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THE INTERACTION OF ARTIFICIAL INTELLIGENCE AND DESIGN THINKING IN THE DEVELOPMENT OF HR AND DECISION-MAKING TRENDS

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I dedicate this paper to the memory of my beloved grandmothers. Thank you for believing and instilling the love and hunger for knowledge in me. “Neka bude što biti ne može, neka bude borba neprestana”.

Abstract

This paper is a qualitative exploratory study, and a suggestive theory that aims to explore contemporary trends in HR policies in relation to technology. More precisely, the paper is a content-analysis research, aimed to explore the relationship between decision-making and data-driven business environment, and the extent to which AI and DT augment decision-making, if at all. Artificial intelligence is a physical concept which is used to describe and examine the impact that technology has on HRM practices. Design thinking is an abstract concept used to describe and examine the evolution of best leadership practices in terms of HRM processes. Before I started conducting this research, my focus was on AI, as a concept bound to change the face of traditional decision-making. Copious amount of data that is produced, extracted and stored daily, requires respective analysis. As such, I approached my respondents with the knowledge I gathered through personal research and during the creation of theoretical framework. As the research were advancing, I began to realise the extent to which these concepts provide insights into the relationship between the culture of design (thinking) and notion of artificial (intelligence) in decision-making. These two concepts were used to test the extent to which decision-making can be augmented with their use, and how they influence organisational hierarchy. From the side of the technology, AI is looking into the nature of Big Data and how it is used to exploit information for competitive HRM. DT is used to exploit the extent to which Big Data is used to broaden decision-making solutions. Together, this paper is examining the potential of these relationships, and if it in fact renders greater decision-making advantage, by accelerating the process with AI and disrupting traditional decision-making with DT. The paper used the Big Data Maturity Model (BDMM) to filter the findings and study this relationship accordingly. The model is comprised of five interconnected stages which test big data maturity of companies, as well as of their employees. Stages were divided according to goals of the paper and the two concepts. Moreover, the codes that were used to filter the findings served as additional differentiating points in the stages. The research provides insights into the synthesis of AI and DT and how they are perceived by decision-makers. The conclusions give an overview of advantages and challenges faced by HR managers when implementing AI and DT in decision-making and the subsequent room for research of this relationship.

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1. Introduction

This paper will examine the relationship between the concepts of Artificial Intelligence (AI) and Design Thinking (DT), how the two correlate and influence the development of Human Resource Management (HRM) trends. More precisely, this paper will seek to analyse the disruptiveness in decision-making caused by AI assisted by DT.

First off – Design Thinking. As a concept, DT emerged as an innovative form of decision-making, popularised with the development of business and technology. Charles Owen of the Illinois Institute of Design describes DT as "the creation process through which we employ tools and language to invent artefacts and institutions. As society has evolved, so has our ability to design" (Owens, 1993). According to this definition, DT consists of two phases, analytical research and synthetic invention (ibid). Due to the rapid nature of industrial changes, heavily influenced by technological boom, the need to react to them rose exponentially. To this end, DT consists of complex processes that underpin the development of organisational structures. From the perspective of decision-making, it implies processes where the makers of those decisions eek alternative solutions to gain an informed insight (Gavade R.K., 2014). In that regard, fundamental premise of DT is the idea of "Human-centric" approach (Albert Loyola, 2018). The same can be applied to everything: be it in terms of interaction among people, management, recruitment, engagement, performance evaluation, even the physical space in which people work – all can be analysed and re-evaluated through the lenses of DT (ibid). By doing so, companies put their employees at the fore of delivery model, by assimilating the "what" behind people's needs, and "what" they dislike about the delivery (ibid). In other words, it takes the data collected from employees as customers, and ties the feedback to decision-making strategy. How this data is obtained relates to AI and that will be explained separately.

In terms of HR, human-centeredness allows several processes to take place simultaneously. The intrinsic value of DT implies undisrupted flow of innovation, which in turn disrupts traditional "waterfall" HR processes and gives an added value to "human aspect". DT in HR focuses on experience (ibid). It enables decision-makers to empathise with the customer, define the problem, provide the solution, and test if the solution is plausible or not. By developing teams that explore customer experience and those that create design solutions, HR departments simultaneously discuss both the problems and the ideas. This will be the core of research on DT, and this topic will be additionally evaluated. The product of DT is called collaborative design approach, which involves "design process across different business units and functions which brings a new perspective to problem-solving" (ibid). This method is developed in line with the natural course of human decision-making. Moreover, the acquisition of knowledge, i.e. data, is a time-consuming process in which companies invest great financial assets to a dual end: to ensure that the extracted information is relevant to their operation and to optimise operating costs based on the same. To this end, it is important to emphasise that DT gives more room to prototyping in decision-making, and this directly relies on AI.

Enter Artificial Intelligence. In its core, AI is "any intelligent agent (e.g., device) that distinguishes between different environments and can take a course of action(s) to increase the success of achieving predetermined objectives" (Oana, Cosmin, & Valentin, 2017). As phenomena in technology, AI is beyond its infant stage. However, in terms of its entrepreneurial and industry-wide function, it has yet to be examined before it can be fully implemented. Same as DT, the intrinsic value of AI lies in the need to achieve a certain goal in shortest, thereby most effective, period possible (Davis, Bagozzi, & Warshaw, 1992). In other words, AI is emphasizing cognitive skills, same as DT emphasises empathy and creativity (soft skills). Users and analysts all agree on one thing: the benefits of AI are too great to be ignored (Forbes Insight, AI Issue 1, 2018). Furthermore, decision-makers see the long-term (dis)advantage in the application of AI. On one hand, they acknowledge that those who do not implement AI, or at least consider some form of its application, will face a big setback in the coming years when its use becomes widespread. On the other – easier said than done. Given the algorithmic nature of AI, decision-makers will also have to plot several steps prior to its implementation. This is where the parallel is made between AI and DT. By combining the two, AI is used to extract the information, while DT is used to interpret it. Together, they are used to provide the solutions, and predict the outcome. This way, the "human factor" comes into play with the added value of AI. To make this relationship happen, both decision-makers and AI-developers face a set of challenges on the path to its realisation.

I will outlay quintessential ones, and the same will be examined in closer detail throughout the paper. First research question, Big Data Management (BDM) (Forbes Insight, AI Issue 2, 2018). If companies ensure they are using the right tools and methodologies to extract data, they will most certainly produce meaningful results. In this sense, decision-makers will need to upskill and create the right analytics teams to make sense of the information they extract. In terms of DT, they will need to work side by side with developers to ensure the right strategies to implement AI-driven strategies and channel the insights collected from Big Data. This ties to the second research question, which will test the willingness of decision-makers to incorporate AI in their decision-making. In that sense, the paper will examine their opinion as to why BDM is important for the improvement of some process. Third, and final, research question combines the insights from the first two, and studies the challenges in user-competence. In other words, as decision-making is bound to de driven by vast amounts of data, decision-makers will need to evolve and reshape their processes. There will be three levels of decision-making, each with a unique property: (1) to understand and create the decisions based on extracted information, (2) to create the appropriate strategy and (3) to create AI-related process itself (ibid). The outcomes of these processes will reflect two separate courses of AI – DT relationship. According to business analysts and AI evangelists, the future of AI in HR comes down to creating the perfect artificially intelligent employee portal – a place which provides comprehensive and immediate information to workers, with the ease of use, and without the halt caused by procedural management (Forbes Insight, AI Issue 3). On the level of decision-making, AI enhances task-delegation to a new level, and by employing AI assisted tools, companies provide HR with a unique tool to help asses candidates, improve their decision-making and development. By the same token, apropos human-centric decision-making, it helps decision-makers and developers identify weak points in their operation and ways in which AI can be used to reduce costs incurred by faulty processes and improve the existing. Therefore, AI and DT further question the principle of leadership, but with an underlined sense of purpose (Albert Loyola, 2018). To sum the goals of the paper: firstly, big data extraction and exploitation, i.e. what is the strategic benefit of BD for HR managers. Secondly, what is the level of willingness to master the implementation of AI and DT, i.e. the awareness of their potential. Lastly, what are the obstacles behind the implementation of AI and DT to this end. Key take-aways will reflect the next great must in terms of HRM and related trends.

2. Theoretical framework

Technology brings about the improvement of processes that become obsolete with the growing numbers and evolving needs of human civilisation. By the time we entered XXI century, we opened the doors to era of BD. With all the breakthrough that is taking place in the field of AI, humans are still at the centre of its development. We are creating copious amounts of information in everyday life and work. According to Moore's law (Gordon Moore, 1965), the capacity of micro components doubled exponentially from the second half of XX century util 2012, at a pace of every two years. In 2015, Intel stated that this rate decelerated to a rate of two and half (Intel, 2015). How does this information tie in to this research? It means that this trend is allowing decision-makers to store increasing silos of information. Where there is information – there is knowledge, and the transformative power of today's data allowed many companies, i.e. decision-makers, to evolve at an unprecedented pace. To that end, I set out to explore the impact that AI has on this evolution, and how far it can be used augment our decision-making processes. By feeding their databases with galore of information, decision-makers can predict future behaviour by learning on past finding and improve decision-making. This is the most basic premise of AI and how it can be applied to assist in this sense. By focusing on alternative ways of interaction and exploitation of BD, we come to realise how DT can be used for the same purpose. The following chapters will elaborate on how we came to be data-rich, what is the extent of our capabilities and willingness to exploit this data, and what are the challenges associated to the implementation of AI and DT. Hence, we need to study the systems that connect AI and DT to among each other and to decision-making. To that end, theoretical part will parse the idea of AI and DT in interconnected narratives that elaborate decision-making mechanisms. Furthermore, theoretical body will anticipate current challenges faced by decision-makers, and ways in which AI-driven processes can help solve and improve decision-making. It will dive deeper into how organisations came to be fuelled by infinite volumes of information, and how this data is translated to competitive edge.

2.1 AI: Information-based organisations

As discussed previously in the paper, one of the challenges will be the worker of tomorrow. In other words, they will have to possess a set of skills completely unique and relatively new compared to those that are currently in demand. We are talking about knowledge-based skills. Consequently, companies will be more knowledge-based, consisting of specialists from separate fields, connected through a network of feedback systems, largely founded on technology. Therefore, we are looking at information-based organisations, united with synchronised flow of information between top-down management (Peter F. Drucker, 1992).

