Leveraging and Being Leveraged by Big Data & AI

An Exploration of Tech Strategists' Sense-Making of Human–Machine Dynamics in Strategic Decision-Making

LUND UNIVERSITY

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An Exploration of Tech Strategists' Sensemaking of Human–Machine Dynamics in Strategic Decision-Making

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ABSTRACT

It is amidst the digital saturation of life, globalised interconnections, and accelerated global AI market growth that we are witnessing today that new complexities and challenges emerge in strategically navigating these environments. This thesis explores the emerging dynamics of strategy and Big Data and Artificial Intelligence through a qualitative research design employing semi-structured expert interviews and conventional qualitative content analysis. The aim is to gain a deeper understanding of the perspectives of people working at the intersection of strategy and Big Data and Artificial Intelligence. Therefore, we pursue the question of *How do tech strategists make sense of the dynamics of strategic thinking and BD & AI in strategic decision-making?* We argue that there is a perceived necessity for a symbiotic relationship between human strategic thinking and Artificial Intelligence. This is understood as a mutually enabling and augmenting dynamic allowing for more efficient navigation in complex system environments. Underpinning these dynamics are socio-technical logics, which construct specific fields of possibilities. These socio-technical dynamics have implications reaching beyond the confines of individual organisations. They reach the very fabric of society and, ultimately, how we continuously construct our own realities.

Key words: Artificial Intelligence, Big Data, strategic thinking, strategic foresight, decision-making, socio-technical imaginaries, knowledge and power

Word count: 33,287

‘The essential questions that define knowledge, authority, and power in our time:
Who knows? Who decides? Who decides who decides?’

— Shoshana Zuboff: The Age of Surveillance Capitalism

‘The true sign of intelligence is not knowledge but imagination. Imagination embraces the entire world, and all there ever will be to know and understand.’

— Albert Einstein

Quotes Image: Sociotechnical Transformations
(TechNative, 2021; edited by authors)

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
BD	Big Data
C-QCA	Conventional Qualitative Content Analysis
DDDM	Data-Driven Decision Making
DL	Deep Learning
HITL	Human in the Loop
IT	Information Technology
ML	Machine Learning
NLP	Natural Language Processing
RPA	Robotic Process Automation
VUCA	Volatility, uncertainty, complexity, ambiguity
XAI	Explainable AI

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1 Introduction

Who would have imagined a few decades ago that our TV could suggest what our next favourite show can be. Or that we will have self-driving cars capable of avoiding accidents as they navigate the road. It appears as if the entire world has become fuelled by imagination, becoming a little more intelligent every day. Smart-watches, smart home devices, smart cities, or smart governments; transformational Artificial Intelligence (AI) is weaving itself into the fabric of our everyday lives. The ubiquity of digital technologies has shifted our contemporary era from the prefix “e-” to the prefix “smart” (Gomes, 2019). Much of our world today is powered by *AI* and, consequently, *Big Data* (BD). However, not many understand what lies behind the curtain of these almost mythical terms and processes. In a way, these terms, for most of us, are mere buzzwords. They sound intriguing, modern, and innovative but ultimately elude our full comprehension.

1.1 Research Problem and Aim

Nevertheless, the buzzword nature of BD and AI does not take from industries’ serious growth with these technologies. According to Grand View Research (2021), the global AI market is expected to grow between 2020 and 2027 at a compound annual growth rate of 40.2%. In conjunction with this growth, we can already observe how AI has become a constant presence in our daily lives. In this context, academic literature has increasingly started to pay attention to these developments. Whereas some authors specifically discuss the potential benefits of these developments, others have focused on the detrimental effects, such as discrimination and social sorting, exploitation, and surveillance (Lyon, 2003; Ferguson, 2017; Browne, 2015; Zuboff, 2019).

In light of these developments, few have paid attention to “on-the-ground” realities in industries and corporations (Daugherty & Wilson, 2018; Trunk, Birkel & Hartmann, 2020). More specifically, what is often omitted are the perspectives, narratives, imaginations, and overall sensemaking of the people who work with AI on a daily basis. Even more so, the relationships and dynamics that develop and manifest between these humans and AI in contexts where strategic decisions are made have seldomly been discussed or given a platform. This can be attributed to a general skills gap in connection to AI as well as widespread illiteracy of these issues (Chrisinger, 2019; Jarvis, 2020; Financial Times, 2020). In other words, much of what is going on eludes non-experts and is thus neglected. With increasing digitalisation, datafication, and the emergence of BD & AI technologies, today’s environment is confronted with novel forms of complexity. These complex systems pose new challenges for strategists. As such, it becomes necessary to understand how these complex systems are navigated strategically and, correspondingly, how decisions are made in the context of BD & AI.

Therefore, it is our aim with this qualitative exploratory study to understand how people working at the intersection of BD & AI and strategy, whom we call “tech strategists”, make sense of various dynamics pertaining to this intersection in the context of strategic decision-making. Our thesis further aims to provide a demystified view of the field of BD & AI by giving voice to experts from this field. Additionally, we aim to offer a more nuanced understanding of the perspectives held by the people working with BD & AI and strategy.

1.2 Purpose and Research Questions

The purpose of this qualitative study is to explore the tech strategists’ sensemaking in order to contribute to bridging the perceived gap in understanding. Correspondingly, we further aim for this thesis to function as a stimulus to a wider demystification of BD & AI technologies. To this end, we ask the following question:

How do tech strategists make sense of the dynamics of strategic thinking and BD & AI in strategic decision-making?

We explore our research question through conventional qualitative content analysis (C-QCA) of fourteen semi-structured expert interviews. The following operational questions will help to answer our research question:

1. **How do participants characterise BD & AI?**

   In order to arrive at an understanding of the dynamics of both strategic thinking and BD & AI, it is necessary first to grasp our participants' sensemaking of BD & AI. This question probes the characterisations, logics, and narratives surrounding BD & AI in the context of strategic decision-making.

2. **How do participants characterise strategic thinking?**

   This question addresses the second element of the explored dynamic, that is, the characterisations and associations of strategic thinking in the context of strategic decision-making.

3. **How do participants perceive and envision the relationship between strategic thinking and BD & AI?**

   This question inquires about the participants' sensemaking of the meeting points of the previously deconstructed parts of the dynamic in terms of both perceptions as well as envisionings of the relationship.

Taken together, these operational questions enable us to construct an *assemblage* of the participants' sensemaking of the explored dynamics of strategic thinking and BD & AI in the context of strategic decision-making.

1.3 Relevance to Management

This study ties into the wider field of Management in various ways. First, a growing field of literature discusses the emerging convergences of data science, Artificial Intelligence, and strategic — foresight functioning as a joint approach to better dealing with the future uncertainty of today's fast-paced, interconnected world in (strategic) decision-making. However, as this academic field is still very nascent, the diversity of academic insights that arises from combinations of different research designs, analytical frameworks, and researcher positionalities is still low. Nevertheless, with AI saturation in today's world and the largely mystified nature of both BD & AI and strategic thinking (/foresight), it is necessary to engage in research that contributes to developing a nuanced, grounded understandings of the ways in which individuals come to perceive and make sense of this new frontier, in a way that is accessible to less data/AI literate readers.

Second, with the projected significant growth of the global AI market and corporate as well as academic literature dealing with the ways in which AI is disrupting, and understood to disrupt further, businesses across industries (Dewalt, 2018; Daugherty & Wilson, 2018; Accenture, 2018), increasing awareness of the underlying logics and narratives surrounding BD & AI rises to prominence. Amidst the digital saturation of life and these disruptive movements, exploring questions of knowledge and power becomes more relevant, particularly in spheres of more extensive influence on organisations and broader environments, such as strategic decision-making. Such investigations, and by consequence, our thesis, engage fundamental questions concerning knowledge and thus power: Who knows? Who decides? Who decides who decides? (Zuboff, 2019).

Finally, given our aim of providing a demystified view of the field of BD & AI through our participants' sensemaking accounts, we identify various stakeholders of this research project. These include: future generations of students who will undoubtedly stumble across issues relating to BD & AI; our participants themselves, who on various occasions expressed the desire to see the final product of our research and hope to gain insight into other perspectives; and finally, anyone who is interested in the intersectional field of BD & AI and strategic decision making.

1.4 (De)limitations

We purposefully chose a qualitative research design. We did so to be able to pursue our aim where we specifically want to understand subjective positions on a particular phenomenon. This choice, by definition, limits us in the sense of not developing claims to generalisability or representativeness of our study on a broader scale. We acknowledge that the data generated and the findings discussed stem from *our* interpretation of the material. However, in order to ensure validity, we use rich descriptions of our participants' responses, make sure not to alter any conveyed meanings, clarify our positioning as researchers, and ensure transparency throughout the research process. On a technical note, we chose to conduct our interviews online through Zoom. This was motivated by the ongoing pandemic; however, we acknowledge that, as such, we did not have access to the "full" range of potential material as would have been the case with an in-person, face-to-face interview setting.

Although not a delimitation per se, but worth noting in connection to the choice (and consequent implications) of our research design — our researcher position(s). In this sense, although we have both adopted a social constructivist outlook, advocating for a multiplicity of truths, each of us has shaped this study differently based on our individual positions. As a graduate of Peace and Conflict Studies and based on previous AI-related research, Veronika has grown to adopt a critically analytical approach to knowledge production processes associated with AI. Woo Seung's position in this project was marked by an environmental science and technology educational background, as well as a problem-solving and practical approach towards our research puzzle. As such, we were able to leverage our complementing backgrounds and mindsets in order to enrich our analysis in diverse ways.

