environment (through using new KPIs and data analytic models) through the ability to use KD technical resources.

This research borrowed the second frameworks from IT business literature, which is resource based view in IT value creation (Melville and Kraemer, 2004). This is not the first research to utilise this approach for improving sports performance. The resource-based view has been used to understand the resources required for team managers and coaches to improve their training and match strategies (Smart and Wolfe, 2003; Lechner and Gudmundsson, 2012; Costa *et al.*, 2018). But this research is novel in using it for investigating the relationship between IT resources and organisational complementary resources in the creation of expected values in the knowledge discovery and in football contexts. In other words, exclusive reliance on IT resources is less effective than when the KD process is supported by complementary resources.

Neither frameworks have been applied in previous studies of computing and football. The adaptation of these frameworks could provide deeper understanding of the practices and processes that exist between the coach and data analyst in analysing football data. This research is the first to combine two frameworks in KD literature to understand the value co-creation process. This process has been developed from IT resources and complementary resources to obtain new outcomes (using data analytics to derive new KPIs and data analytics models), new football team capabilities (better understanding of external and internal environment), and higher performance for the teams involved (ROI on players and match results).

The analysis has informed the development of a new KD maturity model to assess the ability of teams to utilise KD in value creation. The corners of the maturity models are IT resources (hardware and software), competences of data analysts and competences of team managers, agile practices, and sophisticated use of KPIs and data analytics models. The levels of maturity are ad-hoc, defined, managed, and optimised, with ad-hoc reflecting a lack of resources required to realise value from KD technical resources to the optimised level, which describes the highest utilisation of the resources to gain value.

7.5 Recommendations

1- Recommendations for Data Analysts

Data analysts need to be competent in using numerical analysis, software applications, communications, and football knowledge. The more that an analyst (producer) has these competences, the better he will be able to contribute to the KD process and help the consumer digest and absorb knowledge, enabling it to be reflected in practices. In the modern context, KD tools are now too complex to be learned from online learning. Instead, they should be studied under formal education. However, there are no colleges or academic institutes in Saudi Arabia delivering training on KD tools, football, numerical analysis, and communications to data analysts. There is no certification or any awarding body for accreditation as a football data analyst professional. None of the respondents in this study had received formal training on football data analysis, instead coming from a range of unrelated backgrounds. In Saudi Arabia, no academic institution covers this field, which no research being conducted into the improvement of data analyst competences. This weakness was observed in interviews with local data analysts, who had limited knowledge regarding basic analytic approaches such as regression, correlation, and data mining techniques. Although some where aware of the technologies, only one demonstrated awareness of annotation or other technologies. Rapid changes in technologies necessitates the involvement of research institutes, such as the production of magazines to ensure that data analysts are kept aware of recent trends. However, no such specialised news source exists for the Arab audience.

2- Recommendations for the Coach

As the consumer of knowledge outputs, the coach should have a positive attitude towards the use of these quantitative analysis and reports in their practices, informed by profound knowledge of quantitative analysis to enable them to contribute to this process. Currently, most ‘big’ teams are led by international coaches who have developed knowledge and competences. However, local coaches are less capable with numbers and have poorer attitudes towards statistics, perhaps because current coach accreditation does not require study of KPIs or technologies in sports. All courses reflect coaching and techniques, but none include use of data or technology in training. Therefore, training in such competences is essential, as seen in data analysis courses introduced by associations in other countries, such as the Football Association in the UK. Coaches need to familiarise themselves with data analytics and new technologies to be able to communicate effectively and constructively with team data analysts.

3- Recommendations for Team Managers and Policy Makers

Policy makers shall institutionalise the use of data analytics and KD logics in the ecosystem using different mechanisms. According to (Scott, 2010), institutional pressures can be mimetic, normative, or coercive. Mimetic pressures can occur when local teams compete against international teams several times, which will push coaches and data analysts to study what others are doing, potentially leading them to mimic these international teams and become more advanced. Currently, because the SPL lacks a data analytic and data knowledge culture, the attitude towards using data analytics for discovering knowledge is less than it should be. The next pillar of institutionalising KD logics is normative pressure, which pertains to the establishment of certification for practicing data analysis in football and coaching professions in Saudi Arabia. This accreditation would help increase the competence of human resources, enabling them to better cope with advances in technologies for absorption into the planning processes. Policy makers should therefore establish standards in coaching and data analysis informed by research, in an attempt to encourage adoption of KD principals in this industry. The last pressure is coercive, which means the use of laws and regulations to encourage data utilisation and protection of knowledge between teams.