These companies (will) have evolved from the traditional model of bureaucracy, thereby changing the hierarchical structure of management. In doing so, they have taken middle management out of the equation, substituting it with modern technology (ibid). This change in management implies the ensuing results: First, possibly the greatest competitive edge that information-based organisations gain with this change is that by analysing their decision-making, decision-makers can do so simultaneously with other processes involved in decision-making. In other words, they can presuppose their strategy, as well as the challenges implied by it (ibid). Another great aspect of this change can be observed in team autonomy. By taking the middle management out of play, companies render greater level of responsibility to lower levels of management, which is where all the BD, i.e. knowledge, is stored (ibid). Decision-makers have always disposed with plentiful information, albeit, the same was regarded as a controlling mechanism rather than a rich source of data. By reversing this principle, and enriching information with purpose, decision-makers gained knowledge (ibid). By default, knowledge they now possessed suddenly required specialisation to understand. In this way, we make a full circle to the start of the chapter, which implies worker with a specific set of skills needed to decode this knowledge and extract it for the benefit of decision-making. This simultaneously poses the primary challenge for decision-makers in terms of AI – once extracted, how do decision-makers manage big data and to what end?

The following chapter will go more into the nature of BD, and subsequent challenges.

2.2 AI: Big data

As described previously, companies are bound to be driven by BD (Tambe, 2014). Same as AI, BD is influencing the creation of new business models on a yearly basis. With the vast number of its sources, ranging anywhere from "social media, Radio Frequency Identification (RFID) tags, web information, mobile phone usage to customer propensity expressed and uploaded on line" (Davenport, 2014), BD is recognised as one of the areas that will have the most significant impact on decision-making. On one hand, BD can be obtained from within and outside the company, thereby providing multi-faceted insight into worker behaviour. On the other, this comes as a challenge, in terms of its extraction, relevance and management (Gandomi & Haider, 2015). As discussed by McAfee, Brynjolfsson, Davenport, Patil and Barton (McAfee, Brynjolfsson, Davenport, Patil and Barton 2012) "businesses are collecting more data than they know what to do with". Therefore, decision-makers are ought to obtain the skills necessary to collect BD, manage it, and figure what they take out of it. Simultaneously, they need to be able to recognise its relevance and how to align it to workers and strategies.

Alas, data-driven decision-making is bound to have certain flaws in its implementation. Work with big data is cumbersome and often inconvenient since it involves ample amount of structured and unstructured data. In this regard, companies that are conceived on BD will have the upper hand against those who are only starting to extract its value. To get to this point, decision-makers will have to team up with the right data scientists to interpret data they are gathering. In terms of AI, greatest challenge will be the "A-trifecta" (automation, AI, analytics), and risks related to BDM. In terms of DT and BD, it will be important to look beyond current challenges and anticipate future ones. In other words, methods will have to follow problems, and so will software development have to become an integral part of decision-making.

The following chapter will elaborate on the understanding and strategic conversion of BD.

2.3 AI: Converting big data to strategical decision-making

Considering the abundance of data that they now have at their disposal, companies can inspect consumer patterns better than ever and improve their products accordingly. In terms of this paper, decision-makers can use this information to observe the impact of their decisions on employees and act upon it (Gandomi & Haider, 2015). According to Gregor, Martin, Fernandez, Stern, & Vitale (2006), investment in BD generates four types of benefits: strategic, informational, transactional and transformational. In terms of strategic, BD can improve competitive edge, or change the characteristics of decision-making processes. In terms of informational, BD can impact anything between the information and communication flow within and outside the company, thus improving decision-making. In terms of transactional, benefits of BD translate to investments made by decision-makers to support and enhance operational management. Lastly, in terms of transformational, BD benefits reflect in modifications that decision-makers make to their structure (ibid). Assuming the strategic potential between AI – DT relationship, BD packs a host of cumulative benefits. Primarily, it improves the alignment of business strategy and IT development. Secondly, it increases companies' promptness to arising changes in business environment. Finally, BD signifies the expansion of cognitive capabilities, since the investment in technology requires staff upskilling. In doing so, companies create new opportunities by unlocking the chain of value which they were not previously involved in. In terms of decision-makers, challenge will be to define which of the said benefits generates the greatest value for their line of work, implement AI accordingly, and see if this adoption meets the desired results. In addition, they need to understand how the same is used to develop their workforce. This is simultaneously related to the second challenge, i.e. the willingness of decision-makers to implement AI in their decision-making, and the reasons behind their motivation and/or expectation.

The following chapter will further analyse this regard and explore decision-making capacities.

2.4 AI: Level of preparation

Every new technological occurrence, by default, comes with a will factor. While organisations harness BD to their competitive and structural dominance, many of them are not proficient with the information they gather (Goes, 2014; Sanders, 2016). In other words, while decision-makers understand that they are operating in data-rich environment, do they possess the knowledge, capacity, or the willingness to capture and exploit its value? (Ross, Beath, & Quaadgras, 2013)

To understand the willingness behind BD, we must trace its origin. The era of BD is characterised with invasive technologies that have reshaped the face of reality (Beniger, 1986; Castells, 1999; Katz, 1988; Lyon, 1988) and convoluted the organisation of information (ibid). Depending on how we look at it, decision-makers are struggling to unlock the value of BD and turn it to competitive intelligence (Caesarius, 2008). BD is the result of several factors: process of digitalization (Kallinikos, 2006; Zammuto, Griffith, Majchrzak, Dougherty, & Faraj, 2007; Zuboff, 1988), development of the Internet (Kjaerulff, 2010), arrival of social media (Bruns, 2008; Jenkins, 2006), and the creation of devices connected to network (Borgia, 2014). Process of digitalization had already been propelled when IT was incorporated in companies, which enriche their volumes of data (Kallinikos, 2006; Zammuto). The emergence of the Internet changed information management (Jacobs & Yudken, 2003; Zittrain, 2008), prompted new communicational capabilities and transformed working conditions (Cramton, 2001; Hinds & Mortensen, 2005). This was the first wave. The second came with the creation of social media. As one of the greatest modern age phenomena, social media had the most invasive effect on everyday lives of people (Bruns, 2008; Jenkins, 2006), by augmenting collaboration (Wagner & Majchrzak, 2007) and innovation (von Hippel & von Krogh et al., 2003). Finally, “Internet of Things” (IoT) spurred network-connected devices that allowed further BD generation and maintenance (Borgia, 2014). In such environment, traditional IT tools were not enough to capture and exploit BD (Constantiou & Kallinikos, 2015). Which goes back to the second and third question, whether decision-makers are willing to explore technological capacities of new technologies, and if so, what is the level of their competence? To that end, following chapters will explore how DT is connected to AI and what are the challenges in their implementation.

2.5 DT: Role of DT in BD-driven decision-making

While previous chapters focus on AI and BD, as well as the benefits associated to their implementation, the following chapters explore the role of DT in decision-making and its respective challenges. Simultaneously, they round the third overall research question, the challenges related to implementation of AI and DT.

When we speak about DT, it is important to consider the full picture of society. In developed countries, companies are always looking to elicit innovation. Academia does so by investing in schools and programmes that aim to embed innovative thinking in curriculum (California Management Review, 2007), while companies provide hands-on experiences to students (ibid). In the second half of XX century, the complexity of new technologies compelled both parties to create a platform for design process. Practitioners at that time realised that they had to work across multidisciplinary fields to be able to deliver practical design solutions. To do so, they had to join forces with scientists (J.C. Jones,1966; C. Alexander,1964). “First generation” (H.W.J. Rittel, 1972) of design theories and methods pushed them to approach complex issues, disintegrate them in smaller problems and seek appropriate experts to solve these problems (ibid). “Second generation” of design theorists expanded this process in a social context (L.L. Bucciarelli, 1988). In other words, the process was less viewed as top-down, and included a broader scope of opinions. This convergence changed the perspective from problem-solving to problem-formulating. Looking back at the definition by Charles Owens from the start of the paper, DT takes place happens when design thinkers and decision-makers take the insights from practice, transform them in abstract ideas (prototype), and then convert them to artefacts and institutions (C. Owens, 1993). In terms of HR, these artefacts imply policies that decision-makers create to improve their decision-making capacities. With the increasingly competitive and rapidly changing technological environment, companies yearn to understand the principles that rule innovation, and decision-makers seek the ways to integrate them in their decision-making. This goes back to BD management and decision-makers willingness to exploit it, and how DT can be used to this end.

The following chapter takes a closer look into the challenges behind the implementation of DT.

2.6 DT: Challenges when embedding DT in decision-making

When we discuss challenges related to the implementation of DT in decision-making, we must do so from two angles. First, it is important to distinguish between design and thinking (Sean D. Carr, Amy Halliday, Andrew C. King, Jeanne Liedtka, and Thomas Lockwood, 2010). Second, it is important to teach DT to decision-makers (ibid). From the first angle, DT presents a distinctive problem-solving approach, where design plays an integral role in the decision-making process, or any process for that matter. From the second angle, companies need to decide whether to equip every decision-maker with DT, or only those who understand can identify the relevance between its application and their decision-making benefit. In other word, not every decision-makers work is based on a meticulously designed strategy, since some processes only depend on technical aspects that require little, to no technological upgrade. Therefore, it would only make sense to distinguish between those who theorise design, and those who implement it. Hence, main challenge that arises is how does one embed this concept in decision-making? How do decision-makers define where DT is necessary for their decision-making?

This is where AI again comes into play and the following chapter will round up the third research question, or the challenges behind the implementation of these two concepts in decision-making, and how they interact together. In addition, it will provide an overview of theoretical part, and how it ties in to Methodology.

2.7 AI & DT - Challenges

To understand every challenge elaborated in previous six chapters, I will first provide a table which shows their relationship. Next, I will provide ways of approaching the questions to define how the same will be treated and examined in the methodology, and rest of the paper.

Table 1: AI and DT related challenges

Challenges	
AI	DT
Big data management	
Willingness	
User-competence	

According to Table 1, what we see is the focus of each challenge in terms of AI and DT. In what was discussed in the beginning of theoretical framework, and subsequently elaborated in chapters, I considered both the benefits and challenges of this relationship in terms of decision-making. In doing so, we saw that decision-makers must first understand the concept of BD and the effect it has on their decision-making. To do so, they need to identify their skill gap in terms of BDM, collect it from internal and external factors, structure it, and identify the most relevant information. This ties in to the second. By managing data, yes, they collect the information, but are they prepared and willing to design corresponding strategies and engage with these concepts to unlock their value? This leads to the third and final interconnected challenge. After differentiating between data that is important for them, and identifying its value, decision-makers need to anticipate the challenges when passing this value and realising its potential. In terms of HR, they need to identify how they can use BD to improve recruitment, management, appraisal and development, and see which area can benefit the most from the implementation of new technologies.