1.5 Thesis Outline

The thesis consists of seven chapters. The *introductory* chapter introduces the reader to the focus of our study. Additionally, we discuss the methodology as well as our analytical lens. We have positioned our research within the field of Management while highlighting the study's corresponding relevance for this field of study. Chapter two, *Context*, offers a backdrop of BD & AI technologies, strategic thinking and foresight, and emerging convergences between foresight and BD & AI. We have chosen to embed a discussion on previous research within this contextual chapter. In Chapter three, *Theoretical Framework*, we map out the theoretical points of departure for our analysis. It consists of a discussion revolving around the notion of complex systems, a theorisation of design thinking foresight, socio-technical imperatives of contemporary data technology, and challenges in strategic approaches to navigating complexity. In *Methodology*, we outline our methodological principles and considerations, discussing our approach to the material using C-QCA, which is followed by the presentation of *data* in Chapter five. Chapter six, *Analysis*, unfolds an understanding of the data through our conceptual lens and reflects on the relevance of this concept. Finally, in our last chapter, *Concluding Discussion and Remarks*, we reflect on our insights and interpretations while offering an answer to our research question. We highlight the implications of this study as well as potential pathways for further research.

2 Context

Our research puzzle comprises intersecting themes, which are built upon several complex concepts. Complex in the sense of being founded on various interlinked notions themselves, lacking consensus on a clear, unambiguous meaning, and often being (mis)used to mean everything, and thus often also nothing. Hence, we deemed it necessary to provide readers with a contextual basis of Big Data & Artificial Intelligence, strategic thinking, and their subsequent marriage. This, in turn, facilitates a better understanding of the analytical discussions in this study. Therefore, this chapter offers background information, discussions of frequently presented meanings of the involved concepts, whilst clustering and reviewing extant literature debating our two themes, as well as literature emerging at the convergence of the two fields — which is where we situate our research.

2.1 Big Data and Artificial Intelligence

It seems as if there is always new technology on the horizon, making bold promises, exciting people about endless prospects of innovation. Just as we thought we had reached the pinnacle of technological breakthroughs, Artificial Intelligence made its way to the top of both academic and corporate spheres. Although the idea of robots and intelligent machines can be traced far back in time, many believe that we are only scratching the surface of what is possible (Duan, Edwards & Dwivedi, 2019). Computers still cannot "think", but emerging cognitive computing is increasingly capable of automating tasks requiring perceptual skills, reasoning from partial information, and learning (van Belkom, 2019; Schatsky, Muraskin & Gurumurthy, 2015).

2.1.1 Evolution

Since antiquity, philosophers and mathematicians have been playing with the idea of artificial beings endowed with intelligence, conceptualising various machines capable of reasoning and learning (Shashkevich, 2019; Duan, Edwards & Dwivedi, 2019; Buchanan, 2005). However, we have only started seeing more significant developments in the past seventy years, a period itself marked by phases of higher and lower interest ("AI springs" and "AI winters") (Manyika & Bughin, 2019; Schuchmann, 2019; Schühly, Becker & Klein, 2020). The 1950s saw the founding of the field of AI research and the idea of machine learning, i.e., developing algorithms that could automatically extract patterns from datasets to make predictions and real-time decisions (Future Today Institute, 2021). But the possibility of exploring AI did not appear until 1970, with the advent of the first microprocessors (Council of Europe, 2021). However, programming was still reliant on rule-based logic (think: "if-then" individual rule programming) rather than actual learning, rendering use low among other cheaper and simpler solutions (Schühly, Becker & Klein, 2020). Another AI spring came in the 1990s when IBM's Deep Blue beat famous chess player Garry Kasparov (Press, 2018). This defeat, however, remained symbolic since the algorithm only managed to treat a limited number of possible moves, far from the capacity to model the complexity of our world (Somers, 2013; Council of Europe, 2021). Descending into another AI winter, AI had almost become taboo, with more reserved terms such as "advanced computing" being cited (Council of Europe, 2021).

Fast forward to the past decade; an AI boom is roaring, explainable by significantly higher processing power and access to volumes of data (McKinsey & Company, 2020; Schühly, Becker & Klein, 2020). The discovery of high-efficiency computer graphics card processors, which accelerate learning algorithms, has enabled considerable AI progress at a lower cost (Council of Europe, 2021). Similarly, ubiquitous networking (4G/5G) and increasing datafication, i.e., rendering nearly all parts of our lives into data, make it possible to feed AI with data to learn from (van Belkom, 2019; Burgess, 2018; Dewalt, 2018). The new technological equipment has led to developments such as Google's AlphaGo algorithm, which beat the world champion of Go, a game with more possible moves than the number of particles in the universe (Council of Europe, 2021). This has been made possible with more funding and the major shift from rule-based to machine learning programming (Schühly, Becker & Klein, 2020). Machine learning systems can now follow a self-learning or trial-and-error approach automatically (Heintz, 2021).

2.1.2 Beyond Buzzwords: AI

The unsteady evolution of the AI field is also mirrored in the current lack of a generally accepted definition. Although AI systems fill our daily lives, often without us noticing, a clear understanding of AI is elusive, even within academia, rendering AI essentially a buzzword. A clear-cut definition is made further difficult with the 'AI effect', i.e., when the label of AI is stripped off something after it has 'proven itself' (e.g., as was the case with GPS systems) (van Belkom, 2019:2). 'Once the mystery has been solved', it becomes 'automation' rather than 'intelligence' (van Belkom, 2019:2). Nevertheless, several ways of tackling the elusiveness of AI can be identified within the existing literature.

The first and perhaps the most obvious understanding comes from deconstructing the term itself. AI can be understood as a broad set of meanings loosely tied under the concept of *intelligence* (Ng, 2016; Heintz, 2021). AI is often defined as the theories and development of computer systems performing tasks typically requiring human intelligence (Russell & Norvig, 2009; IBM, 2020). Focus is placed on understanding intelligence and building engineering solutions to expand human intelligence through AI (Heintz, 2021). Herein, a definition of AI is further undermined by historical changes in what is considered a measure of intelligence, shifting from pattern-finding to more complex connotations (Heintz, 2021).

Secondly, the types of *capabilities* of machines to mimic human intelligence are brought into focus, ranging from reasoning, learning, problem-solving to essentially freeing humans from the need to explicitly program a computer how to perform tasks (Winston, 1992; Russell & Norvig, 2009). AI can thus be explained as 'a system's ability to correctly interpret external data, learn from such data, and use those learnings to achieve specific goals and tasks through flexible adaptation'

(Kaplan & Haenlein, 2019:17). In this regard, some assert that studying the problems the world presents to "intelligence" rather than studying humans can help in developing such capabilities (McCarthy, 2001).

Thirdly, several experts define AI as a branch of computer *science* in which computers are programmed to do things that generally require human intelligence (Council of Europe, 2021). AI is often contrasted with RPA (Robotic Process Automation, e.g., autonomous vehicles), which automates processes at the level of repetition, while AI has the capability to learn and self-correct (van Belkom, 2019; NICE, 2021; Yarlagadda, 2021). Fourthly, publications differentiate between purely software-based AI systems (e.g., search engines, voice assistants) and AI embedded in hardware (e.g., autonomous cars, drones, IoT[1]) (European Commission, 2019). This *architectural* approach emphasises AI's system nature as applications of AI are embedded as components of larger IT systems rather than stand-alone systems (European Commission, 2019). Fifthly, AI is also described through its *functioning* with a focus on rationality. It is understood as a chain of perception (of its environment to collect and interpret data), reasoning (on what is perceived), and actuation (deciding what the best course of action is and acting accordingly) (Russell & Norvig, 2009; European Commission, 2019). What is highlighted here is that any action performed can modify the environment so that AI will need to use sensors again to perceive and learn from the evolved information (Russell & Norvig, 2009). Sixthly, there are definitions of AI spotlighting the main *applications* of AI today. AI is seen to be making various processes more efficient and less biased, contributing to faster and cheaper decision-making (Agrawal, Gans & Goldfarb, 2018).

With growing discussions and applications of AI, the European Commission (2019) has composed an encompassing definition of AI[2], which attempts to incorporate the notion that AI use in decision-making is relative to the goals we are trying to achieve. Although it does imply that AI modifies environments and

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[1] IoT refers to the *Internet of things*, i.e., 'a network of physical objects' ("things"), which are embedded with sensors and other types of software in order to connect and exchange data 'with other devices and systems over the Internet' (Oracle, 2021).

[2] This full 'updated definition' states that: '*Artificial intelligence (AI) systems are software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal. AI systems can either use symbolic rules or learn a numeric model, and they can also adapt their behaviour by analysing how the environment is affected by their previous actions.*' (European Commission, 2019).

brings about specific (un)intended effects, a considerable body of literature explicitly defines AI through the ethical and cultural *questions* it brings forth. According to Stephen Hawking, AI can mean 'the end of the human race' (Hawking in Cellan-Jones, 2014). Others point out AI's association with surveillance, social sorting, discrimination or reinforcement of existing inequalities (Zuboff, 2019; Lyon, 2003; Ferguson, 2017; Browne, 2015).

Despite the absence of agreement on a clear definition of AI, a three-level classification is broadly supported, distinguishing between: *Artificial Narrow Intelligence* (a form of AI doing specific tasks, e.g., speech recognition; all AI applications today are specialised and narrow), *Artificial General Intelligence* (human-level AI; currently a hypothetical form that would be able to perform all human intellectual tasks), and *Artificial Super Intelligence* (also hypothetical; transcending our brain's ability in all possible domains including social behaviour) (van Belkom, 2019:3). Current narrow AI is commonly divided into three layers: *Artificial Intelligence*, *Machine Learning* (ML), and *Deep Learning* (DL) (see Fig. 1 below).