7.6 Research Challenges

7.6.1 Acceptance of research practices

One of the main challenges for this research was the collaboration with organisational bodies, which was problematic due to conservativeness and the competitive environment. As a result, communication and response took a very long time, which was exacerbated by the busy schedule of the target audiences (i.e. coaches and analysts). The large distance between cities also made it challenging to travel around and accept other invitation. Travel from Jeddah to Riyadh by air takes a minimum of 2 hours and about 3 hours to Dammam. Additionally, the cost in funding, time and effort was very high. This research involved more than 3 overseas trips and more than 15 domestic trips (i.e. by car or internal flights) to collect, validate and verify the data collected. More than 10 virtual meetings were also done, supplemented by numerous telephone calls.

7.6.2 The collaborative culture between higher education and sports bodies

From the experiences of this research, it is apparent that no clear research collaboration exists between academia and sport authorities, perhaps due to minimal interest or a lack of clear guidelines in this area. However, I found great support and collaboration after visiting sport authorities in Saudi Arabia, who were very collaborative and supportive. Therefore, while the initial stages were very challenging, after meeting and discussing my research with representatives from these bodies, the process became easier.

7.6.3 Collaborations, Connections and Transparency

Relationships and connections are very critical in this kind of research, requiring extensive effort from the researcher in terms of travel and arranging meetings. Collaboration tended to be slow due to the busy schedules of the professionals in this field, which made scheduling data collection difficult. Transparency is also an extremely important concern in this field, due to the competition, sharing of information, education background and the tolerance for the impact of research in this field.

7.6.4 Cost: Inability to meet all coaches/data analysts

The cost for overseas and domestic travel required extensive investment of funds and time from the researcher. This part of the research was primarily funded by the researcher himself. Traveling time and distance (e.g. a minimum of 2 hours) made it challenging to address all invitations. This was exacerbated by the difficulties of arranging calls with the participating professionals.

7.7 Research Limitations

This research is interpretive in nature, aiming to understand and taxonomise the various factors contributing to the realisation of value from investment in KD technologies. As the study adopted a social construction of reality and qualitative, there are three inherent research limitations: generalisability/applicability in different sports/country contexts, the ability to test the results objectively, and the quantification of the impacts of different factors on performance.

7.7.1 Generalisability/applicability of findings

This research targeted top teams in different leagues in Saudi Arabia to develop a constructive framework that could serve as a roadmap for other teams to obtain value from investment in KD resources. Generalisability and applicability of the findings are limited to top teams in SPL. Precautions should be taken if the research recommendations are applied to bottom teams, other sports in Saudi Arabia, or to football teams in other Arabic speaking countries in the Middle East.

The comparison was made between top teams that had different levels of adoption for KD resources and therefore different levels of realising value from them. Even though the researcher had the opportunities to meet with a local Olympic team, with the national Olympic team and with high level sport authorities, there were clear indications that there is extremely limited usage of technologies outside the national team. Considering KD practices in teams from low leagues teams would be an excellent opportunity to see analysis affects their practices and enables their progression to higher leagues.

This research has not studied or investigated the challenges faced by teams from lower leagues, who are likely to have less access to data analysis due to limited financial resources for hiring international coaches, data analysts, or even buying KD resources. This research therefore offers insights into the teams in the football sector in Saudi Arabia, but not bottom teams. The interviewees were also exclusively involved in the football industry, therefore care should be taken in the adaptation of findings or methodologies to other sports. Football has more financial resources than other sports in Saudi Arabia, as well as more competition and higher levels of care from sports policy makers. Application of the findings to other sports in Saudi Arabia could therefore entail other challenges.