To round the literary review: the paper started with seemingly remote concepts: AI and DT. The paper presupposes that today's organisations are already implementing AI and/or DT in their decision-making, while considering ways to further embed or combine them. Research hypothesis suggests the following idea: AI augments decision-making, by upskilling decision-makers exploitative capacity in terms of BD, with the use of disruptive and innovative nature of DT. To uphold this hypothesis, both concepts need to yield mutually beneficial constructs. Innovation must derive more long-term than short-term solutions. DT is implemented at various stages in companies, same as AI. Together, they constitute a competitive edge, comprised of structured and knowledge-rich information. Ultimately – to which extent does the causality of these two concepts enhance decision-making, to what extent are decision-makers willing to consider these concepts to achieve the potential of this relationship, and what are their challenges?

3. Methodology

This paper studied the relationship between AI and DT and how the two affect and/or disrupt current trends in HR. More precisely, it provides an overview of current trends in decision-making, and anticipates the challenges that decision-makers will face in the upcoming years with the rise of artificial technology and data-driven decision-making. These constructs were used to define the processes that decision-makers will use to anticipate these challenges and prepare their strategies accordingly. Furthermore, these concepts gave an insight into the level of technological competencies of decision-makers, and how the same are used to anticipate and adapt to evolving decision-making landscape. To that end, the paper examined the skill gap in the decision-making of today and how the they intend to overcome this gap. Moreover, the paper examined the skills that decision-makers of tomorrow will have to possess to meet the demands, and how they use AI and DT to streamline and augment their decision-making processes. When broken down in two, the paper distinguished the challenges related to AI and DT. In terms of AI, the paper collected and sorted a broad array of articles related to the application of AI, BD management, and how it is used to facilitate decision-making, thus augmenting the entire process. Given its popularity, and abundance of material, articles and content related to AI were easy to come by, however the challenge was to sort them out and distinguish the ones that relate to this research. In terms of DT, the study focused on articles that considered the idea of design in strategy and how thinking in this way translates to decision-making.

To this end, key words that were used in the search of articles covered areas from AI, BD, BDM, HRM, DT. To name a few: "Decision-making", "AI", "AI in HRM", "Embedding AI in business", "AI and Decision-making", "Future work trends", "Disruptiveness caused by AI", "Big Data", "Data-driven", "Business Intelligence", "Design thinking", "Design theories", "Design Business", and etc. These were some of the many search results that were used to cross-reference and find appropriate content. Other related content included IT portals and magazines that explore the idea between the relationship of AI and business development. These include Forbes' Insights, "AI Issue 1,2,3", as well as online forums and organisations that write on this, and other tech and DT related topics (Ignite, Intel, Microsoft, IBM etc.). The challenge further lied in identifying the questions that permeate both concepts as well as the steps that decision-makers take to connect them. The study is qualitative, i.e. exploratory, with open-ended questions. It is a suggestive theory with room for future research. Findings of this paper were based on the questionnaire collected from a sample of 10 respondents, namely HR managers and HR practitioners from the area of Technology, Big Data Science, Health, Recruitment, Training, Development and Construction. The diversity of respondents enabled to capture the correlation between AI and DT through various form of its application in their decision-making. Furthermore, it inspired some of the respondents to contemplate this relationship further. Sampling was simple selected, with the use of questionnaire to collect data necessary for this research (See Annex 1). Questionnaire contains 13 open questions. Questionnaire was handed out manually, or presented online during the interviews, and the interviews were conducted in person and through Skype. Questionnaire was designed as a combination of semi-structured and episodic interviews. The sample is composed of 10 questionnaires that were presented to correspondents, all of whom are full-time employed professionals working in HR and tech development. In addition, some of the respondents were not Portuguese nationals. The reason behind the international aspect was to obtain as much information from different cultural and working environments, which enriched the findings of this paper.

The core of this study consists of ample data on both concepts, which simultaneously presents the first great challenges of this research. Data structuring was vital for the study. Hence, it was necessary to create a systematic review of AI and DT to lay the foundation for the research. This structuring was inspired by Tranfield's Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review (Tranfield et al., 2003). According to this review, theoretical and methodological part consisted of two phases: first phase consisted of AI and DT related articles that make the bulk of the research to support the concepts defined in introduction, and second phase focused on scheduling interviews with respondents who best matched research questions. In first phase, data was configured in a way that enabled challenges to arise logically and allow the reader to assume the questions related to challenges. In second phase, a Big Data Maturity Model (BDMM) was used to analyse the findings from interviews and open room for conclusions. Interviews were designed to capture the following information: i) Extent of the use of AI in decision-making; ii) Data management and strategical convergence; iii) Extent of the use of DT in decision-making; iv) Expected benefits and challenges in the implementation of concepts; v) Willingness and user-competence.

4. Data analysis

4.1. Model of data analysis

As displayed in Table 2 below, BDMM is used to investigate the maturity of company's data maturity. In terms of this research, it was modelled in line with the codes on the level of decision-making and analyse the findings accordingly. Primary focus of this model lies on BD, but the structure helped analyse the findings related to AI and DT and compare each stage accordingly. First stage, **Strategic alignment**, is divided in two subdomains, *Strategy* and *Processes*. While *Strategy* analyses the extent to which data is relevant to company's strategy, *Processes* analyses the extent to which data is exploited in decision-making to achieve the strategy of a company. Second stage, **Organisation**, is once again divided in two subdomains which further explore this relationship. Though it is more related to employees, I related it to decision-makers, as they are still effectively employees of a company. As such, *People* domain analyses the extent to which decision-makers are aware of the potential of BD. At the same time, *Culture* sub-domain analyses the extent to which BD is considered an important asset in decision-making. These two stages are directly related to first set of questions which explore the concept of AI, and its extent in decision-making. Third stage, **Governance**, was used to group the findings from first two stages and determine the structures that decision-makers use to manage BD, and the level of their preparedness (willingness) to do so. Consequently, last two stages, **Data** and **Information technology**, were used to analyse BD lifecycle and the maturity of decision-makers in terms of the challenges related to big data extraction, management and exploitation. More precisely, (Data) *Management* subdomain analyses the BD lifecycle, from acquisition to exploitation, while (Data) *Analytics* subdomain explores the way BD is understood and later exploited. This stage was more convenient for the set of questions related to Design thinking, as it gave respondents space to express their views on how they treat BD. Finally, **Information Technology** stage has a more objective approach to BDM, both from the perspective of AI and DT, by analysing the maturity of IT environment through *Infrastructure* subdomain, and resources of data collection and interpretation through *Information management* subdomain.

The interviews were transcribed and coded individually, and later grouped in one common coding table. The codes were created with DocTools, a Microsoft Word add-in that extracts and displays comments from Word and allows tabular overview, as well as further filtering through Microsoft Excel. As seen in Figure 2, the coding was divided in two branches – AI and DT. By narrowing the content from interviews and transcripts, I was able to create codes that reflect research questions. In the beginning, the notions of AI and DT did not have a direct relation, but by cross-referencing them through the categories, I was able to extract information relevant to questions set out in the beginning of the paper. Further down the line, I used and modified research questions in line with the BDMM (Table 2). This model is used in big data-driven companies, or those that are just beginning to explore the potential of big data, to determine their data maturity. In terms of this paper, it was particularly useful to divide research questions and examine the findings accordingly. Following the principle of inductive reasoning, I allowed the analysis to be driven and shaped by the information provided by the correspondents. In doing so, I eventually created a matrix which displays most significant findings and gives space for conclusions to be made.

Figure 1: Coding branch and categories

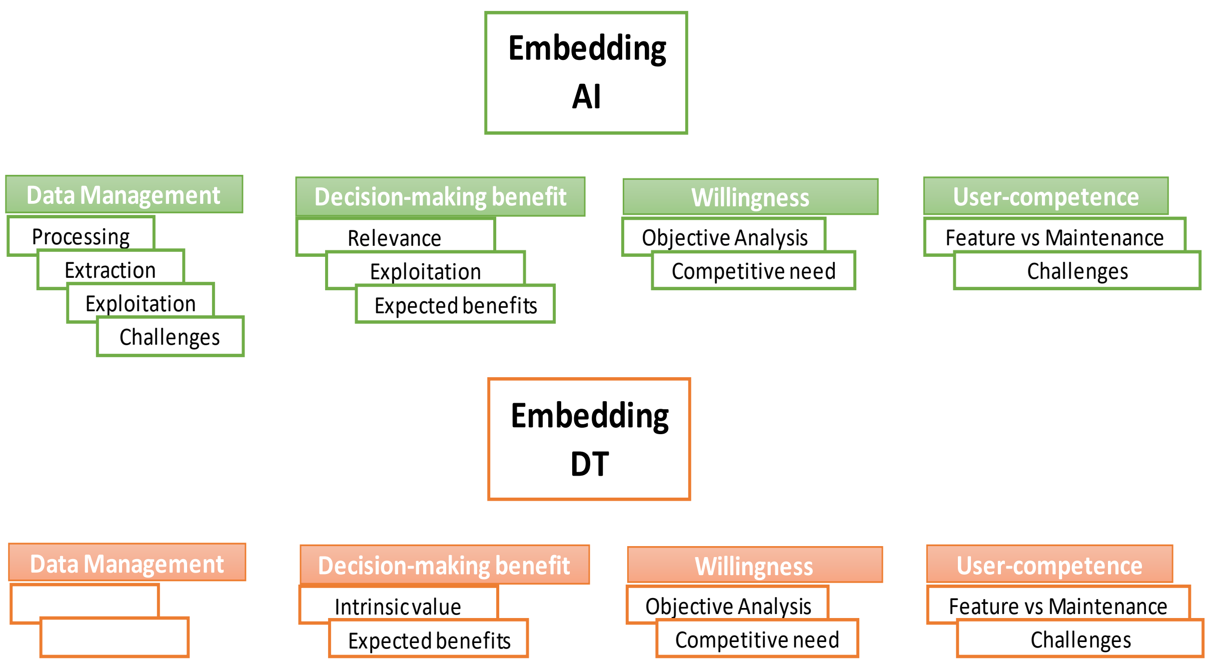

Table 2: Big Data Maturity Model (BDMM)

Strategic alignment	**Organisation**	**Governance**	**Data**	**Information Technology**
Strategy	People		Management	Infrastructure
Processes	Culture		Analytics	Information management

In sum, the five stages round up the three goals of the paper, namely:

1. BDM,
2. Willingness
3. Challenges associated to implementation of AI and DT

4.2. Coding framework

When it comes to codes relative to BDMM model, I divided them in those related to AI and DT. The categories were the common thread between them. This categorisation allowed me to draw a parallel between the following codes: Data management, Decision-making benefits, Willingness and User-competence.