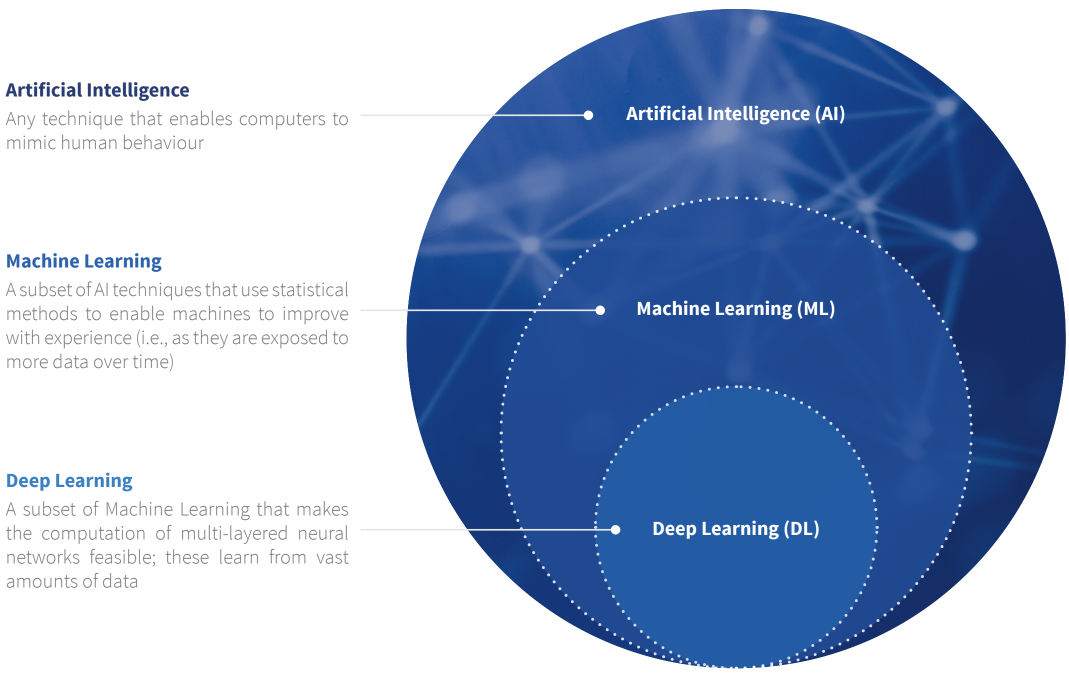

Fig. 1: Layers of Artificial Intelligence
(adapted from Ng, 2016; Ceron, 2019; Singh, 2018)

While AI covers the capability of mimicking our behaviour in specific tasks through sets of rules, ML can generalise output from input data through a learning experience (Ceron, 2019; Ng, 2016). DL, as a subset of ML, is distinguished from ML in terms of how the algorithm learns from datasets using so-called neural networks[3] with three or more layers, making it capable of processing large datasets (Ceron, 2019). The main difference between ML and DL is that while ML uses 'human extracted features from data' to learn and improve, DL can 'learn the important features in data by themselves' (Ceron, 2019).

2.1.3 BD & AI Relationship

In understanding AI from any vantage point, we will always encounter the association with (Big) Data. Data is the fuel that powers Artificial Intelligence (Greer, 2019). In order to understand this special relationship, we first need to grasp what it takes to drive AI initially – (Big) Data. In simplest terms, what makes BD new or different to old, traditional, and small forms of data, is precisely the unbelievable amount of data. It is more — a lot more. However, BD encompasses not just a never-before-seen *volume*, it additionally sports *velocity*, *veracity, volatility*, and *variety*[4] (Yeung, 2020; Greer, 2019). Velocity refers to the speed data can be made available. The aim is to gain access to data and, hence, information as real-time as possible. If someone uses their credit card or Google Maps, the information of such (trans-)actions must be immediately available and processed. Veracity describes the accuracy and completeness of any data. Volatility, on the other hand, focuses on the validity of data in the context of time. In other words, is data that emerged 24 hours ago still valid now and, subsequently, for how long should data be stored. Finally, variety in BD refers to the multitudes of different (potential) sources of data streams. Credit cards, smartphone applications, "cookies", and even our "smart" vacuum cleaners are all means to gain access to a variety of data (Zuboff, 2019). All of these "Vs" are

[3] Neural networks can be, to a certain extent, compared to small children. As Schühly, Becker & Klein (2020:147) explain, 'they need a lot of energy and time, but already possess a powerful brain (processing power) and learn most of what defines them later on by observation and feedback (data).'

[4] Some sources (Arockia, Varnekha & Veneshia, 2017; Impact, 2016) discuss even longer lists of "Vs" of Big Data, adding terms like value, validity, virality, etc.

interconnected and reinforce each other. For instance, what makes up the *volume* of BD is partly determined by the need for *veracity* through *variety*.

These complex and interconnected aspects of BD make it a daunting task for "humans" to process, understand, and benefit from the potential of raw data flows. Put differently, traditional data analytics approaches seem incompatible for generating the maximum value promised through BD. Thus, cognitive computing such as AI is adopted to aid humans with handling BD for acquiring insights, process improvement, and decision-making (Davenport & Mahidhar, 2018; SAS, 2021). AI makes BD analytics "simpler" by automating and enhancing data preparation, data visualisation, predictive modelling, and other complex analytical tasks that would otherwise be labour-intensive and time-consuming (Schühly, Becker & Klein, 2020). Reciprocally then, BD supplies AI algorithms with the necessary information to develop and improve features and capabilities, since without larger volumes of high-quality data, it would not be possible to develop and train intelligent algorithms (Schühly, Becker & Klein, 2020). In other words, through BD, AI holds the capabilities of data analysis and monitoring, pattern identification, and predictions and classifications of outcomes based on past data.

2.1.4 Applications of AI

AI is demonstrating its transformative power in a variety of fields, ranging from healthcare (McKinsey & Company, 2020), education (UNESCO, 2019), finance (OECD, 2020) to peacebuilding (UN Global Pulse, 2020), security (Lyon, 2003; Ferguson, 2017), and many others. Cognitive computing amplifies information technology's power by enabling organisations to use AI mainly in three categories of application: *product*, *process*, and *insight* (Schatsky, Muraskin & Gurumurthy, 2015:117). Product-related applications of AI refer to the embedding of AI systems in products or services mainly for customer benefits. Process-related applications embed AI in an organisation's workflow in order to automate or streamline operations. And lastly, AI is used to obtain insights derived from data in order to inform various decisions. In other words, the aim of leveraging BD & AI is predominantly seen in new value creation (Changchit & Chuchuen, 2018).

As such, companies are adopting AI not only for efficiency but also for increased growth and innovation (McKinsey & Company, 2020).

In the context of decision-making, a core strength of AI is framed as cheap prediction — as a forecasting tool (Agrawal, Gans & Goldfarb, 2018; Davenport, 2018). Through its capabilities of transforming structured and unstructured data into information to be interpreted into insights, AI is said to allow organisations to predict futures more accurately, from potential equipment failures to next-best products (Agrawal, Gans & Goldfarb, 2018). In other words, AI enables organisations to be *descriptive* (draw insights), *predictive* (anticipate future developments), and *prescriptive* (obtain recommendations for decisions to achieve goals) (Zuboff, 2019; McKinsey & Company, 2020; Agrawal, Gans & Goldfarb, 2018).

The most notable AI techniques encompass *Natural Language Processing* (NLP), i.e., the capability of AI to understand (read, write, speak, listen to) language (Yse, 2019). NLP is used in order to extract topics from communication, from which it can, e.g., perform sentiment analysis or create predictions from speech (Yse, 2019). Another prominent technique is *Computer Vision*, which consists of methods that provide imaging-based inspection and analysis, e.g., object detection or face recognition (Heintz, 2021). With *Data Analysis*, there are methods such as data mining, which is the process of identifying anomalies, patterns, and correlations within large datasets to predict outcomes — based on the premise that future events will develop and behave similarly to past events — to increase revenues, cut costs, or improve customer relationships (Deb et al., 2017; Agrawal, Gans & Goldfarb, 2018; SAS, 2021).

Correspondingly, Ng (2016; 2020) argues that understanding what AI can do is the first step to understanding how it can fit into organisations and strategies. However, while possessing knowledge and skills to use a specific AI technique efficiently for a given problem is important, the quality of the data fed into a model is paramount for the outcome (Ng, 2020). In this sense, an increasing body of literature also points towards extensive requirements and challenges associated with AI projects. Recurring arguments affirm that building, using, and maintaining AI successfully is dependent on how organisations set, align, and communicate their visions (Ng, 2020), whether organisations have the necessary infrastructure

(Davenport & Ronanki, 2018; Fountaine, McCarthy & Saleh, 2019), diversity and competence (McKinsey & Company, 2019; Davenport, 2018), pursue interdisciplinary collaboration as opposed to siloed structures (Wilder-James, 2016), embrace a digital mindset (Frankiewicz & Chamorro-Premuzic, 2020), refrain from 'moon shot' applications (Davenport, 2018), ensure ethical AI (European Commission, 2019), and understand how AI will be incorporated into their context (Ng, 2016).

2.1.5 Limitations of AI

The variety of opportunities and necessities associated with AI suggests that AI is not just a new set of tools but a new world, changing almost all aspects of organisational life. Yet, the challenge is to look beyond the hype and discover AI's true applicability, which means also acknowledging its limitations.

Firstly, as we established, AI is data-hungry. One of the biggest limitations of AI is that it *depends* on large volumes, variety, and velocity of data. This means that AI is not effective where little data is available. In such cases, work needs to go into creating datasets or real-world data collection that is often unstructured and needs to be cleaned, which is often expensive and time-consuming (van Belkom, 2019). As previously indicated, AI acts on past data and thus can tell us little about a future that is qualitatively different from the past. Moreover, data can also be inexplicable, causing AI to assign causality in cases of correlation (van Belkom, 2019:9). Additionally, humans not only learn from factual knowledge, but we also learn from interactions whereby we gain tacit (unconscious) knowledge, which we often take for granted. This makes it difficult for AI to learn about a world where a lot of knowledge is not specifically noted down to be fed into AI as data (van Belkom, 2019:10).