Finally, there is a limited degree of generalisability from Saudi Arabia to other countries in the Middle East. For example, the level of English among locals is different in countries such as Jordan, Lebanon, the Emirates, and Egypt, potentially making it easier for teams in these countries to stay up-to-date with recent updates in the field. However, teams from these nations are also likely to have less access to financial resources than Saudi teams, making investment in KD more difficult. All of these factors can create differences in the results and recommendations.

7.7.2 Objective testing of results

Since this research is qualitative in nature, the ability to test results objectively was a challenge. There are two epistemological stances: social construction of reality and positivist. In positivist research, there is an assumption that respondents do not know and the role of the researcher is to test theories using quantitative and objective tools using correlational analysis and regression methods. Due to the limited number of participants in Saudi Arabia, the significance of the results will less meaningful. Having constructed the framework in this study, future research could test the components in wider contexts, such as a Middle Eastern study of different coaches/data analysts, or even a global study.

7.7.3 Quantifications of the impacts of different factors on performance

Since this research is qualitative, the ability to quantify the impacts is limited. There are some intuitive based tools that can be used to quantify qualitative inquiries, such as Analytic Hierarchy Process (AHP). However, the AHP requires extensive time and effort from the respondents, which was not feasibly in the current research due to the extreme time limitations placed on coaches and data analysts, which already affected willingness to participate in this study. This limited time and availability of participants, it was preferable to benefit from gaps in their extremely tight schedules by validating and verifying the maturity model, rather than quantifying and weighting different factors.

7.8 Future Research

There are two directions for future research that have arisen from the limitations of this research: namely, to quantify and test research findings, and replicate this research on different contexts. In addition, there are three other research opportunities inspired by the research findings: understanding the role of cultural values on KD, investigating the institutionalisation process of KD logics in the football industry, designing a new software application to manage the communications, and lessons learned in the knowledge discovery process. These are outlined below.

7.8.1 Testing and Quantification of the research models

As noted in the research limitations, although these findings have been validated and verified, they have not been objectively quantified or tested due to limitations of sample size. For this reason, future research should test the research results using questionnaires distributed to coaches and data analysts at football teams in different countries in order to reach a significant sample size (e.g. 60) (Hayes, 2012). Quantification can also be done through AHP, fuzzy logics, Delphi approaches, pairwise analysis and other tools. However, as noted above, these methods require more engagement from the coaches and data analysts, so should be undertaken as a part of future research to improve the quality of findings and to make them useful for wider audiences, as discussed in the next section.

7.8.2 Replicability of the study on other contexts

The context of this research is football in Saudi Arabia. Different contexts include the level of team performance (top versus bottom league), country, or qualifications, background and education of the coach, background and education of the data analyst, and even the native language of the data analyst and coach. These factors may lead to different implications and recommendations.

Even though the research findings offered new insights into KD in performance, it would be interesting to see how cultural background influence these practices. In Saudi Arabia, there are different forms of education, coaching systems and certification, as well as variation in terms of competition strength. The study in the KSA context can be taken as a foundation for other studies to be undertaken in countries and continents. The different FIFA certification also might influence KD activities, since other countries have different coaching programmes and levels. Additionally, low league teams should also be studied, as they may face different challenges and issues, including minimal access to financial resources, which hinders their ability to access the technological and human resources required for knowledge discovery.

7.8.3 Investigating the institutionalisation process of the knowledge discovery logics in the football industry

The recommendations of this research propose that institutional pressures are used to push teams to use KD tools, techniques, and approaches in dealing with data. Integrating knowledge discovery into team planning logics has not been studied in the literature. Indeed, there is a general lack of research into the values governing KD logics in the football industry as a whole, perhaps because practices are not sufficiently mature. Globally, KD and data analytics in general are still relatively new and need further investigation.

This research illustrates the need for discovering insights into plans, the need for the communication and value co-creation process to be structured, the need for decisions to be augmented by verified knowledge, and the need for new dimensions of realities to be explored through the use of indicators and analytic models. There may be additional values past this initial list, so techniques and tools should be used to routinize and structure KD logics into the practices of contemporary teams to facilitate the rapid absorption of developments in technology.