AI Codes

Within Data management, I examined how BD is stored and managed within their respective companies. Within these questions, I focused on data processing, extraction, exploitation. Based on these questions I was able to understand the respondents' understanding of BD.

Within Decision-making benefits, I examined how BD is used for AI-augmented decision-making. Within these questions, I focused on its relevance, exploitation and expected benefits. Based on these questions I was able to understand how BD is aligned to decision-making, and overall, strategy.

Within Willingness, I examined the difference between theory and practice. Within these questions, I focused on objective analysis and competitive need for AI and in decision-making. Based on these questions, I was able to measure their preparedness to embed AI and in decision-making.

Within User competence, I examined the challenges that decision-makers encounter in the implementation of AI. I focused on feature versus maintenance aspect of AI and challenges in its implementation. Based on these questions, I was able to understand whether it is worth the effort or the investment, according to their expectations.

By exploring the added value of AI in decision-making, I was able to move on to questions related to DT and codes closer to that concept, and how they are connected with AI in terms of decision-making.

DT codes

Within Decision-making benefits of DT, I examined the benefits of having DT as a part of their decision-making. I focused on the intrinsic value of DT and the expected benefits thereof. Based on these questions, I was able to understand if they are aware of the concept and the extent to which they implement it in decision-making.

Within Willingness aspect of DT, I examined the extent to which they aim to embed in decision-making. I focused on the competitive analysis as in the previous set of codes, with the added category of challenges related to the integration of DT in decision-making. Based on these questions, I was able to understand how it differs from integrating AI in decision-making, because DT is more of an abstract concept.

Lastly, within user-competence related to DT, I examined more where DT can take place in decision-making. I focused on feature versus maintenance aspect of DT and challenges in its implementation. Based on these questions, I was able to understand whether it makes sense to consider it as a separate decision-making aspect.

All taken together, codes reflect each stage and subdomain of BDMM and provide an overall, but consistent, analysis of the application of AI and DT in decision-making. The following part elaborates on these stages and their respective sub-domains. Ultimately, the research leaves more room for further exploration on this subject, maybe even the same relationship, as the two concepts seem to complement each other in terms of organisational structuring and decision-making.

4.3. Analysis of findings

To achieve the maximum coherence and cohesion of findings, I created the following structure. I divided the analysis of findings in three layers:

1. According to BDMM which will serve as the overarching theme of data analysis
2. According to goals of the paper which are following the structure of BDMM
3. According to codes that follow the dissemination of goals

In doing so, I created a bottom-up approach of the findings from (3) codes, through (2) goals, to ultimately the stages of BDMM.

Secondly, and as described in 4.1., the model has 5 stages, namely: Strategic alignment, Organisation, Governance, Data and Information Technology. To analyse all 3 research questions line with the model, I divided the stages in 3 groups, whereby each group consists of a BDMM stage and corresponding research question:

A. **Strategic alignment** and **Organisation** which cover the *first goal* of the paper (see below)
B. **Governance** which covers the *second goal* of the paper (see below)
C. **Data** and **Information technology** which cover the *third goal* of the paper (see below)

A1. Data extraction and exploitation – whereby I elaborated on Data management and Decision-making benefits codes of AI and DT

B1. Willingness – whereby I elaborated on Objective analysis and Competitive need code of AI and DT

C1. Challenges associated to implementation of AI and DT – whereby I elaborated on User-competence code of AI and DT

Below is the tabular overview of the model according to described goals in A1, B1 and C1:

Table 3: Overview per phase/goal/code

<table>
<tr><th></th><th colspan="2">First goal</th><th colspan="2">Second goal</th><th colspan="2">Third goal</th></tr>
<tr><td>Phase</td><td>Strategy Alignment</td><td>Organisation</td><td colspan="2">Governance</td><td>Data</td><td>Information technology</td></tr>
<tr><td>Goal</td><td colspan="2">Data extraction and exploitation</td><td colspan="2">Willingness</td><td colspan="2">Challenges associated to implementation</td></tr>
<tr><td>Code</td><td>Data Management</td><td>Decision-making benefit</td><td>Objective analysis</td><td>Competitive need</td><td colspan="2">User-competence</td></tr>
</table>

I will start each following section with an explanation of the goal and stages of model related to that goal, with the corresponding codes. A note for the reader: This is where the fun starts!

A1. Data extraction and exploitation

First section will focus on the first two phases of BDMM and the first goal - the way BDM impacts all levels of an organisation and the way in which it is aligned with the decision-making strategy (Pearlson and Saunders 2013, Buhl and Heidemann 2013). Within the **Strategic alignment** stage, *Processes* subdomain will cover Data management, while *Strategy* subdomain will cover Decision-making benefit, in terms of AI. Within the **Organisation** stage, both *People* and *Culture* subdomains will focus on the extent to which decision-makers are aware of the potential of BD and the extent to which it is considered a trusted asset in their decision-making, in terms of DT.

In terms of the **Strategic alignment**, and *Processes* subdomain, when I first started interviewing respondents, I wanted to understand their view of BD, how they recognise its relevance and extract it, and how they make sense out of it. I will start by referring to one of the respondents who said about BD:

> *"I think that the huge difference is that the way we structure data today, the dimensions that you can assign to data, the data that is very unstructured on the source, that we can get some structure on that data, using speech, using tech analysis, using social data"*
>
> *Respondent nº6*

What is important to define here is the notion of BD which implies both structured and unstructured data (Lycett, 2013). What this data provides for decision-makers is an unrivalled field of opportunities to quickly process large amounts of information (LaValle et al., 2011), thus making more informed decisions. In terms of BD, this what they say for decision-making:

> *"First of all, means knowledge, getting access to a kind of knowledge that's almost nearby wisdom. That leverage a little bit more the knowledge and makes you go a little bit further ok?... data that at first moment seems unstructured at all, and then when we apply algorithms and analysis on that data, we can relate it, and that's where you can get some additional relations and additional insights over the data…let's put it like this: Velocity means speed, it means that we can get there faster, ok"*
>
> *Respondent nº4*

In terms of AI, this is what they say for decision-making:

> *"I'm in the field since the 90s. I did my PhD in that field, and the last AI, and for me Artificial Intelligence is mainly the engineering and mathematics. So, it's a cross, cross, a cross-discipline between computer science, psychology, mathematics, statistics and all these kind of things, with the main goal to help people finally to make better decisions based on data."*
>
> *Respondent nº8*

> *"So, where I see Artificial Intelligence is part of Industry 5.0, is actually enabling humans to do more of that specific intelligence they have, that is unique to the humans, and spend less time, you know, going through admin and all these garbage tasks. So it's just actually understanding more importantly, placing more importance on human intelligence than ever before… it takes away a lot of that manual process and that actual back-breaking work and enables HR departments, recruitment departments, to spend their time on devising HR strategies on recruiting, using that human intelligence, which means the quality of the work should increase, to see Artificial Intelligence will take a lot of their, you know the historically donkey-work away... AI,*

in partnership with human intelligence, through a greater outcome. Not automation and replacing humans, actually enabling the human to do what a human does better than anything else."

Respondent nº5

Now I would like to align BD and AI in terms of HR. Here are some of the interesting reviews by the respondents:

"I think that AI is, well, if not applicable to all domains, its applicable to majority of domains. So, in that sense, I also believe that AI is applicable, or can be applied to HR challenges… And I think that it is only more recently that the majority of companies start to get more data about the employees, well besides of course normal data for payroll of course, that is. But data related with competences, great data related with, for instance, something with which AI could be applicable, in the recruiting process, and the selection process, HR receive CVs, receive interview notes, and all that stuff, and there is a decision… If the companies get this data, and then data about how this guy actually during the experience life in the company, is evolving, is assessed, is improving or not improving the competence, with AI and algorithms, we could come to a point, to a kind, where if you submit to AI a set of data on the new candidates, we could a lot of insights about 'this could be a guy to join!' and probably we'll get to a point that, a guy that it seems for us not a first choice, based on all the knowledge that was collected at the AI capability, it could be a surprise say that 'this could be a good guy'"

Respondent nº6

"It can improve many parts of our society, such as employment part, but I can tell you that, for the recruiters, as our main goal at the moment where I worked, it could be a good advantage if we have Artificial intelligence to do part of our work. To screen and search a candidate with this, we already have a great, a huge advantage for this… I think that for Human Resources it can be motivating, and it can bring some

compromise in their engagement from the part of the employees that are working with it.”

Respondent nº10

“Well, let me just say, HR department - it’s an HR department, ok? It deals with things which are in HR. That’s one. The other thing is, we have to look at our function and the people that perform their functions… But also, you have a lot of effectiveness in decision. So, the help, the kind of, you should look at AI for example as an companion for a guy who wants to make a decision and relies on what the algorithm can bring to him.”

Respondent nº4

“Another thing is, I also see AI in HR as support for the career path, the development path, helping which competence, hard or soft, should be developed by this specific type. So, I see space over there, I don’t feel that we in Portugal, we are doing a lot on that space, but I feel the opportunity for that.”

Respondent nº6

And to sum up this line of thought before moving to downsides of BDM:

“And I think technology, in general, has potential there to help people learn better, to track their progress better. So, there's potential there, and particularly AI, it’s a good weapon right? It can help people find content that they can use to learn.”