Secondly, as Ntoutsi et al. (2020) highlight, datasets and thus AI algorithms are permeated with our values and can reinforce real-world *biases* leading to discriminatory decisions. In light of this, the AI community has been developing methods to detect and mitigate bias in dataset training and throughout other parts of AI models, as well as ways of understanding how data influences AI behaviour (O'Neil, 2016).

Thirdly, one of the most discussed limitations of AI is the so-called black-box effect. It refers to the opaque layers of neural networks, which make it impossible to trace and explain how a given decision was made (Blackman, 2021; Hosanagar & Jair, 2018). AI *explainability* constitutes a major limitation in applications necessitating a fully explainable process. Consider the different demands for explainability in Netflix movie recommendations versus illness diagnostics (Adadi & Berrada, 2018). With increased applications, the demand for explainable AI (XAI) has emerged, aiming to develop techniques enabling explainability (Adadi & Berrada, 2018).

In connection to the above, AI entails limitations from an *ethical* perspective with the value alignment problem, i.e., AI delivering results without the ability to consider environmental factors and consequences (van Belkom, 2019:10). For instance, YouTube recommendation systems, which, based on the goal of efficiently providing viewers with the content they will enjoy, can create filter bubbles and polarise populations. Furthermore, without realistic expectations of the technology, AI hype may lead to applications that are not yet precise or useful (Linden & Fenn, 2003), possibly further undermining levels of trust bound to AI.

Conclusively, with the convergence of vast research, exponential growth of data, improvements in computing power and storage, and giant players such as Amazon, Google, Facebook, or Netflix constantly inventing new ways of leveraging data, the current age resembles an unprecedented moment (Iansiti & Lakhani, 2020). Not only are we faced with multitudes of ethical and technological questions bound to the possibilities and limitations of AI; in addition, we are left with a general sense of uncertainty.

2.2 Strategy and Strategic Thinking

The future cannot be precisely predicted, but it can be envisioned and steered towards specific goals. The concept of strategy generally evokes images associated with such future-bound thoughts and activities. But although the term is commonly and conveniently used, it is often applied in almost infinite ways.

Similarly to our previous discussion on AI, the terms strategy and/or strategic display a similar buzzword nature (Sterling, 2003; Sull et al., 2017).

2.2.1 Beyond Buzzwords: Strategy

Strategy is often associated with deliberate decision-making to ensure long-term success(es) (Schühly, Becker & Klein, 2020:8; Sloan, 2020). Grant (2019:15) defines strategy as 'the means by which individuals or organisations achieve their objectives'. We can already see the complexity involved in talking about strategy — it can be viewed as a means to an end, a sequence of activities, a plan, process, art, science, skill, or experience.

Corporate strategies are often formulated as coordination *devices* and targets establishing directions for organisations to follow in order to ensure long-term success and sustainable competitive advantage (Sterling, 2003; Ackoff, 1970; Porter, 1996; Mintzberg, 1987; Mintzberg, 1996; Watkins, 2007). Resource-based views on strategy portray strategies as *plans* ahead of time where prioritisation under limited time and resources available is a key aspect of strategic endeavours (Onyeaghala & Ukpata, 2013; Roberts & Stockport, 2009; Grant, 2019). In this context, successful strategies are also seen as those that incorporate the capability of dealing with the *unknown*, which affects prioritisation and planning (Yadav, 2014; Teece & Leih, 2016).

In contrast, some argue that an overreliance on often rigidly set plans and procedures can be detrimental to an organisation's adaptive potential, which is deemed pivotal in successful strategising today (Schühly, Becker & Klein, 2020; Teece, 2007). Such Darwinian accounts of strategy highlight that strategies need to be dynamic and generative *processes* rather than static and finite plans (Sloan, 2020). They render *adaptation* a strategic expectation associated with creative thinking, complexity management, and execution speed (Trujillo-Cabezas, 2020). The latter is emphasised in recent literature, which spotlights how challenges emerging with globalisation and digitalisation are shaping previously understood principles and practices of strategy towards more *proactive* and adaptive approaches (Schühly, Becker & Klein, 2020; Berman & Dalzell-Payne, 2018).

Strategy can be viewed from several perspectives. Some look into the past for strategies as repeated patterns for success; others look towards the future. All viewpoints imply a *will* to win, an element of *competition*, a framework for *success*, a determined *aim*, a unifying *intent*, and resource *allocation* (Sloan, 2020:8). The notion of decision-making permeates all understandings along with the differentiator between strategy and tactics (i.e., the specific (sub)steps taken to accomplish a strategy) — *time*. Time is a necessary resource inherently bound to strategy, highly impactful, but also rare (Schühly, Becker & Klein, 2020). In combining the various viewpoints with the aspect of time, we can arrive at a deeper understanding of strategy. At its core, strategy is about *choice*.

2.2.2 Beyond Buzzwords: Strategic Thinking

Strategy is involved in how we choose to develop our organisations, projects, or even individual lives. Seen as a dynamic process then, through strategy, we think about what kind of a future we want to create and the means to achieving such futures. This aspect of *thinking* bound to strategic endeavours has been the subject of much academic debate. And although strategic thinking has been recognised as a focal point for the field of strategy, there is no singular definition or general agreement in the literature on what strategic thinking entails. It has become a synonym for a range of vague notions, some complementary, some competing. Strategic thinking has been addressed at the level of individuals as well as organisations (Bonn, 2005). It has acquired definitions ranging from a focus on the dynamic capabilities associated with strategic thinking (Teece, Pisano & Shuen, 1997), the resources necessary for such thinking (Porter, 1985) to organisational psychology and leadership (Schoemaker, Krupp & Howland, 2013). Some of the most predominant conceptualisations understand strategic thinking through the foci of *strategy development*, *mental processing*, and *perspectives and activities* (Liedtka, 1998). Nevertheless, these are often evolving and not mutually exclusive.

In discussing *strategy development*, Henry Mintzberg (1994) asserts that strategic thinking should not serve as an umbrella term for anything associated with strategy. He suggests (1994) a clear distinction between strategic thinking and strategic planning. Strategic *planning* is about analysis, breaking down a goal into steps, formalising those steps to be implemented, and articulating anticipated consequences; whereas strategic *thinking* is about synthesis, it involves intuition and creativity to formulate an integrated vision of where an organisation should be heading (Mintzberg, 1994; Liedtka, 1998). In other words, strategic planning is about "finding the dots", while strategic thinking is about "connecting the dots" (Mintzberg, 1994). Although using the term 'crafting strategic architecture' rather than strategic thinking, Prahalad and Hamel (1994) join Mintzberg as they attach themes of creativity and exploration to strategic thinking. The division between thinking as divergent, creative and planning as convergent, conventional (also called strategic *programming* as something that is practised (Mintzberg, 1994)) is echoed by others. They highlight that with strategic thinking, not only are the sources of data for strategy different, but the analysis of the data also differs (Dhir, Dhir & Samanta, 2018:273; Heracleous, 1998).

In the context of this division, there is a spectrum of literature arguing for an interrelationship and dependence between strategic thinking and strategic planning (Heracleous, 1998; Liedtka, 1998; Hussey, 2001). Some argue that they are distinct but complementary thought processes (Graetz, 2002; Sloan, 2020); others discuss whether strategic thinking occurs before, during, or after strategic planning (Goldman, 2012). Sloan (2020) stresses that *both* intuition and rational analysis are essential tools. She maintains that good strategic thinking requires awareness and embracing of both tacit and explicit knowledge; therefore, strategists should have the capacity for both analysis and synthesis (Sloan, 2020).

The second cluster takes the thinking nature further by exploring the various types of mental processing involved, e.g., inductive and deductive thinking, critical and logical thinking (Bonn, 2005; Liedtka, 1998; Ohmae, 1982; Goldman, 2012). Strategic thinking is discussed as an organisational attitude, a type of thinking that helps introduce new possibilities, challenge assumptions, update mental models, and envision future changes (Shaik & Dhir, 2020; Pagani, 2009).

The third cluster discusses the perspectives and activities involved in strategic thinking. Liedtka (1998:122ff.) puts forth five dimensions of activities: having a systems (holistic) perspective, being intent-focused, thinking in time, being hypothesis-driven, and focusing on intelligent opportunism (i.e., being responsive to opportunities). Focusing on the perspectives involved, *systems thinking* is increasingly attached to strategic thinking (Senge, 1990; Liedtka, 1998). As Kaufman (1991:69) asserts, strategic thinking is characterised by 'a switch from seeing the organisation as a splintered [set of] parts competing for resources, to seeing and dealing with [an organisation] as a holistic system that integrates each part in relationship to the whole'. The systems thinking focus is gaining prominence in connection with a revitalised interest in complexity theory, which treats the nature of organisations as living organisms occurring as complex, adaptive systems in broader, mutually influential systems (Colchester, 2016a, 2016b). In this context, some authors (Jelenc, in Sloan, 2020) push for a shift from a strategic thinking focus on strategic models to the people in complex systems.

Taken together, many academic discussions draw a sharp dichotomy between analysis and synthesis in strategy. Some even question whether the topic of strategy and strategic thinking should be taught at all, given the multitude of contextual elements coming into play in strategic processes (Goldman, 2007). Consequently, a look at certain older ideas surrounding strategic thinking can be considered. The ancient Greek view of strategy revolves around the ability to oscillate between 'cosmos' (order) and 'chaos' (unstable and unlimited affairs) in order to (re)steer a desired course (Sloan, 2020:9). Translated to the above issue of dichotomic visions of strategic thinking, the ability to constantly *oscillate in tandem* surfaces. In this context, Voros' (2003) way of methodically distinguishing between *strategic thinking*, *strategy development*, and *strategic planning* may provide a sense of clarity (see Fig. 2). The idea of oscillation is reflected in this division as Voros (2003) argues that problems arise when one is elevated to superiority rather than being perceived as part of a much broader iterative process.