7.8.4 Designing a new software application to manage the communications and lessons learned in the knowledge discovery process

KD is a value co-creation process that uses constructive communications and available technological platforms with statistical and analytic models to gain new insights. Constructive communications can therefore help in the creation of new analytic models. Research should be conducted to systemize the communication process to enable the value co-creation process to become easier, faster, and more efficient in utilising lessons. Research should investigate the design of a library of questions, indicators, and analytic models that have the level of errors, relationships, acceptance criteria, and retrospectives required to track the evolution of KD. The technical perspective requires the development of new information architecture to map this knowledge for fast, efficient retrieval, filtering, optimisation, and evolved to develop new knowledge in shorter time and with less efforts.

7.8.5 Benefits management techniques and approaches in Knowledge Discovery

Benefits management is a new approach to the realisation of value from investment in change (Badewi, 2016; Breese, 2015; Serra and Kunc, 2016). It defines the ownership, identification, planning, realisation, auditing and exploitation of benefits (Ward and Daniel, 2011). The value from investing in knowledge discovery technology may be increased by structuring and framing KD based on benefits management. For instance, if a coach identifies the benefits from investment in KD technologies, this may be an opportunity to obtain benefits before procuring the technology. If benefits are planned before data analysts are hired, the job description and specifications for this position could be clarified and made more transparent and effective. Planning for benefits also creates a sense of ownership in terms of the perception of the need to change the practices to realise these benefits. Additionally, planning and framing the process for realising benefits could help a team manager audit and control the realisation process. Finally, exploiting benefits could help data analysts and coaches to brainstorm ways to realise new benefits from the current technologies, increasing utilisation of these technologies and raising the potential performance of the team.

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Appendix (Questionnaire)

KDMMFA Questionnaire

This section includes the questionnaire used in developing the KDMMFDA.

Questionnaire

Q1.2 In your football club what is your primary position - Please select the one is close to your responsibilities.
Team Manager - Head coach - Assistance Coach (Second Coach) - Supporting Coach (Fitness, Physical, Goalkeeper and so on) - General Manager of Football - Data/Video Analyst - Other - Please specify
Q2.1 This part of the Knowledge Discovery Maturity Assessment Model in Football is the Information Technology (IT), tools, technologies and infrastructure used by the team or club by the coaching team for collecting, obtaining and analysing the data.
In your analysis practices, which, tools and technologies you often use?
Use of recorded videos and clips in your analysis Use of professional football databases Use of purchased or obtained reports by professional football websites Use of LPS: Local Positioning System and GPS: Global Positioning System, technologies Use of football field (pitch) cameras Use of the body sensors Use other sports wearable devices Use specialised analytics software (e.g. SPSS and R) to enable you develop new algorithms (e.g. ANOVA, Correlations analysis and t test) Use of artificial intelligence analytics software (e.g. R software, Python) to develop new models (e.g. Neural Network and Genetic Algorithms)
Q2.2 Any comments about the IT environment?
Q3.1 The next part of the KDMAMF is focusing on the Data Analyst or (Video Analysts) Competency in analysing football data.
Q4.1 Data analyst(s) availability at the club or the team as:
Team of analysts - Part time team of analysts - One analyst - One part time analyst - No dedicated analysts
Q4.2 The scope of the following questions is related to the Data Analyst or Video Analysts competences. Where: 5= Very Competent - 4= Competent - 3= Average - 2= Weak competence - 1= Very weak competence

Data analyst is able to import relevant data from professional databases to include them in spreadsheet applications or software (i.e. Microsoft Excel or Apple Numbers). Data analyst is able to code the match key performance indicators and propose opponent teams' analysis. Data analyst is able to use spreadsheet (i.e. "Microsoft Excel" and "Apple Numbers") in comparing players performance and team's performance. Data analyst is able to use "Excel" for statistical modelling. Data analyst is able to use sophisticated data analytic applications (i.e. SPSS and R) for doing structured statistical analysis such as (i.e. ANOVA, Correlations analysis and t test) for testing proposed relations. Data analyst is able to use sophisticated data analytic applications (i.e. R software or Pythons) for utilising artificial intelligence (i.e. Neural Network and Genetic Algorithms) for discovering new pattern in the data. Data analyst knowledge and expertise of the football concepts, strategies, techniques, and approaches. Data analyst profound experience in football strategies (training, transferring, and match strategies). Data analyst ability to interpret the reports and provide useful meaning of the data. Data analyst ability to propose constructive and insightful football match analytical ideas from the data and data resources available. To define the communication requirements from the team managers or head coach (i.e. which reports are required and when to hand them). Data analyst ability to produce reliable reports (level of error in reporting data is accepted). Data analyst ability to define who shall be communicated, by what, and when (e.g. players, media, other members in the coaching team). Data analyst ability to intemperate and explain the technical report with an accepted level of interpretation (i.e. not too much subjectivity, not too few explanation and interpretation).
Q4.3 Any comments about the Data analyst competencies
Q5.1 The following part of the KDMAMF is focusing on the Team Manager or Head Coach competency in the analysis practices of football data.
The Following questions are related to the Coach
Team manager/Coach is a fan of data in planning Team manager/coach believes in the importance of statistics and analysis in improving the planning and developing match strategies