Respondent nº4

So, what we saw here is one side of the coin for BD, how it enables enhanced decision-making by providing ample information. In connection to HR, most respondents agree that AI would have the most positive impact on recruitment, by accelerating the processes and increasing the volume of information. However, volume is the other side of the coin. In addition to Velocity and Variety, these three V’s are used to describe BDM (Laney, 2012). BD can be overwhelming in content, thereby creating more confusion than advantage. This became the separating element for the BDM (first code of AI), and key *Processes* subdomain. By understanding the *Processes* subdomain in terms of extraction and exploitation, we can examine first research question and understand how AI interacts and (if it) improves decision-making. This is what one of the respondents who has hands-on experience in AI-aided recruitment said in that regard:

> *"… data needs to be classified. So, an AI stack needs to understand the context of the data to make sense of it, otherwise it's just machine learning and it's pointless. It doesn't do anything… If you imagine from an HR perspective you know, you're setting an AI stack to understand if you have the skills and experience for the job, right? All you should care about, all right as a recruiter, is if you, your profile is of someone with the skills and the relevance for holding my opportunity. I should not care about your sets, I should not care about your ethnic origin, I should not care about anything other than what it is important to determine whether you are a right fit for the job.*
>
> *Respondent nº5*

Further down that line of thought:

> *"it can be hard sometimes to cut through the fog, as we say, when you are in the middle of the process and you don't know exactly what to do next.. sometimes you have so much information or data, that's not information yet, that you don't know what to do."*
>
> *Respondent nº2*

> *"So, the bigger we get, the more information there is, or ideas, the more things that are running at the same time, which means that it gets harder for people to get a full picture of what's going on. I would say today the challenges are mainly around the fact that since we're growing, there's a huge amount of information." (R1, P12)"*
>
> *Respondent nº1*

To this end, according to Forbes' statistics from 2015, as much as 50% of big data-related ventures in big organisations are never completed (Marr 2015). These, and other challenges related to BDM will be later examined in C1. In terms of A1, we saw the downside of BD, and here is how AI helps in that sense:

"Artificial Intelligence is really, really accurate, it's unbiased, it's, you know, it works extremely quickly with data etc. … From an AI perspective, within the, within the HR, well within, you know, the recruitment context, is about creating a taxonomy and going into extremely granular detail about what someone does as part of their role ok… Now, what AI does, is understands what you do, what your skills and experience is, what your interests are, and make sense of that"

Respondent nº5

In other words, the benefit of supporting decision-making with AI is immense since these algorithms are capable of processing tons of data within the same period it would take a human to process one (Moore, 2016, p. 12). Further in that sense:

"data that at first moment seems unstructured at all, and then when we apply algorithms and analysis on that data, we can relate it, and that's where you can get some additional relations and additional insights over the data…So, that data lake has all the information ok, the kind of a lake that has everything in it. And you should, let's put it, you should build data set of this data lake, that are more related to the kind of questions that you want to put the top-down approach. So, I'll just put the data set that can bring me this information from the data lake, so that I can narrow ok, the analysis to obtain what I want. So, you should go from data lake to data set"

Respondent nº6

"… if you think about decision-making process in three parts, the first part efficiency, the second part relevant information, and third part final decision, based on elements that are relevant and critical for a business. I would say that AI can help with the efficiency and also with data relevancy, but it can never help in the part of what is critical for the business, but I can see a robot thinking about what is critical in terms of recruitment profile for vacancies."

Respondent nº10

What does this mean for the prospects of decision-making? AI can undoubtedly augment the decision-making process, but it takes understanding and trust of decision-makers in algorithms to achieve it. Some researches already generated evidence of algorithms outdoing humans in many decision-making scenarios (Kahneman, Rosenfield, Gandhi, & Blaser, 2016). According to IBM, one of the leading big data-driven companies and its CEO, it is believed that within 5 years “all major business decisions will be enhanced by cognitive technologies” (Gini Rometty, 2016). Reality is becoming increasingly complex, compelling decision-makers to process more and more data daily. While discussing these downsides with my respondents, and ways of overcoming them, I identified a recurring theme from many of them, which was relevance. This was already mentioned couple of times in previous examples, but later it became the separating component in the expected benefits of AI-augmented decision-making (second code of AI), and key for *Strategy* subdomain. Following statements explain this theme better:

> *“It depends on what the business is looking for I think. Because, I don't, I don't think it's about, you know, relevant or non-relevant data. It's about what you need to make relevant decisions. For some of those decisions, you know, you have, there are some data that can be useful, and some data that won't be useful. Like for all kinds of decisions, there are, you know, is, it's gonna be different. So, I think it's kind of depending on what kind of decision you wanna make, and the kind of information you're gonna have, whether the data will be relevant or not”*
>
> *Respondent nº3*

> *“we know the moment we’re ingesting a data source at the beginning, we’re choosing to ingest that because its relevant…we deal with source code and version-controlled data, and in our case all those data sources, everything in there is relevant at some point, it’s stored. We don’t use all of that data of course, like when we parse source code we, we label it automatically with over like a hundred and fifty different components. We usually never use or apply all hundred and fifty. Determining which features are relevant, we use ML for us. Sometimes we don’t know a priori which are the relevant features… So, we actually need to learn the ML language, and which are the relevant features. Well, often we have a good idea, then we do the learning and get a much better accuracy.”*
>
> *Respondent nº1*

Therefore, relevance greatly affects the volume of BD that companies absorb, thus its variety and velocity. But what does that mean for HRM? I asked the respondents:

> *"Now, from an HR perspective, what you do with the results of the AI depends on what your outcomes are as an organisation ok. So, what it should actually do is inform the decision-making process of an organisation by basically providing extremely accurate data decision, data-driven answers without any emotion, without any bias whatsoever. That's what it does."*
>
> *Respondent nº5*

Therefore, what this research suggests is that decision-makers should use AI to target specific information and avoid analysing every dataset that may be relevant for their strategy. Here is the conclusion from the same respondent:

> *"We use AI to enhance performance, to put the right opportunities in front of the right skillset, to decode that talent, and then acquire more of it… It is for understanding what data is important, relevant and legal, to use to form decisions. Because AI is based on data"*
>
> *Respondent nº5*

So, the key takeaway here to sum the **Strategic alignment** suggest that the volume and variety of data surpass the capacity of decision-makers to analyse BD manually, and that technology has advanced to the extent where it can process greater sets of data (Foster Provost and Tom Fawcett 2013). Hence, in terms of decision-making, it is important to blend the right information with the right dataset, formulate the problem, and implement AI to provide insights, thus solutions. Moreover, these solutions do not necessarily have to be one-time big decisions. I am suggesting multileveled solutions that can be implemented in each department accordingly to make the best use of information it possesses.

To close the first stage of the model, and open the analysis for second stage and DT, I will quote a definition of data-driven decision-making (DDD) formulated by Brynjolfsson E., Hitt L.M., and Kim H.H. and suggest some of the implications based on the findings provided above. First, DDD "refers to the practice of basing decisions on the analysis of data rather than purely on intuition." (Brynjolfsson E., Hitt L.M., and Kim H.H, 2011). According to this, there are two ways to augment decision-making: by making decisions that mine data to create "discoveries" and to create decisions that allow faster and more accurate decision-making (ibid). In both cases, BD is regarded as an abundant source of information which, if extracted and managed properly, should generate informed and efficient decision-making.

In terms of the **Organisation**, *People* and *Culture* subdomains dive deeper in the gap between intuitive and data-driven decision-making. In terms of *People* subdomain, it is first important to distinguish between data management and data-analytic thinking, which directly relates to DT. The two make for a unique skillset that decision-makers require to understand the potential discussed in *Processes* and *Strategy*. In his book on "The Design of Business - Why Design Thinking Is the Next Competitive Advantage", Roger Martin argues that between intuition and analysis, Design thinking offers a "third path". (Roger Martin, 2009). During interviews I used this formulation to see if DT holds up as a bridge between analytics and intuition. To uphold this formulation, I sought to elicit the value of DT in data-driven decision-making, and in return, another recurring theme started appearing. This time it was the emphasis on the intrinsic component of DT (first code of DT) and human-centred approach. Here are some examples by the respondents:

> *"I can go back in time a little bit. I think when I first was introduced to design thinking, I came from, I came from business management background, so I was used to making decisions based on numbers and information that I already had, or on assumptions… And when I was introduced to design thinking I realised that I had, not only that I had the authorisation to talk to people, the purpose to talk to people, but a framework how I could do that. And so, the fact that it starts with the people that are most affected by the problem, and the fact that it involves other people in decisions, that it's collaborative, I think it's those two are the most important ones, for me."*
>
> *Respondent nº2*

> *"So, what I think the Design Thinking get as a key point and helpful point, is the, it's word co. it's the co-design, it's the co-develop, it's the involvement. That's for me the huge thing, instead of a set of high skilled guys in a room, discussing, but without input from the guys that in the end that will make some use of that. So, in the end, that's the key aspect of Design thinking."*

Respondent nº6

"The main area that we think Design Thinking can help us is on the problem-solving, let's put it, way of doing things ok? So, empathise phase of Design Thinking, it's more, it's very, very rich in terms of information, and the AvA phase also ok? So that's the two things that Design Thinking have brought us and helped us in the problem-solving… It's very open and it brings, let's put it like this: a bit more emotional, if you want, to a very classical way of problem-solving for example ok?"

Respondent nº4

This was particularly relevant for the expected benefits (second code of DT) and *Culture* subdomain. In other words, data science depends on the close relationship between decision-makers and data scientists, which is what the paper suggests, i.e. that DT can assist and improve decision making when it comes to BDM. According to one Harvard Business Review, companies where decision-makers and scientists do not understand each other's significance or role, does not yield the expected outcome of BD and renders it useless, even at risk of making harmful decisions. (Harvard Business Review, 2012). This was vital for the *Culture* subdomain, or the extent to which people are aware of BD potential, and the extent to which DT is trusted in decision-making. In terms of the potential, couple of respondents gave an example of how data can be overlooked, or even misinterpreted. In his words:

"Because you know what, the danger is you implement AI badly, all right you're better of having no AI than implementing it badly. People don't understand why they're doing it when buying into it, when they use it. I can use AI to give you a ton of data, and you don't use it, it's pointless"

Respondent nº5

"So, you should have been able to know it, but it didn't put into your decision-making process. Because, making wrong decisions is freedom of mankind... But, to make a decision if you should have known it better, that really give a headache… What is missing in many cases is to have a full view of all available data"

Respondent nº8

Therefore, when applying AI, decision-makers must approach it with purpose, not just for the sake of its implementation, otherwise they it cannot produce results on its own. In terms of the trust, the notion of DT as an innovative way problem-solving seems to resonate with most respondents, since traditional decision-making is being increasingly challenged by the variety of BD, and societal factors such as the age gap in workforce. In the words of another respondent:

> *"I would say that younger generations are more close to this approach than older generations, and especially when you try to set a Design thinking approach on a corporation. If you put in the room a guy that is in the company for 25 years, and he will be challenging that room in the same way as a guy who just joined 3 years ago, this is not easy. The guy will feel that he's, it will be, he's position is in stake. And that Design thinking is a challenge."*
>
> *Respondent nº6*

Therefore, the key takeaways in terms of the **Organisation** suggest that DT can assist in BDM by prototyping solutions according to their value proposition, i.e. intrinsic value. Second, decision-makers can implement DT to create a framework for problem-formulation and assign new dimensions to their decision-making processes.

To close the second stage, I will refer to Martin's understanding of DT once again. In terms of effective business design, he draws the parallel between designers and decision-makers. While designers work based on projects, with specific deadlines which "disappear" when they are formulated and implemented, decision-makers can use DT to centre their decisions around permanent delegation of tasks, (Martin, R. 2005a). It is exactly this idea that rivals conventional decision-making and enables DT to enhance decision-making.