Fig. 2: Methodical Division: Strategic Thinking, Strategy Development, and Strategic Planning (adapted from Voros, 2003)

2.2.3 Foresight

As globalisation and datafication magnify information flows, the discussed iterative process becomes ever more complex. *Strategic foresight* can be described as a particular way of doing strategic thinking, which focuses on expanding the range of *how to think* strategically. In other words, strategic foresight entails imagining potential future scenarios and outcomes in connection with specific decisions. Although the concept of foreseeing the future is one of great debate through human history — it seems we have always longed to know what the future holds, foresight only emerged as a disciplined approach several decades ago (Hammoud & Nash, 2014). The definition of strategic foresight drafted by the Organisation for Economic Cooperation and Development (OECD, 2021) captures the essence of various definitions: ‘Strategic foresight is a structured and systematic way of using ideas about the future to anticipate and better prepare for change. It is about exploring different plausible futures that could arise and the opportunities and challenges they could present. We then use those ideas to make better decisions and act now’. In other words, foresight can be seen as the *ability* to create and maintain a coherent and functional forward view and to use the arising insights in organisationally useful ways in order to deal with future uncertainty (Slaughter in Haarhaus & Liening, 2020).

As the explanations signal, foresight can be distilled to imaginative preparations for various futures. A core feature is that foresight both *envisions* an expected future and multiple (commonly three/four) alternative futures (Schühly, Becker & Klein, 2020; Duijne & Bishop, 2018). Yet, it is not concerned with predicting what will be, but what ideally *could be* if we could make it happen. It constitutes a way of looking at the future. And while there is often no fixed time horizon[5] for using foresight, four distinct kinds of futures are considered: *possible futures* (“what might happen” with a certain likelihood based on expectations, including knowledge that we do not yet possess), *plausible futures* (“what could happen” based on our current knowledge, yet does not have to be likely to happen), *probable futures* (“what is likely to” based on current trends without incorporating uncertain events), and *preferable futures* (“what do we want to

[5] According to the UNDP (2018), everything beyond the present can be described as foresight. Different sources offer varying ranges, e.g., short-term foresight (within 0–3 years), mid-term (3–5 years), and long-term (5 years or more).

happen / what should happen" based on our own judgement, regardless of plausibility or likelihood) (Voros, 2003; UNDP, 2018)[6] (see Fig. 3).

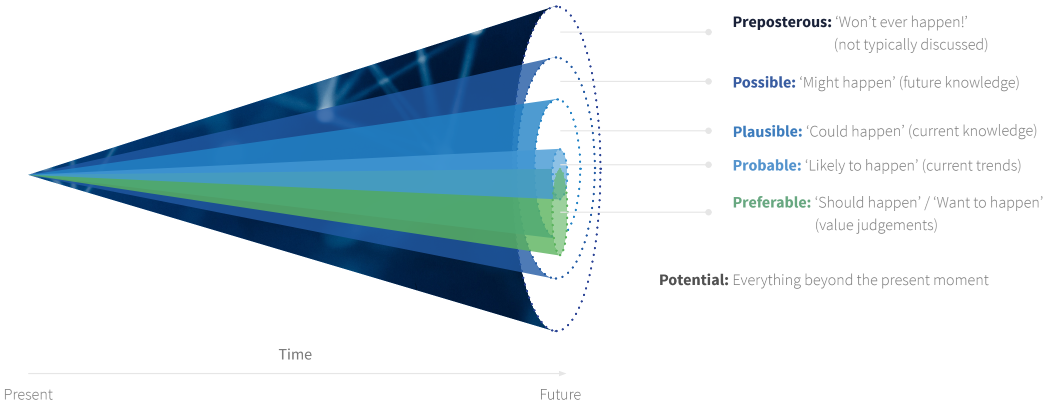

Fig. 3: Types of Futures Considered in Foresight (adapted from UNDP, 2018; Voros, 2003)

As the presence of preferable futures implies, the main goal of strategic foresight is not to "get the future right", but to expand and reframe the range of plausible developments that need to be taken into consideration (UN Global Pulse, 2021). As such, strategic foresight is becoming an essential strategic thinking methodology for organisations' ability to navigate our rapidly changing globalised environment. As a process, it involves a variety of tools and methods for the creation of visions of the future that would direct strategy development (Hammoud & Nash, 2014). In this context, Roubelat (in Bootz, 2010:1590) emphasises that foresight should not simply expand and explain cognitive maps of decision-makers but that it must try to build shared representations of an organisation's evolvement. In simpler terms, foresight should engage people in dialogue on preferred futures and ways of making them happen.

A number of benefits are thus articulated in connection with the performance of foresight in the context of the iterative view of strategy. In their study, Hammoud & Nash (2014) show that the main reasons for engaging in foresight approaches lie in the ability to innovate, form a competitive edge, and influence consumers' perceptions. Others argue that foresight also helps in solving complex problems, identifying drivers of change, systematically assessing risks

[6] Amy Webb, a quantitative futurist and professor of strategic foresight, proposes an alternative way of structuring futures — not in 'time lines' but rather in 'time *cones*' (Webb, 2019). She argues that successful futurists think in the 'short- and long-term simultaneously' by working with four categories of futures: tactics, strategy, vision, and systems-level evolution (Webb, 2019).

and opportunities, creating capacity for future-readiness and organisational alignment, as well as the opportunity to shape the future and make better strategic decisions (Duijne & Bishop, 2018; European Commission, 2020).

In 2017, the European Political Strategy Center released a publication encouraging organisations to incorporate foresight into their decision-making processes to encourage long-term future reflection (European Commission, 2017). Similarly, Miller (in Haarhaus & Liening, 2020:4) argues that being 'futures literate' increases a manager's capacity to adapt quickly and persist in a rapidly changing environment.

2.2.3.1 Foresight in Practice

Although foresight practitioners agree on the main goal of the foresight process, the road varies in practice (Hammoud & Nash, 2014). Typologies can be found, including methods such as weak signal analysis, trends analysis, forecasting, backcasting, visioning, horizon scanning, or the Delphi method (UNDP, 2018). More assessment-bound methods include cross-impacting or wind-tunnelling, but grey areas between methods exist (Börjeson et al., 2006).

Perhaps the most widely used foresight method is *scenario building*. Scenario building deals simultaneously with 'the world of facts and the world of perceptions' functioning as a 'kaleidoscope' (Schühly, Becker & Klein, 2020:25). On the one hand, practitioners are encouraged to zoom in on close things happening in the short term and, on the other, to zoom out for a more holistic view of the distant future (Schühly, Becker & Klein, 2020). The outcome constitutes varied descriptions of how the future world could function — alternative scenarios. Scenario building suggests a focus on designing strategies that will enable strategists to be future-proof under all imagined scenarios (UN Global Pulse, 2021) and simultaneously understand what actions and resources are necessary to acquire such a future-proof position. Scenario building often blends three types of scenarios: *predictive* (responding to the question: "What will happen on the condition of some specified events?"), *explorative* ("What can happen if we act in a certain way?"), and *normative* ("How can something be reached?") (Börjeson et al., 2006).

In general, foresight tools facilitate future-oriented awareness by overcoming existing assumptions, reducing a sense of uncertainty to foster faster and more effective decision making (Bootz, 2010; Ringland, 2010). However, the usability of foresight in practice is tainted by the lack of common language, which is made more pronounced as differing typologies are suggested. In this context, Voros (2003) outlines a Generic Foresight Process (see Fig. 4), which has become a frequently cited framework that contributes to clarifying how foresight can fit into strategic processes. The framework positions the *core* of foresight between the processes of gathering inputs and generating outputs for strategy, embodying three elements: *analysis*, *interpretation*, and *prospection* (Voros, 2003). The framework goes from collecting raw data to sorting the insights through analysis techniques in order to understand 'what seems to be happening' (Voros, 2003:14). A deeper interpretation of the insights follows to examine what lies underneath the patterns detected — 'what's really happening' (Voros, 2003:14). Through methods such as scenario building, prospection pursues to understand 'what might happen' (Voros, 2003:14). This leads to certain outputs, i.e., information on 'what we might need to do', which can inform strategy in the sense of 'what will we do' and 'how will we do it' (Voros, 2003:14). The preferred future can then be decided (developed) and enacted (planned).

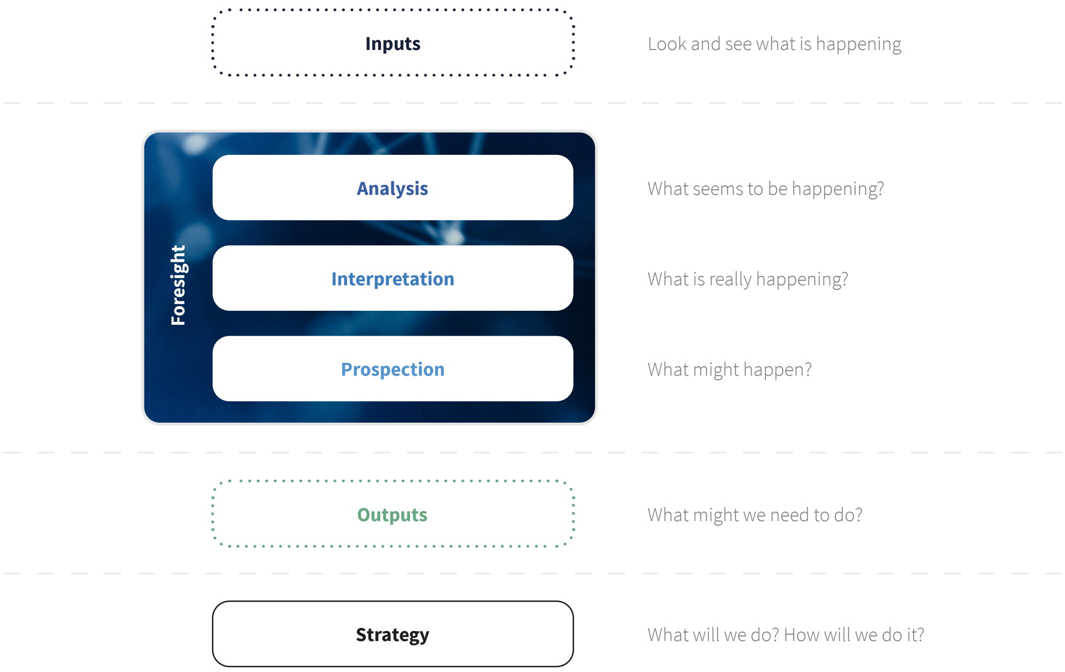

Fig. 4: Generic Foresight Process
(adapted from Voros, 2003)

Nevertheless, bearing in mind the need for dynamic oscillation in strategic processes, Voros (2003) emphasises that while the process may seem linear, it needs to function with continuous feedback loops, and different methods need to be considered in each part of the process, which will affect its outcomes.