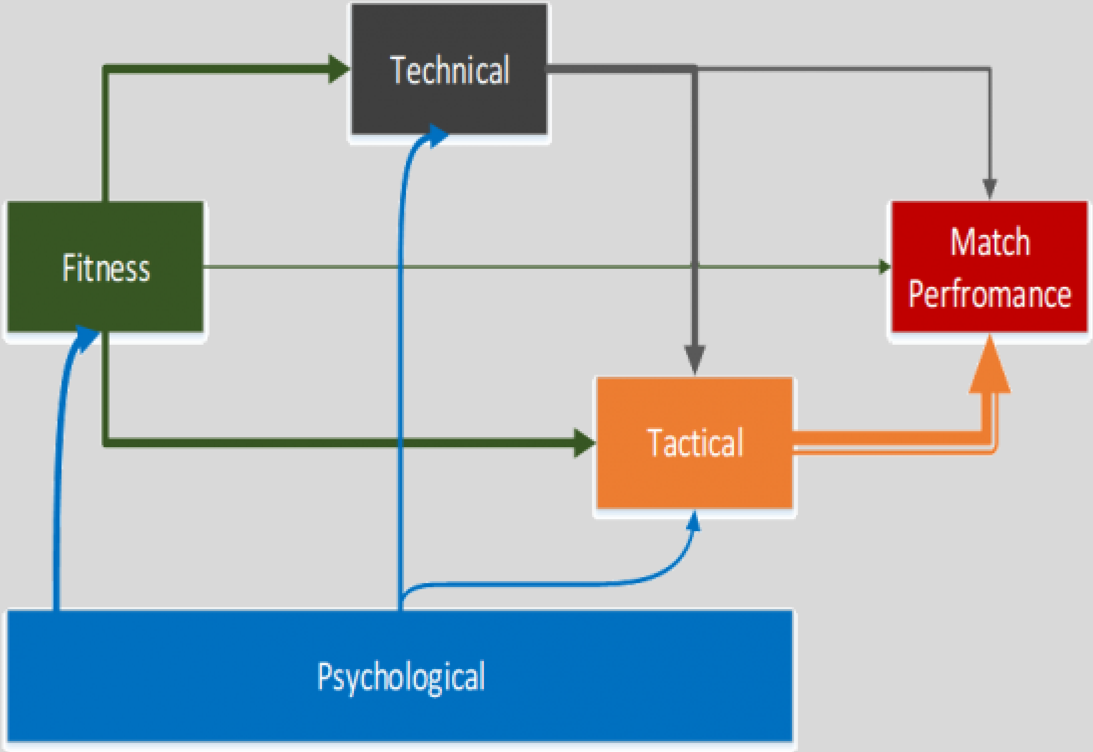
Team manager knowledge of statistical concepts and basic analytic models to compare between metrics (i.e. significance level and "t" test) Team manager knowledge of statistical models to explain and correlate different measures (i.e. when and why to use correlational analysis, regression, ANOVA, and cluster analysis) Team manager knowledge of statistical models to discover new insightful patterns in the data (i.e. when and why to use Neural Network, cluster analysis, pattern analysis and genetic algorithms)
Q5.2 Any comments about the Team Manager / Head Coach environment and competencies?
Q6.1 The next part of the KDMAMF is focusing on the Value Co-Creation analysis practices within the coaching team for analysing football data.
The Following questions are reflecting the practices in the KD value co-creation process.
There are set of questions to work on in order to reach insights and vision of each meeting. There are set of stories to work on in order to reach insights and vision of each meeting. A set of predefined models to describe the problem and integrate them in the stories. A set of predefined tools to describe the problem and integrate them in the stories. Well documentation of stories to be used for lessons learned and improving the story models. There are continuous and periodic meetings between the team manager/coach and analyst. There is clear schedule of meetings with predefined acceptance criteria for what will be discussed and what will be handed. A clear framework for the meetings so that Knowledge discovery process is integrated in the sprint process. Lessons learned are taking into consideration for improving sprints. There are meetings between the team manager/coach and analyst. The communication channels are defined (Who, what, when, and how). Clear communication channels with acceptance criteria of what the information require and why they are required. Knowledge Discovery is integrated in the communication process through setting communication process quality (user questions, stories, stories/question mapping, and acceptance criteria). Lessons learned are documented in the communications and taking into consideration for improving communications practices.
Q6.2 Any comments about the KD value co-creation process?