Whereas first two stages examine the approach to AI and DT, and ways in which they can be used to gain competitive decision-making advantage, third stage will take a more objective look, and examine the willingness behind the implementation of AI and DT. This is the second main research question, and it will provide the reader with more realistic analysis on the relationship between AI and DT. Nonetheless, I must note that BDM remains a broad and insightful field for further research and hypothesising, as it varies from one industry to another. Most prominent research is done in the field of medicine, where AI continuously pushes new boundaries, even outpacing medical practitioners with greater accuracy of results in diagnoses.

B1. Willingness

Second section will focus on the third stage of BDMM and on the second goal of the paper – level of willingness and preparedness to implement AI and DT in decision-making. More precisely, **Governance** focuses more on the organisational structures (Weill 2004) and how these are used to manage BD opportunities. This stage has no subdomains and has a more critical outlook on AI and DT in decision-making.

In terms of my questionnaire, by this stage the respondents would usually share all their enthusiasm and expectations about AI and DT, and this is where the questions would start to examine their willingness. I wanted to go beyond their expectations and focus on their motives. By this time I started identifying patterns of scepticism in terms of the added value of AI and DT, which was perfect for this paper for two reasons: a) their scepticism exposed the limits of structures that are necessary to incorporate AI and DT in decision-making, and b) even with the necessary structures, it exposed the challenges in their implementation. As stated in A1, challenges will be examined in the third goal.

In terms of B1, I came across an interesting article that describes the role of AI in Knowledge Management. Authors pose an interesting question: "There is still no AI system that can converse with a human. The technology is not ready yet. Should one nonetheless attempt to tackle the even more difficult problems in Knowledge Management?" (E. Tsui, B.J. Garner and S. Staab, 2000). The reason I chose to quote this question is because I believe that Knowledge management relates to BDM, therefore, to decision-making. Based on the discussion with my respondents, another couple of themes started to appear in terms of AI and DT, namely, if the two are just a mean to an end or a competitive need. In terms of the first from the angle of respondents:

> *"From my side, I think that for some decisions, for some quick decisions, it can be very useful. But when it involves human ethical related decisions, for me it is very difficult to understand how AI can help think like a human being. I don't think we can program*

everything, we cannot program emotions or intuition easily… I think we can and should use it for decision-making process in times that it doesn't, it doesn't bring a risk what is the human side of decision-making… So, it's important to use it. But, I would never use it as a final, or unique element of decision-making, as a complementary method… So, we still don't have the mentality we need to prepare AI quickly to help us in the decision-making. So, I don't think it is difficult to use, I don't think it will be difficult to use, maybe it will take us little longer than we were expecting to use in a efficient and quick way"

Respondent nº10

"So, to me, mainly because of my work, AI essentially is machine learning using neural networks to me, and so the kind of the first things that I look at today when it comes to AI, one is that the separation between narrow AI and of what we target as human level AI and what's broad AI. And this notion of super intelligence, and I am a very strong believer that for probably for a very long time we will only be achieving narrow AI meaning that we can have specific functions in which we train systems to be very good… but what we, and I think most companies care about is the final result, is not so much about putting AI in our business… Right, so I'd say, it's like we, it really helps us deliver a better product, its more high quality for our customers. And that, if that could be done without the machine learning, we'd do it without machine learning."

Respondent nº1

"so far, we don't have any kind of automation, but would be interesting because, I mean, we have some work on that, but let's say, for all of this, it takes me, I don't know, 6 hours per month, so, is not so much you know? So, yeah, it would be good to have something automated, but it is not like a huge pain that we feel right now, But is not, I'm not prepared to pay a lot of money for that, because it will only save me, let's say, three, four hours per month… I mean, the AI we are applying is from the company to our clients. Internally, we are not applying any kind of AI. So, what we are doing is helping the clients to implement the AI but in ourselves we don't use that much."

Respondent nº7

What is particularly interesting in every statement is that correspondents refer the same example. Even though they contemplate the benefits and the idea of AI in their decision-making, objectively they would go without it. Then again, if need be, both would embed AI in their decision-making. Which leads to the second theme which is the competitive need. Here are a couple of examples to better illustrate that:

> *"Well, because otherwise we're gonna be lagging behind everybody else who is, you know, who is using it. So, yes, I think, in general, you know, people are gonna be doing, here in this company, I mean, many of the companies they are gonna be using more and more AI… But I don't think asking people whether we can implement technology or not, that's you know, I mean, they can say no, but, you see, we have to do it, because we live in these times, and these times are driven by technology."*
>
> *Respondent nº3*

> *"I think it's like thinking about a new habit. We have 21 days to adopt a new habit, to absorb a new habit, and every day I need to look at this new habit, and use it, and make something related with that habit. So, I think that the teams that were working with automation and technology were the teams that everyday were discovering or encountering new things and the communication was very good on the project. So, I think it has to be something like that, people need to discover this new type of working procedures, and they need to do it every day in order to adopt and absorb new technology."*
>
> *Respondent nº10*

Further in terms of HR:

> *"I think the important thing is to understand that we're a tech business with AI at the core, so everyone understands AI. I think the challenge might be ok, is AI will get adopted by pretty much every organisation over time, its obvious right? This isn't going away anytime. So, it's important from HR perspective that it comes down from the top, that is communicated the role of AI within the business and how it's going to*

aid the individual work, to make their lives more productive and better. Because, it goes back to the things at the right of the start of this interview, there's a lot of misunderstanding about what AI is. It isn't here to replace jobs, it's here to augment your ability to be an effective employee. So, I think, you know, a lot of the, whether there are pitfalls with relationship between employees and AI is the misunderstanding what AI is here to do… By the way, you guys have the ability now to learn a new skillset or, you know, there are opportunities that come for me, so, really it's about communication, and communication often comes from an HR department anyway, you know, HR department should kind of set up the communication throughout business"

Respondent nº5

So, what we saw is that AI does not present the crucial aspect in their decision-making, but it still presents an added value in certain aspects. In addition, in terms of HR, the way it is communicated presents the key in its implementation. Next part explores the same idea, but in terms of DT. When asked about the added value or need for DT, this is what they had to say:

"in a normal state in my life, in simple decisions I'd rather not have those processes involved. And also, there's more related to Design thinking now. That I want to be able to think fast, and yeah, we don't need to complicate. There are problems that you can easily create a solution for it, test it, and see what works. Like, you don't need to go through the entire process every time. And, understanding when is the right moment to use the process, or which aspects of it. So, it's related to everyday decisions, but also in business and in projects like, we don't need to use this process all the time."

Respondent nº2

"Because people are used to, a kind of a, of more closed approaches or methodology approach to define things ok, to define and to design new things to their problem-solving, ok? So, when you do something with a level of iteration very high ok, that kind of grows a certain anxiety that tends to put people on defence… But, there's a kind of, of materialistic thing that Design Thinking should have… So, when you prototype, that's one of the phases of Design Thinking, I think that technology a little bit more like Rapid Application Development, the methodology of RAD ok, that's where I think

things can help design thinking and people doing design thinking, to go a little bit further"

Respondent nº4

"I think that's just a good, I mean just a good way of writing processes. Probably, so its elements exist in almost everything we do on product and engineering, but we don't really, we don't have it outlined as "our company uses DT". We actually do, now I think about it, but it's not really something we set out as to do, it's just a way that we build our process… so we're highly process-driven at Sourced, meaning that for everything there's a process, and that means that anybody can answer that process... I mean, almost all of our product development, our, the big ideas, the things that have the impact on our technology, all have come through this process. So, for us it's, it's key. Like, it's not even, it's just a part of how we work on our identity, like no one knows better. If you have an idea, you put it there, and the discussion starts there and from there process takes off."

Respondent nº1

Again, respondents seem to understand what DT implies, but do not give it much credit as a separate decision-making asset. All statements considered, it would appear that DT, in comparison to AI, is met with more enthusiasm, at least in terms of willingness. When contemplated in pair, respondents began to realise the combined value of AI and DT. One respondent put it this way:

"So, what will happen to people that are doing some re-currency kind of function ok, is that Artificial Intelligence can help them, trying to pull you a bit further on their function, and be able to do a way more on the strategic or technical labour instead of operational, ok? So, for me it's positive. And also, Design thinking, also ok, so I don't quite see any aspect of both frameworks that we should be worried about in terms of people. It's a necessary thing, to have both, necessary thing, so that we can go a little bit further as people, as persons… So, what we trying to do is trying to get a nivel [level] of sensibility and knowledge to all of these people trying to help them, and also

warning them about the quality of data, about the management of data, about the profiling of data and all of this."

Respondent nº4

As discussed, the key takeaways in terms of the **Governance** provide a more critical analysis of findings. When faced with a choice choose between AI or DT, or their synthesis, respondents provided realistic insights, mainly because they never contemplated the combination of AI and DT before. In terms of this paper, their opinion allowed me to realise what would be the ways to implement AI and DT in decision-making.

To close the third stage, these findings indicate on one very important similarity between AI and DT – both are heavily conditioned by competition, and both may very well be the changing point in data-driven decision-making The lack of literature on this relationship makes it suitable for future research, but also for the last two phases of BDMM, and third goal, which will examine the challenges decision-makers face in implementation. In that respect, the **Governance** phase was crucial to keeping these findings of first goal aligned to third goal.

Before moving on to third goal, it is important to connect the conclusions of first two. After analysing BDM management techniques in the first, we identified dual decision-making benefits of AI, informed and efficient decisions. After analysing the proposition of DT, we identified new dimensions that decision-makers can assign to their decisions to make the most efficient use of that information. After analysing the willingness of decision-makers in the second, we identified the features that could connect AI to DT and see add value to decision-making. All this leads to the question: what are the challenges on the way of making this merger? Secondly, is it worth the effort? Once we analyse this "feature vs maintenance" relationship (third code of AI and DT), it will be possible to draw conclusions on the competitive (dis)advantage of this decision-making.

C1. Challenges associated to implementation of AI and DT

This section will focus on the last two stages of the model and on the third and final goal of the paper. More specifically, within the **Data**, *Management* subdomain will assess the maturity of BD analysis, from its acquisition to storage and analysis, while the *Analytics* subdomain will assess how decision-makers extract knowledge from data. This stage is particularly important for the third goal because it shows all the challenges that stem from the acquisition of BD, and the implementation of AI and DT, thereby complementing previous two research goals. Lastly, the **Information Technology** stage, investigates how decision-makers organise their IT structure to extract the knowledge from BD. In addition to challenges, this stage is designed to assess how AI and DT can be used to overcome these challenges, if at all.