Besides the lack of common vocabulary facilitating wider use, practising strategic foresight comes with other limitations. Since long-term thinking tends to be uncertainty-amplifying, decision-makers are often biased towards being reactive rather than proactive (European Commission, 2017). Corporate strategic foresight is thus often associated with a lack of trust and support (Rohrbeck & Gordon, 2018; Hammoud & Nash, 2014). As argued by Voros (2003), foresight as a discipline is still rather nascent and necessitates further research to stay relevant and become more widely used. In this respect, executives are beginning to acknowledge the usability of foresight as data-driven approaches are penetrating organisations' strategic processes (Schühly, Becker & Klein, 2020).

2.3 Strategic Foresight and Data Science & AI

In recent years, research on the two previously discussed fields of BD & AI and strategic thinking (and more specifically foresight) has led to a nascent field combining the two — i.e., utilising elements of AI to support foresight practices. One of the latest and perhaps most graspable publications is Schühly, Becker & Klein's (2020) book "Real-Time Strategy: When Strategic Foresight Meets Artificial Intelligence". Their account of how AI can help decision-makers map, monitor, and navigate complexity and uncertainty in our information age, what they call "real-time strategy", paves the way for practitioners interested in exploring this emerging relationship between the two disciplines. Schühly, Becker & Klein (2020:1–2) describe a 'tectonic shift building up at this moment' as decision-makers find themselves amidst globalisation and hyper-connectivity, 'hit[ting] the limit of what they are capable of factoring in[to]' their strategic decision-making. As we '[drown] in a tsunami of facts, figures, fake news, and individual opinions', they answer the question of how one could possibly expect decision-makers to manage such complexity with the *marriage* of strategic foresight and BD & AI (Schühly, Becker & Klein, 2020:2).

2.3.1 Emerging Convergences

Literature discussing the convergences of foresight and AI puts forth various potential benefits arising from this marriage of approaches to dealing with complexity in the context of strategy. Among others, instant pattern identification, reduction in necessary resources (especially time), systematic scanning and monitoring of insights (along with a higher number of data sources scanned and transformed into insights), and the possibility to reimagine business processes (in order to create new value streams) constitute commonly referred advantages. Chowdhury (2019) emphasises that a successful combination of foresight and AI can enable organisations to handle much more complex data more quickly and lower costs while offering a scalable way of preparing for different futures.

Furthermore, entrepreneurial efforts attempting to leverage the intersection of foresight and AI are also emerging. IBM's research department is using deep learning to support foresight scenarios (Sohrabi, 2018) and researching what they call "AI Machine Foresight" (Quitzau, 2019). An AI-powered foresight company, Shaping Tomorrow, speaks of the multifaceted benefits they have identified with AI content scanning, which can produce insights for foresight activities in seconds (Kehl, Jackson & Fergnani, 2020; Shaping Tomorrow, 2021). Futures Platform (2021) describes how an AI-powered dynamic content tool is improving foresight radars. Boysen (2020:246) underlines the potential of BD & AI in foresight by stating that AI can enable us to identify patterns in data that 'we would not be able to find using human approaches alone'. Schühly, Becker & Klein (2020) discuss how AI can be "plugged into" the foresight process, i.e., during research, modelling, and monitoring. Others are starting to create practical frameworks of incorporating AI into strategic workflows to aid decision making (Trujillo-Cabezas, 2020; Trunk, Birkel & Hartmann, 2020; Colson, 2019).

Whether we read from the pens of advocates or opponents of this marriage, the field of strategy is *evolving* with AI. As van Belkom (2019:6) remarks that over '150,000 scientific papers have been published on artificial neural networks alone', which 'AI [could analyse] much faster than futurists', there is also another type of research emerging, which asks what the influence of such technological developments is on strategic decision-making processes and *organisational life* in general (Trunk, Birkel & Hartmann, 2020; Davenport, 2018; Schühly, Becker, & Klein, 2020).

As Kaczmarek (2017) points out, although it has become fashionable to talk about how AI will disrupt business and the future of work, 'there has been little or no talk about the ways that AI will change the entire practice of management'. As almost anything can be turned into data and measured, the most notable alteration comes with the concept of data-driven decision making (DDDM). As an approach aiming to facilitate better decisions grounded in complex data, DDDM is presented as a more *objective* form of decision-making made possible thanks to BD & AI (Kitchin, 2014; Brynjolfsson & McElheran, 2016; Soller & Tavakoli, 2020). As DDDM gained in popularity, de Langhe & Puntoni (2020) have argued for the term to be modified to *decision*-driven decision-making, maintaining that decision-makers need to start with questions rather than data when incorporating AI into strategic processes. In this context, Hafezi (2020) states that since quantitative data-driven methods can only project near futures, decision-makers need to utilise a combination of quantitive *and* qualitative methods as they strive to recognise signals to improve decision-making and increase organisational flexibility.

Taking a step back from the various shifts in how strategic decision-making is approached and conducted with BD & AI, Trunk, Birkel & Hartmann's (2020:906) research suggests that not only are AI applications in strategic processes influenced by an organisation's resource allocation and structures, 'this impact is reciprocal'. Their study argues that AI applications are influencing 'the definition of organisational structures', calling into question the understanding of AI as mere '*tools*' used in strategic processes (Trunk, Birkel & Hartmann, 2020:906–909, emphasis added).

2.3.2 Dynamic Complementation

The idea that AI is becoming increasingly embedded within organisations and bringing about changes in workflows, skills, and approaches is also tackled by extant literature from the angle of "human + machine collaboration" processes. Daugherty & Wilson (2018:178ff.) argue that AI incorporation is 're-humanising time' whereby we can engage in more creative, interpersonal activities and the reimagination of business processes thanks to the delegation of time-consuming, repetitive tasks to machines.

The notion of humans becoming more *empowered* through technology permeates most literature on the joint involvement of humans and AI in organisations (Fountaine, McCarthy, Saleh, 2019; Dewalt, 2018; Burgess, 2018). They mostly highlight that humans will be able to focus on contributing to strategic processes with their expertise and intuition because when 'AI takes over prediction' (Agrawal, Gans & Goldfarb, 2018:106), human judgment will be increasingly more necessary to make sense of AI outputs, contextualise insights, and provide value judgments. Some authors also argue that AI in organisational processes implies 'a *role change* for human decision makers' — we become 'supervisors', which will lead to new managerial implications (Trunk, Birkel & Hartmann, 2020:903, emphasis added; Kaczmarek, 2017). This notion of a new form of collaboration with machines is also discussed through an ethical focus on how AI needs to be accompanied by humans. The concept of "Human in the Loop" (HITL) focuses on these processes where humans are "plugged into the pipeline" to improve AI trustworthiness through human evaluation and intervention, in striving for a more *human-centred* approach to AI (Grønsund & Aanestad, 2020; Daugherty & Wilson, 2018).

As 'the lines between human decision making and machine intelligence are blurring' (Schühly, Becker & Klein, 2020:165), ethical questions bound to AI and futures thinking are gaining prominence. There are voices calling for a consideration of 'an oath of ethics' in a data-driven world (Brown, 2021). Some have asked how foresight will address the ethical dilemmas surfacing with solely algorithm-driven decisions (Díaz-Domínguez, 2020), while others have argued that we need a ‘technology-based answer’ to a ‘technology-induced problem’ (Schühly, Becker & Klein, 2020:2).

Looking back at the complex buzzword nature of both BD & AI and strategic thinking, making sense of the frontier between human-based strategic thinking and AI applications bears an impact on the implications of this marriage not only in the context of strategic management but also in wider social spheres.

3 Theoretical Framework

This chapter functions as a conceptual roadmap. We discuss several theoretical points of departure related to our research problem. To begin with, we understand today's world to be a complex system. In this context, we consider two approaches to better navigating and strategic decision-making in complex systems. Firstly, we discuss strategic foresight and its coupling with design thinking. Secondly, we explore dataism/instrumentarianism as emerging narratives surrounding BD & AI applications, underpinned by socio-technical dynamics. Finally, in the last section, we discuss the combination of these theoretical points of departure, which serves as a conceptual lens through which our data is analysed.

3.1 Thinking in Systems

In this section, we first provide a description of complex systems and why we take for granted that today's world constitutes such a complex system. Additionally, in the second part of this section, we introduce an approach to navigating these systems: *design thinking foresight*.

3.1.1 Complex Systems

Whether we are looking at transportation, supply chain management, financial markets, the media landscape, or geopolitics, the number of nodes and the degree of connectivity have substantially increased in the past years. A more discernible level of complexity can be felt in virtually all dimensions of life.