Q7.1 The following part of the KDMAMF is focusing on the analysis practices, models and outcomes within the coaching team.
The Following questions are reflecting the analysis outcomes of the analysis process and practices.
Use of videos and clips in analysis. Use secondary data reports such as STATS, InStats and OPTA. Use of coding systems/techniques to track different players' performance. Use of analytic models to measure the significance of the differences between players such as "t" test. Use of Advanced analytic tools to do context analysis. Use of advanced analytic tools to do simulation analysis. Use of advanced analytic tools to do structured analysis.
Q7.2 Any comments about the Analysis environment and outcomes?
Q8.1 The next part of the KDMAMF is to explore the awareness and use of football Key Performance Indicators (KPIs) during the analysis used by the coaching team within the team or club.
Q9.1 Physical KPIs - are those physiological and fitness measures for the players' abilities. Some of them are traits cannot be changed such as the height and ambidexterity while others can be improved by training such as speed, low/moderate/high intensity running, and recovery rate. Physical KPIs are classified into speed, movement and distance. ***Do you agree with this definition?***
Strongly Disagree - Disagree - Neither agree nor disagree - Somewhat agree - Strongly agree
Q9.2 Which indicators you most often currently use for evaluating physical performance? and if used or not what are their level of importance?

Player Speed: Average player speed per match in different modes (low, moderate, high speed and sprint) with and without the ball. Player speed in different running categories (low, moderate, high speed, and sprint) with the ball. Player speed in different running categories (low, moderate, high speed, and sprint) without the ball. Distance covered: The total distance run during the match. Distance covered with the ball. Distance covered without the ball. Distance covered in different speed categories (low, medium, high speed, and sprint). The maximum speed of shooting the ball. The maximum distance of a throw in. The maximum height of aerial action (i.e. jumping for header).
Q9.3 Any additional comments about the use of Physical KPIs in player or team analysis?
Q9.4 **Technical KPIs** are different individual football physical competencies required to control or to regain the control, to direct the ball, and to build constructive movements during the match. They are classified into off the ball competences (ability to regain the control) and on the ball competences (ability to direct the ball towards a constructive movement) ***Do you agree with this definition?***
Strongly Disagree - Disagree - Neither – Agree - Strongly Agree
Q9.5 Which indicators you most often currently use? and if not, will you use it? - and what are their level of importance?
% Success rate of the attempts to regain control on the ball (e.g. tackles or interceptions). % Success rate to take on (e.g. dribbling). % the players ability to win aerial interactions. Significant change in the speed with the ability to build a constructive pass or goal. i.e. 80% change in speed within 1 min leading to successful attack. % of successful shots towards the goal in different situations (in plenty area, outside the plenty area, when marked by 1 person, by more than 1 person). % of successful free kicks towards the goal from different zones (e.g. right, left, middle zones).