In terms of the **Data**, it is important going back to the first goal and connecting it to this one. It describes BD as a mean to "extract new insights or create new forms of value" (Davenport, 2014). In terms of this goal, it was important to understand the processing that precedes the acquisition of BD, and now we will examine the challenges that decision-makers face with this acquisition. Whether it is the skill, organisational structures, or the maturity of decision-makers, AI and DT in decision-making depend on *Management* and *Analytics*.

When we talk about *Management* in terms of AI, we are addressing the physical aspect of BD lifecycle, or acquisition, storage and analysis. By this stage of the interview, the reviews were mixed between respondents who interact directly and indirectly with BD. Some referred more tangible challenges, while other contemplated its ethical adversities. Here are examples of both:

> *"Data is messy. So, cleaning data is by far the number one that you`re gonna get from every single person. Is getting, you know, getting the clean data. Our challenges often end up being skill, so everything that we do, like every six months, we can process a bigger skill, let's put it this way. So, a lot of this skill end up being challenges, yeah, that`s kinda what I would say, skill, performance and cleaning your data"*
>
> *Respondent nº1*

> *"The greatest challenge is data quality. That is the major concern, ok, data quality. Because you have the answers that you are looking for, searching for, it will depend*

on your data quality, the one of the main things. And then the next one is the data governance. Who can accept what, because there are answers that can be responded, discoveries that can be made, but not suitable to all people. That's the other question, is data profiling or something like this. Cause it's quality profiling. Data quality, it's also a kind of a technical problem. Because it relies on the sources, how things are done, in terms of operation, and how things are kept or stored in a data set."

Respondent nº4

What we see is that data structuring appears as a recurring theme in terms of the challenges. And then there is the ethical aspect of challenges. Namely the legality of data access, and human – robot ratio. Let's look at couple of examples in that regard:

"I think the validity and accuracy of data is really important. You know, we live in a world of fake news, and alleged usage of data to influence people's mind. So, the veracity, accuracy and also the legality of acquiring data is really important. Obviously, you got GDPR, you know, in place. And also, it's really important to any data that is important to making the type of decision you need to make within an organisation, and data that the person who provided the data, is happy with you accessing it, all right. So, it's a big mind field, you know, it's very easy for organisations if they wanted to get access, or it could be easy to all sorts of information, but from an ethical perspective, you know, it's about making sure that that data is legal to our access and it's important for what you want to do."

Respondent nº5

"*Yeah, if the robots, if I can say, could do all the, let's say, the robot over the humans, I prefer the humans do the majority of the work… for instance, if you are talking about factories, they could increase the production, they could increase the profit margins of the factories, but we don't, we cannot forget to have these robots doing the majority of the parts. We have to have the humans working with the robots. So, I would say that we do, humans working with robot, but humans have to be in charge of the robots, not the opposite.*

Respondent nº9

As discussed in 2.2, BD lifecycle is long and demanding for both AI and DT. Decision-making requires distinguishing between structured and unstructured data, then skill to process that data, and finally the ethics in its management. This directly touches on user-competence (third code of AI and DT), which explores BD related skills. Here is a possible way of how AI could assist in that decision-making aspect:

> *"The challenge will be how to structure and relate this data and forget we need of course business insight, business knowledge, but we'll come up with some interesting stuff. I think what will give the, what are today on our hands available in terms of technology that will give us the next mile, is the tools that can derive, structure, and derive data by itself… So, in that sense, I also believe that AI is applicable, or can be applied to HR challenges. Probably, there is one challenge at the beginning, which is AI is, as we discussed in the last few minutes, is heavily supported on data. And I think that it is only more recently that the majority of companies start to get more data about the employees, well besides of course normal data for payroll of course, that is. But data related with competences, great data related with, for instance, something with which AI could be applicable in the recruiting process, and the selection process. HR receive CVs, receive interview notes, and all that stuff, and there is a decision… based on all the knowledge that was collected at the AI capability"*

Respondent nº6

What is important to note for *Management* based on these statements in terms of AI is the topic that was discussed in previous two chapters. First, the 3 V's of BD are crucial to understand the information that decision-makers extract, and then the structures that process this information. In terms of BDMM, if first two stages are aligned with this one, *Management* becomes more of a technical element, and gives room for *Analytics*. *Analytics* then gives more room for DT, as a conceptual model, to be used to overcome challenges in BD lifecycle. Let's look at couple of decision-making challenges related to DT:

> *"I think, the challenges are related also with collaboration. Especially the collaboration with the end, with the target on the thing that we are co, that we are*

addressing, because the thing is, people don't like to, in a space with more people, don't like that, to show that, it was their own path… And people, of course, this will be different in different countries, with different cultures but, let's say as a general, people are not used to be discussing face to face and being challenging face to face and saying that "no, that's definitely not the way, I will not use that, I will not see it that way".

Respondent nº7

"Yes, it is a slow process, it is time-consuming, and well that means that, you know, people sometimes want to have pretty quick answers to the things they wanna do, and you know, design thinking is not that. Design thinking takes time… So, design thinking is to design, processes, systems, you know, projects and what not, and then when you have to implement the solutions that you are designing with this design thinking, then you can use technology… design-thinking is a process that does not depend on technology. You have to use technology to use design-thinking."

Respondent nº3

This last statement was particularly important to address the connection between AI and DT, and challenges related to decision-making. For *Analytics* subdomain, it shows that DT can be also overwhelming in content, same as BD, based on the processes it involves.

So, the key takeaways for **Data** support its definition. While the potential of BD lies in making informed decisions, it takes equal amount skill to manage and understand it. This goes back to what was discussed in chapter 2.2 of theoretical framework which reiterates that decision-makers are compelled to acquire the skills to manage BD to be able to align it to business strategy.

To close the fourth stage, we see that volume of BD presents as much of a challenge as an advantage. Decision-makers not only need to possess technical and cognitive skills, but they need to find a way to connect them, so that they better understand and exploit the knowledge in cooperation with data-scientists. And this is precisely what will be examined in the final stage of BDMM, which is the IT environment and structure of information that decision-makers dispose with in their work with BD. At the same time, it will further explore the challenges in the implementation of AI and DT and give a complete overview of challenges.

In terms of the **Information technology**, it will be a direct continuation to **Data**, but with a specific emphasis on the IT structure. In that sense, it uses two subdomains to examine the structure, through *Infrastructure* and *Information Management*. Here we will see additional examples of added value of AI and DT in decision-making, by exploring if they present a valuable feature or just a tool that requires additional maintenance.

First, *Infrastructure* can basically be regarded as a follow-up subdomain to *Management* from **Data**, since it is concerned with structures that enable the acquisition, storage and management of BD. Here is an example of how a challenge affects the structure:

> *"The most, well, there are two challenges: Data extraction and also, the data maintenance. Which is also tricky. For example, in our case, how we do it is, we use our clients' already existing knowledge bases. like the FAQs, like the history of interactions, like some documents they have, and we use it to feed our system. But also, let's say, after one year, after two years, the most part of this information is already out of date. And there's a need to go there to refresh it. Which is also a challenge. So, this challenge is how to keep the data accurate. --- what we do is a lot of manual work, like in the centre we already have some accelerators, like we have what we call industry templates. So, we already have, for example, the making templates, the insurance templates, that are sets of normal interactions between banks and insurance companies, that we already use to accelerate this part. And in that part, so yeah, this helps. And also, in the maintenance what we do, is that we have so many general controls. That, they, these tele controls that warns us "ok there's one that was left one year ago. Please go there and check if everything is ok." But, it's like, not the best, ok? So that's a thing that we are struggling now, and we need to improve.*"
>
> *Respondent nº7*

Hence, BD structuring, and adequate HR communication, are the necessary prerequisites to solving the challenges. And when asked how AI can help in that regard, the respondent followed up with:

"In my case where it helps, we have our clients using our solution, and we have a model that we call the AI trainer. It's where we have the possibility to see how the chatbot of each client is behaving. So, if he's answering well or not, and what kind of answer it is giving for certain questions, and that help us to understand if it was good or bad and for us by seeing that, by giving the new rules, the AI will learn from the process. So, at the same moment we are learning from the AI and teaching to the AI. Is like a loop. So, we are learning what the system is answering, and at the same time, we are deciding if its right or wrong, so this right or wrong suggestions by ourselves are feeding again the algorithm and it goes like this, ok? So, it's like a teamwork between human and the AI."

Respondent nº7

So, what this example is showing us is that companies require significant planning before even enabling the decision-makers to extract knowledge from BD. In terms of AI, it shows that is important to first determine where it adds value, determine the guidelines, and then feed it with BD accordingly. In the words of respondents:

"What data are you using to inform decisions, what algorithms are the AI stats using, who put them together, are there any biases from the coders, from the programmers right, who is auditing this? That's the thing one has to be careful when you look at that AI right? AI is neutral, unbiased as long as the people that created that AI stack are neutral and unbiased as well. So, you have to be very careful in terms of, cause AI isn't a sentient being, it's a series of complex algorithms that are undertaking tasks up, that very smart coders have put together. But given the fact that very smart coders are thin on the ground, and they have very unique skillset it can be difficult to audit and understand it you know. What is the process in place to ensure that my AI stack is you know, adopting all correct legislation, all HR best practices?"

Respondent nº5

"You were using AI, but you didn't know for what. So, maybe if you find a relevant, if you found something relevant, then you would have implemented it easier, or better?... it's like something that we start looking at AI like the resolution of all our problems, so

waiting for everything. And in that sense, we ended using it in a way that was not as well thought as we could be, so more uses, we wanted it for more objectives than we should have. So, I think it's not a matter of bad use or inefficient use. I don't know very well what I want it for and then wait for everything, so let's hope."

Respondent nº10

Let's look at couple of reviews in that same sense, but for DT:

"I think that Design thinking has a good point of, we think of all the ideas and all the concepts, then we go back to prioritise five or six ideas that are more important for us. So, in terms of decision-making and that relation, for me Design thinking helps a lot in broadening the decision, but also prioritising what is more relevant. So, we start thinking, what's in it for us, what we want and we think, think, think and we got lots of variation on the subject. But, when we start, then let's concretise and consolidate this in a concrete plan."