In taking this perception for granted, a *complex system* can be characterised as a special kind of a system. A system is simply a set of parts (also called elements) connected to each other (i.e., there are relations between the elements), which starts simple and subsequently undergoes a process of evolution to become more complex (Systems Innovation, 2021; Colchester, 2016a; Colchester, 2016b; Ladyman, Lambert & Wiesner, 2010). This evolution towards complexity involves two processes — differentiation (i.e., a system comes to involve more elements) and integration (i.e., the elements become more interconnected and interdependent) (Colchester, 2016b; Systems Innovation, 2021). Consequently, summarising the main characteristics of a complex system then is to view it as a product of four features: *numerosity*, *non-linearity*, *connectivity*, and *autonomy and adaptation* of elements (Colchester, 2016b; Systems Innovation, 2021). This means that complex systems are systems with large numbers of interacting elements, whereby these interactions are non-linear (i.e., minor shifts can produce major consequences) (Colchester, 2016b; Systems Innovation, 2021). Complex systems are thus dynamic, and relations between elements form a connected whole rather than functioning as a mere sum of all its elements (Colchester, 2016b; Systems Innovation, 2021). However, elements have a degree of autonomy through their capacity to adapt to their environments according to own sets of instructions and behaviours (Colchester, 2016b; Systems Innovation, 2021). Consequently, a complex system may display evolutionary dynamics (Colchester, 2016b; Systems Innovation, 2021). In other words, elements of a complex system, as well as the complex system as a whole, can adapt. Taken together, mutual synergies and feedback loop dynamics are central to complex systems (Colchester, 2016b; Systems Innovation, 2021). As such, thinking about or in (complex) systems — systems thinking — is bound to understanding elements of a system as intimately interconnected and explicable only by reference to the system as a whole (Colchester, 2016b; Systems Innovation, 2021).

Correspondingly, systems thinking has implications in the context of decision making, whether we are utilising foresight methods, BD & AI applications, or relying on something completely different in order to better navigate complexity. Decision making in complex systems is constantly influenced by as well as influencing the above four features of complex systems.

Yet, there are also three interrelated properties of complexity at play. First, considering that the *speed* of element behaviours may occur at unequal rates, the level of decision making complexity can increase as element (and system) behaviours occur at unexpected speeds and durations; thus, making it difficult to obtain knowledge useful for decision making (Systems Innovation, 2021; Mack et al., 2016; Tiefenbacher, 2019). Second, even if we manage to obtain useful knowledge, the presence of *multiple possible interpretations* of element behaviours contributes to the level of complexity (Systems Innovation, 2021; Mack et al., 2016; Tiefenbacher, 2019), especially when causal relationships are unclear and we are faced with "unknown unknowns" (i.e., not knowing what we do not know). And third, because adaptation and autonomy of elements are at play (Systems Innovation, 2021), it is difficult to see patterns in element behaviours that will be constantly repeated without *qualitative change*, thereby contributing to the challenge of prescribing future actions that would lead to desired futures.

To sum up, complex systems are marked by numerous, non-linear, interconnected, interdependent, and adaptive elements. Complexity increases with varying speeds of element behaviours, the possibility of interpreting these behaviours in different ways, and changes in a complex system that are qualitatively different to what has been known and experienced before[7]. Hence, when we talk about various approaches to decision making in order to better navigate complexity and design for preferred futures, it is necessary to acknowledge that any foresight or BD & AI applications involved in decision making will take place in a complex system. We need to adopt a systems thinking lens — we need to think in complex systems.

3.1.2 Design Thinking Foresight

Strategic thinking does not occur in a vacuum when we talk about complex systems. Strategic thinking is bound to our awareness, understanding, and making sense of the things we perceive from the world around us. Without this awareness

[7] Some approaches discuss the term "VUCA", which represents the concepts of volatility, uncertainty, complexity, and ambiguity. In our theoretical approach and in line with systems thinking theorists (Mack et al., 2016; Tiefenbacher, 2019; Colchester, 2016b), we consider complexity as the main feature of complex systems and see the other three terms as features that are part of complexity and complex systems.

(foresight), strategy can easily become blind to contextual change. Simultaneously, if foresight is not strategic, it can easily become speculation and disconnected from purpose (Copenhagen Institute for Future Studies, 2021).

However, thinking in complex systems predicates that foresight is inextricably linked to the multitudes of ways in which we see the world as it invites us to (re)imagine alternative scenarios and developments (Schühly, Becker & Klein, 2020). It opens up to reflexive scrutiny of our way(s) of 'looking at the world and the way that others look at the world' (Systems Innovation, 2021:6). Correspondingly, what stands 'at the heart of systems thinking is a recognition of our *subjectivity*' (Systems Innovation, 2021:6, emphasis added). Our worldview shapes what we do, how we approach decisions, how we balance decisions, and in reciprocity then, how we *create* the world around us (Systems Innovation, 2021). In this context, foresight can be seen as a way of capturing connections and fragments of these mutually constituting and constitutive processes in order to delineate and enable the unfolding of our preferred future. In other words, through strategic foresight, we focus on working with the (eco)system connections around us to bring *our* strategic vision to life.

In acknowledging the need for (re)imagination and connecting with the world around us, there is an overlap between strategic thinking (as foresight) and *design thinking*. The 'key nexus point' is the design thinking idea that all that is designed and brought to life will, axiomatically, exist and be used by people *in the future* (Gordon, Rohrbeck & Schwarz, 2019; Evans, 2014; Selin et al., 2015). Similarly to foresight, design thinking focuses on a 'non-predictive understanding of plausible future states', where 'the primary focus remains capturing a deep understanding of users [(ecosystems)] in the present time' (Gordon, Rohrbeck & Schwarz, 2019). '[N]eeds-finding', 'deep listening', or 'undertaking a learning journey to tune into users' behaviours, preferences, and needs' form the starting points for future envisioning and designing (Gordon, Rohrbeck & Schwarz, 2019). As such, the contrast between linear thinking and systems thinking becomes noticeable. That is, the difference between using a tool that is available to tackle a problem and mapping a system, finding possible leverage points, and working with others to guide problem-solving (Systems Innovation, 2021). Put differently, the difference between 'doing the wrong thing right' and 'doing the right thing right' (Systems Innovation, 2021).

Summing up, we find that both the design thinking and strategic thinking functionings in complex systems 'take stock of future uncertainty' (Gordon, Rohrbeck & Schwarz, 2019) by embracing ecosystem needs in order to develop better designs, better strategies — to make decisions that will be more attuned to future developments. However, coming back to the intrinsic subjectivity embedded in envisioning and designing for strategic futures, the question remains as to which subjectivities become part of these designing discussions. Which worldview becomes foreground based on what needs? Or, in other words — *whose* (re)imagination matters.

3.2 Imperatives of Ubiquitous Technology

In the following section, we discuss socio-technical dynamics as well as aspects of instrumentarianism and dataism. Generally, socio-technical dynamics refer to the social functionings of technology. In other words, we focus on the *relationship* between humans and machines. Instrumentarianism and dataism can be seen as a specific manifestation of such socio-technical dynamics in the context of BD & AI. We begin with a general theoretical discussion on the nature of socio-technical dynamics and then move to more specific cases of instrumentarianism and dataism.

3.2.1 Socio-Technical Dynamics

Today's thick surround of digital instrumentation is not only visible in the emergence of new devices and their increased usage, but it has also led to (a return to) socio-technical conceptualisations of the dynamics between humans and technology. In recognising that technology increasingly touches upon almost all aspects of human existence, Jonas (1979) asserts that the socio-technical field of thought ruptures any sole foci on the instrumentality of technology. It does so through its philosophical undertones, which focalise the notion of technology as a 'generative force' with the capacity to reconfigure relations, identities, modes of knowing and being (Ruppert, Isin, Bigo, 2017:2). In bringing 'social thickness and complexity' into the realm of technology (Jasanoff, 2014:3), socio-technical theories advance the idea of *socio-technical imaginaries* — 'collectively imagined forms of social life and social order reflected in the design and fulfilment of technological projects' (Jasanoff & Kim 2009:120). Through this notion of socio-technical imaginaries, we are encouraged to think about the ways in which technological visions enter social life, and with that 'visions not only of what is attainable through technology, but also of how life ought, or ought not, to be lived' (Jasanoff, 2014:6). As such, the idea that technology is something neutral and merely a means to an end is contested (Jonas, 1979; Heidegger, 1977; Bernstein, 1991). Instead, the substantive nature of technology becomes foregrounded — the 'power it confers, the novel objectives it opens up or dictates, and the altered manner of human action by which these objectives are realised' (Jonas, 1979:12). In the context of BD & AI, these technologies can be understood as active agents that shape how we know and experience the world (Kafer, 2019). Correspondingly, it becomes insightful to consider the ways in which BD & AI not only enable certain problems to be solved but also how they become *definers* of problems.

As an analytical concept, socio-technical imaginaries also sensitise us to the ways in which 'human subjectivity and agency get bound up with' technological development, manifested in altered identities, institutions, discourses, and thus 'deeper normative notions and images' underl[ying] expectations[8] (Taylor, in Jasanoff, 2014:10). In this sense, by understanding how data-driven applications are bound up with various normative logics, such as prediction for certainty and efficiency[9], we can examine how BD & AI can *enact* certain modus operandi as its underlying objectives interact with society. A practical example is the extraction of advertising data on consumers wherein data collection and storage

8 Jasanoff (2014:35) argues that studying socio-technical imaginaries is 'best suited' in conjunction with 'methods of interpretive research and analysis' probing 'inquiries into meaning-making', which is in line with our research design.

9 In his Postscript on the Societies of Control, Deleuze (1992:6) advances the idea that certain types of machines 'express social forms capable of generating them and using them'. In this context, the logic of efficiency can be linked to imperatives of capitalism. Shoshana Zuboff (2019:8) takes this connection further in the context of contemporary BD & AI practices by discussing a new economic logic — surveillance capitalism — 'in which the production of goods and services is subordinated to a new global architecture of behavioural modification' that is enabled through today's architecture of computer mediation.

seems *natural* given that it is suddenly *there* for transformation into value, and thus the normality of collecting, calculating, and storing is established.