Number of innovative movements in the match (new dribbling, tackles, passes or movement).
Q9.6 Any additional comments about the use of Technical KPIs in player or team analysis?
Q9.7 Tactical KPIs - are defined as metrics to measure the players' ability to position himself in the pitch effectively and efficiently in such a way the probability of passing, possessing, scoring and intervening are improved. The tactical KPIs are measured by player, unit of play (set of players), tactical lines (e.g. attacking, defending, or midfield line), or by the team. They are classified into passes, possession, and playing style. **Do you agree with this definition?**
Strongly Disagree - Disagree - Neither agree nor disagree – Agree - Strongly Agree
Q9.8 Which indicators you most often currently use for evaluating passing and intercepting performance? and if not, will you use it?
Overall all passes performance index: % of successful passes per match (e.g. spontaneous passes, 1 to 1 passes, unit passes, constructive passes, and long passes). % of successful spontaneous passes: SP is defined as the passes without having a clear intention to build a constructive attack (i.e. due to pressure from opponents). % of successful 1 to 1 passes: 1 to 1 passes is the several passes between two players only aiming to construct an attack, penetrate defensive line or shift the direction of the play. % of successful unit passes: unit passes are the several repeated passes between more than two players. % of successful constructive passes: constructive passes are more than 2 passes with more than 2 players aiming to construct an attack or shift the play direction. (e.g. second ball and third ball). % of successful long passes: Long passes is a movement of the ball from a zone to another zone or from tactical lines (e.g. from back to front, from the left side to the right side or from defending to attacking line). E.g. successful crosses/ counter attack. % of successful interceptions from short passes or long passes (crosses or counter attacks).
Q9.9 Which indicators you most often currently use for evaluating team playing style? and if not, will you use it?

Team/player minutes played with or without the ball. Time played in offence, defence, and midfield. Ball recovery time: Average time required to regain the ball. Total Possession. Distances between attackers and defenders: The average distance between the attacking and defending lines. Maintaining distance between players (close down space): The % of the time that distance between players within the ball range is lower than the coach defined space in each zone. Offside (Tolerance) Management (such as % of the successful deliberate offside (avoidance) and % of the successful avoiding opponent deliberate offside.
Q9.10 Which indicators you most often currently use for evaluating player positioning performance? and if not, will you use it?
% of successful (constructive change) changes of players' positions in the pitch during the match. The duration of a player being in specific zone. Player density: % of time played in the player specified zone. Marking (man to man marking – Zonal marking) : The ability of a player to mark an opponent's players – or zonal area of the pitch.
Q9.11 Any additional comments about the use of Tactical KPIs in player or team analysis?
Q9.12 Psychological KPIs - is the ability to play in the standard performance under different psychological pressures. I.e. psychological resilience indicator. Do you agree with this definition?
Strongly disagree - Somewhat disagree - Neither agree nor disagree – agree - Strongly agree
Q9.13 Which indicators you most often currently use for evaluating Psychological player performance? and their level of importance?
Resilience: % of change in the performance indicator in different contexts (e.g. opponents, home/away, fan support, get paid well). Ethical indicators: number of cards or injuring other players. Discipline indicators: % Body language/facial expressions of anger against the coach/referee decisions. Manipulative indicators: number of free kicks against opponent.
Q9.14 Any additional comments about the use of Psychological KPIs in player or team analysis?

Q10.1 The next questions will be regarding the Key Performance Indicators (KPIs) Balance Score Card (BSC).

Q11.2 KPI Balanced scorecard relation importance. Not Important Important Very Important 0 10 20 30 40 50 60 70 80 90 100

1- The role of physical/fitness indicators on the tactical indicators. 2- The role of physical/Fitness indicators on the technical indicators. 3- The role of physical/fitness indicators on match performance. 4- The role of technical indicators on tactical indicator. 5-The role of technical indicators on match performance. 6- The role of match tactical indicators on match result. 7- The role of psychological indicators on physical indicators. 8- The role of psychological indicators on technical indicators. 9- The role of psychological indicators on tactical indicators. 10- The role of psychological indicators on match performance.
Q11.4 Would you like to add any comments about the BSC?
Q12.1 In which country do you currently work?
Q13.1 Current Football/Soccer Team
Q13.2 Please add your email address - A report will be sent to you after analysing the Interview / Online survey.
Q13.3 First and last names. To contact you and address you in the report - if preferred.