Respondent nº10

Again, the recurring theme is that DT gives space for exploration, but it is rather time-consuming, and this is something that implies more maintenance than added value. This directly ties into the *Information management* subdomain which examines the structure of information resources, and how they are used to optimise decision-making. Let's first understand where AI can help in structuring information, and then the added value of DT:

"So, usually the information is relative distributed in all silos, so in all different kind of systems. And they are not really well connected together. So, it means they use some kind of different wording, and different numbers and so on, and so on. And to provide a 360 view on all available information that will definitely help to make relative better decisions. Because, decision-making is not in the sense that the computer decides what to do next, but to give the human the ability to not make a wrong decision."

Respondent nº8

And the combined value:

"Considering that on Design thinking we need to get the input from everyone and we need to take options, or decisions over the options, so the thing is, if I use technology, namely AI technology, to help me to capture and to understand the feedback that the parties are providing, and to help me on the different things that people are saying help on the decision process, I can see a space there.

Respondent nº6

And finally, the statement which sums the findings:

"*...design thinking is a lot more collaborative where people will come up with their own ideas and all that, and you use AI to fill in some of those gaps in terms of the data you need or some of the tasks, so I think, yes there is actually a-- its an interesting [undistinguishable], because I've not thought of it in that way but, but yeah I can actually see how AI would significantly aid that type of approach within an organisation right and actually if you think about it, why people use AI and machine learning to provide data to inform decisions. It's actually part of that whole design thinking process anyway because you're thinking of what your challenge is coming up with solutions, but to come up with a solution, you need to find a problem and the outcomes of the solution which is where AI may come in."*

Respondent nº5

So, the key takeaways from **Information technology** reflect the structure that supports the acquisition of BD and its subsequent management. What is important in terms of the challenges are the concepts closer to human thinking, like ethics, and processes that precede its implementation, and both are particularly interesting to examine through AI and DT because they provide different types of challenges.

To close the fifth and last stage, we saw that AI and DT possess the potential to augment decision-making, but it is the challenges in their implementation that determine the rate of their success. Namely, a decision-maker must first analyse if the IT environment in his/her company is suitable for the implementation of advanced technology, then see where it could generate the greatest result, and then continue building a dataset around it, to extract further knowledge.

Before continuing to conclusions, it is important to sum up the findings of this chapter and relate it to previous two. In terms of the first, the distinction between **Data** and **Information technology** implies the distinction between the physical aspect of BDM (acquisition, storage, management, dismissal) (Chen and Zhang, 2014), from the maturity of conceptual view of information within an organisation. Hence, this distinction allows the companies to assess their IT environment, while decision-makers assess its value for business strategy. If the two are well aligned, AI and DT can be taken into consideration. Otherwise, they risk falling in the trap of adding features with no added value, which was perhaps the most tangible challenge finding of this chapter.

In terms of the connection to previous two sections, challenges in the implementation of AI and DT shine the light on the way BD is treated, governed and used to augment decision-making. The two-tier BDMM hierarchy helped parse the relationship between AI and DT into separate components with combined potential. To a certain extent, we saw examples of how the respondents reacted to this relationship, and how they think AI and DT could be combined for the same cause. On the other hand, we also saw that there is still a lot of stigma attached to AI in terms of job displacement, or lengthy process in terms of DT. Nonetheless, the idea seemed appealing to most, and as such leaves ample room for future research, maybe even implementation. To lay the foundations of this hypothesis, I will sum up the findings in a matrix and then continue to conclusions to round the paper.

4.4.Vertical analysis

Table 4: Overview of pros and cons of AI

AI	Pros	Cons
Data extraction and exploitation	• More quality knowledge • Greater accuracy • Unbiased data feed • Increased automation	• Increased volume, velocity, variety • Challenging classification • Data validity • Management issues
Willingness	• Decision-making relevance • Informed decision-making • Added value • Competitive need	• Questionable ethics (Data mining) • Emotional response limitation • Feature vs maintenance • Increased maintenance
Challenges associated to implementation	• Better Governance • Augmentation • Data science • Workforce upskill	• Troublesome structure • Misaligned implementation • Decision-making alignment • Job displacement

Table 5: Overview of pros and cons of DT

DT	Pros	Cons
Data extraction and exploitation	• Rich prototyping • Enhanced decision-making dimensions • Greater opinion input	• Challenging prioritisation • Not suitable every time • Relevance
Willingness	• Contemporary trend • Improved problem formulation • Added value	• Objective need • Time-consuming • Feature vs maintenance
Challenges associated to implementation	• Intrinsic value • Human-centred • Augmented decision-making	• Abstract dimension • Misaligned approach • Data science

5. Conclusions

As seen in Tables 4 and 5, each decision-making benefit of AI and DT has its counterpart. By comparing each research goal, in line with respective AI and DT pros and cons, we can consolidate the findings and get an overview.

In terms of the Data extraction and exploitation, we first see that AI creates greater level of knowledge, but this data does not always come in the form of pure knowledge. As discussed by Laney (2012) in the empirical part, BD must first be filtered through the 3 V's to uncover this knowledge. Simultaneously, in terms of DT, this knowledge allows prototyping, but only to a certain extent, when decision-makers must choose the priorities. Secondly, AI enables accurate findings, but decision-makers must classify them. At the same time, these findings enrich their decision-making capabilities, in terms of DT, but the method is not always suitable. Thirdly, AI on its own creates unbiased data, but the challenge remains to ensure the validity of people who create subsequent algorithms based on that data. In terms of DT, it allows a broader input of opinions to ensure validity, but the challenge remains the relevance of these inputs. Lastly, in terms of AI, it enables faster processing and automation, but the automation requires proper management. When we compare these findings to theory, we conclude that decision-makers nowadays have plenty information at their disposal, and if they manage to enrich the information with purpose, they gain competitive knowledge (Peter F. Drucker, 1992).

In terms of the second goal, first we see the recurring relevance theme, but this time in terms of AI and the ethical respect of data that companies mine. Simultaneously, in terms of DT, we realise that it is a contemporary trend that allows data mining to be used to prototype without limits, but how far can we objectively go with all this information? Secondly, we see that AI enables more informed decision-making, but the limit remains connected to emotional comprehension of AI. In terms of DT, this informed decision-making indeed helps formulate problems with improved quality, but it may not be the most time-effective solution. Thirdly, we see that both AI and DT can be of added value in decision-making, except that in some cases it really does add value, while in some it is just another tool that requires maintenance. Lastly, in terms of AI, since it is a more tangible asset, it provides an additional benefit in terms of competitive upgrade, but this also implies additional maintenance. Looking back at section 2.3 of theoretical findings suggested by other authors, and comparing it to this goal, we conclude that decision-makers realise and acknowledge data-driven landscape, therefore the potential of AI and DT, but the question remains if they possess the necessary level of knowledge, capacity or willingness to exploit its value (Ross, Beath, & Quaadgras, 2013).

In terms of the third goal, first we see that AI enables better governance of BD, but data structuring may be the issue. In terms of DT, we see that it adds intrinsic value to governance, but the methodology may be too abstract at times to organise the structure. Secondly, we concluded that AI augments decision-making processes, but the underlying risk lies in bad implementation, which could incur costs greater than the implementation of AI itself. At the same time, in terms of DT, advantage is that this process is human-centred, but with the wrong approach decision-makers risk the abovementioned consequences from misaligned implementation. Thirdly, we saw that AI and DT directly overlap in terms of decision-making and data science. In other words, data science gives the power to extract valuable information, but decision-makers need to develop close cooperation with data scientists to combine the knowledge with strategy. This was simultaneously one of the greatest challenges elaborated in the theoretical part and perhaps the one that connects the entire AI – DT research. Lastly, in terms of terms of AI, one of the greatest advantages is that it enables decision-makers, and workers for that matter, to upskill, but at the same time, the rising technology, i.e. rise of technological competencies, presents one of the greatest fears in terms of job displacement. Looking back at section 2.4 of theoretical findings suggested by other authors, and comparing it to this goal, we conclude that traditional IT tools and competencies, or at least those that were in use so far, will not be enough to exploit the potential of BD (Constantiou & Kallinikos, 2015).

Finally, we reach the conclusion that decision-making is bound to be influenced at every stage by the amount of BD that has the potential to be extracted. AI can be used to exploit it, while DT can be used to formulate it. The rest is up to decision-makers to understand where its best applicable and implement it accordingly. It remains to be seen whether this relationship can bear fruits, given the challenges that lie on its path.

7. Implications

This research explored the concepts that do not necessarily fall under the same category or field of interest in terms of HR, but the idea was to further enrich the findings on both concepts in one paper and see if they relate and improve HRM practices. The findings show that business environment is constantly being challenged by the evolution of technology and HRM practices. With this evolution, innovation is bound to flourish, and in that sense, it is important to research relationships such as this one, to anticipate the challenges that stand in the way of innovation. In addition to these findings, this paper leaves room for future research on similar, or other concepts or relationships that could be combined and examined to generate further insights. In terms of this research, it suggests that cognitive abilities will be more in demand with the coming evolution of technology, namely in decision-making. Jobs and practices that did not even exist until recently, will be in greater demand than those that have been traditionally sought out so far. In that sense, decision-makers, now more than ever, will have to develop multidisciplinary cooperation with data-scientists and designers to be able to exploit data-driven environment, acquire the right talents and equip the workforce with these skills.

Finally, I invite fellow researchers to complement the idea of technology and design with further practical implications, as there are more aspects that have not been covered within this research, that still leave plenty material for future research. In addition to empirical and business-related aspect, there is the ethical aspect which deserves special attention, and that could generate even closer insights into the data-mining aspect that companies are exploiting to competitive advantage. Furthermore, in terms of this research, I invite fellow students and researchers to study the idea of developing and embedding courses and subjects in school curriculums on the relationship of technology with current systems of education, as the textbooks are continuously being digitalised, leaving the paperback material out-of-date quicker than ever. In this way, there could be a direct relationship between business study and business development, especially in schools and countries which emphasise life-learning models of education, and that keep close connection to their alumni network.

8. Annex 1: Questionnaire

1. What do you link to the concept of AI today? What does it mean to you?
2. Do you use AI in your decision-making?
3. How do you plan data extraction?
4. What are the most frequent challenges associated to data extraction?
5. How does AI improve your decision-making? Provide a specific example.
6. In terms of data exploitation, how do you align the findings with your decision-making?
7. How willing are you to further embed AI in your business? Why?
8. Has the relationship with your employees changed due to the use of AI? Provide a specific example.
9. Are you familiar with the concept of DT?
10. What aspect of DT do you find most beneficial to your decision-making?
11. What are the most associated challenges to the implementation of DT in your decision-making?
12. In your experience, where can technology help in that regard?
13. Is there a part of DT or AI you would not want to see involved in certain aspect of your-decision-making? Why?
14. How do you prepare your workers for this tech? How do they report to you?

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