BD & AI's capacity to beget the problems, which it is called upon to solve (Jonas, 1979:14), unfolds its defining *knowledge-power implications*. One such implication lies in how the offer of BD & AI's *presence* and feasibility of new knowledge, through interactions with society, is turned into a *necessity* generative of new social dynamics. For instance, BD & AI in retail has enabled the monetisation of human behaviour and experience (Zuboff, 2019). In the field of peacebuilding, more sensor-based remote data collection and analysis methods are being employed for preventive peacebuilding, marking a shift from traditionally more reactive approaches (Burns, 2014; UN Global Pulse, 2020). As such, BD & AI can be viewed as what Haraway (1989:55) terms 'meaning machines'. Following the shifts in the above examples, BD & AI are increasingly co-present in the attachment of certain meanings to social relations. Borrowing from discourse theory (Jorgensen & Phillips, 2002; Chouliaraki & Fairclough, 1999), various meaning-forming forces commonly interplay with each other, attempting to attach or exclude certain meanings. Consequently, multiple imaginaries can coexist in tension or a dialectical relationship[10] (Jasanoff, 2014), whereby changes in the traditional order of dominant discourses can lead to social change. Ultimately, seeing BD & AI only through its *Object* (tool) nature cannot suffice if we are to understand contemporary socio-technical dynamics. We need to consider the additional lens of *Objectives*[11] emerging in a reciprocal *process*, shaping human capacities, ways of knowing, and thus experiencing the world.

3.2.2 Dataism and Instrumentarianism

Building upon the capacity of technology to shape realms of problems and consequently to shape how we think about problems(-olving), we can examine

[10] It is worth noting that discourses, which have become so firmly established through tensions and historical struggles over meaning are generally regarded as "objective" (Jorgensen and Phillips, 2002:36–38). Objectivity essentially denotes that traces of power have become so effaced that the contingency of knowledge, and by extension, the social world, has been forgotten (Jorgensen and Phillips, 2002:36).

[11] In order to differentiate the terms "Object" and "Objective" in this socio-technical sense from the words "object" and "objective", which we also use in relation to our research methodology, we capitalise the socio-technical terms (i.e., aiming for a noticeable difference between "O" and "o").

one such form of problem-defining influences in contemporary BD & AI practice. With most parts of our lives being rendered into data formats (through search queries, smart devices, sensors), processes of datafication have spurred a strand of new socio-technical Objectives — *instrumentarianism*. The logic of instrumentarianism refers to 'the instrumentation and instrumentalisation of behaviour for the purposes of modification, prediction, monetisation, and control' (Zuboff, 2019:352). It is, therefore, about the combination of processes and equipment necessary for BD & AI to collect and analyse human behaviour through sensors (instrumentation) and the social relations orienting the user of predictive analytics to the collection and analysis of human behaviour in a mutually necessitating logic (instrumentalisation).

The mutual necessity is founded upon two interlinked imperatives. First, *extraction* whereby increasingly more data is to be continuously collected (Zuboff, 2019:87), and second, *prediction*, which steers into the direction of increasingly more sources for extraction being identified for more accurate predictions of human behaviour (Zuboff, 2019:200–201). Correspondingly, continuous digital developments (particularly algorithmic advancements and exponential increases in computing power (McKinsey & Company, 2020)) are necessitated in order to be able to make sense of new data sources in more accurate and faster ways. The socio-technical dynamics fuelled by the instrumentarian logic are made apparent in a two-fold Object-Objective manner. On the one hand, as these technologies become cheaper and more accessible and, on the other, as discourses such as "uncertainty constraints strategy", "prediction lies at the heart of decision-making under uncertainty", and "prediction tools increase productivity" (Agrawal, Gans & Goldfarb, 2018) become widely articulated — further driving the need for better computing and thus the ability of prediction and behavioural modification.

Under closer scrutiny then, what underlies this socio-technical functioning of BD & AI is a specific *epistemological* lens. With near real-time and explosive data availability stimulating extraction, prediction, and consequently (modification) actions upon those insights, zooming in on large datasets and leveraging the predictive power of data-/AI-driven analytics (to make sense of those volumes of data) is made possible in previously unimaginably data-rich and measurable ways. A new knowledge production methodology is enabled — *dataism*. Dataism offers a convenient benefit: rather than having to develop theories to be tested and explored, this 'new data analytics seeks to gain insights that simply emerge from the data itself, without apparent interpretation being imposed upon it' (Systems Innovation, 2018). Chris Anderson (2008) called this shift towards new ways of knowledge production 'the end of theory'. He argued that: 'we can throw the numbers into the biggest computing clusters the world has ever seen and let statistical algorithms find patterns where science cannot [...] Correlation supersedes causation, and science can advance even *without* coherent models, unified theories, or really any mechanistic explanation at all [...] Who knows why people do what they do? The point is they do it, and we can track and measure it with *unprecedented* fidelity.' (Anderson, 2008, emphases added).

In presupposing data as facts, untainted by theoretical biases, neatly packaged into high-resolution datasets, the Objective becomes to predict rather than understand human behaviour and the world's complexity. 'Prediction trumps explanation' (Hood, 2015). In highlighting the key benefit of being able to reveal patterns 'we didn't even know to look for' (Dyche, 2012), dataism comes to influence not only the basis of decisions, but it consequently influences the very notion of what *can be*, and *cannot be*, considered a solid foundation for making decisions. Hence, in understanding BD & AI technology through the socio-technical lens as a reciprocal process rather than a static linear possession (tool), dataism represents the foundation of the Object-Objective interplay. It explains how BD & AI can shape our very way of thinking and perceiving the world, and thereby the ways in which we (re)imagine futures. In essence, dataism illuminates BD & AI's potential to dictate novel Objectives.

Summing up, BD & AI entail a generative potential to *shape* social relations through the objectives they enact and the socio-technical imaginaries they construct and are constructed as. Acknowledging that ascriptions of meaning always occur at the expense of other excluded meanings, we can explore the types of discourses around BD & AI, which are becoming accepted as true, thereby shedding light on 'regimes of truth' and, by extension, power relations associated with BD & AI in the social sphere of not only decision making (Foucault, in Gordon, 1980:131–133). However, it is relevant to adopt the understanding of power not merely in the traditional sense as something with negative, constraining effects, but rather power as something that 'provides conditions of possibilities for the social' (Jorgensen and Phillips, 2002:13–14) — forming certain knowledge(s), identities, and modes of social relations. With this accentuation of fields of power and knowledge and the conditions of their possibility (Ruppert, Isin, Bigo, 2019), the various aspects of socio-technical imaginaries offer a more befitting lens for viewing human interactions with BD & AI in the contemporary landscape of cognitive technologies.

3.3 Connecting the Concepts

At this point, we return to our discussion on how the various features of complex systems — most of all the speed, multiple possible interpretations of element behaviours, and their possible evolvement in qualitatively different ways compared to the past — pose a struggle to navigating our world today, and even more so if we wish to do it strategically.

We have looked at two approaches to better navigating complexity and making sense of uncertain future developments. *(Design thinking) foresight* suggests that strategists who engage in a deeper, contextualised understanding of a complex system's needs, and ways of functioning, will be better positioned to anticipate plausible futures and strategically leverage this knowledge to achieve their goals. Conversely, *dataism and instrumentarianism* offer the promise of fast data analysis, understood to be untainted by subjectivities, which can render a complex system and its most probable developments legible in high-resolution in no time.

Whether we are convinced by either approach aiding us in making better strategic decisions, there are two major obstacles along either of the paths. Schühly, Becker & Klein (2020) describe them as strategists' 'true enemies' — *complexity* and *adaptiveness*. First, in order to better understand why complexity problematises both approaches, distinguishing between "complicated" and "complex" is useful. To do so, Schühly, Becker & Klein (2020:127ff.) suggest imagining that we are deep in the middle of a jungle, trying to get to a bridge to escape. A *complicated* problem is usually difficult as it requires substantial effort, but it is 'solvable' (Schühly, Becker & Klein, 2020:127). In a jungle, we can interpret our map, pinpoint alternative routes, assess our equipment, and calculate the shortest and most convenient route. Once we have all variables, relations, and enough information, we can solve it like a mathematical formula and obtain results (Schühly, Becker & Klein, 2020:129). In this sense, either of our discussed approaches offers a way to arriving at a potential solution. However, upon a closer look at the jungle map, 'we realise that there is more' (Schühly, Becker & Klein, 2020:130). The conditions of each route depend on the number of predators, which depend on the water levels, which depend on weather conditions; whether the bridge is open depends on water levels and local villagers, and so on (Schühly, Becker & Klein, 2020:130). 'The magic word here is "it depends"' (Schühly, Becker & Klein, 2020:131). To solve a *complex* problem, we need to consider a vast amount of variants with large numbers of alternatives, which increase exponentially with each piece of information (Schühly, Becker & Klein, 2020:131). Herein, the dataistic promise may be more appealing to those who would prefer *decontextualised* but faster probability analytics as opposed to relying on more time-consuming foresight methods.

Nevertheless, this becomes problematic with the second "enemy" — adaptiveness. In a jungle, we may figure out patterns in predator behaviour and opt for a certain route (Schühly, Becker & Klein, 2020:134). However, as a slight change occurs on the way and elements of the complex system (jungle) adapt to new conditions, this adaptation creates a 'completely *new* system behaviour' — rendering the previous strategy (potentially) 'obsolete' (Schühly, Becker & Klein, 2020:134). This adaptation essentially means that extracting data, assigning probabilities, and drawing insights becomes misleading and inapplicable under *qualitative* change. As such, relying on (big) data *alone* creates an illusion of a "god's eye view" with "predictive power", which falls short to a description of the future as somewhat of a "potential past".

As such, because decision making in complex systems constitutes a challenge that cannot be approached solely through one of the approaches described above, we choose to use both the instrumentarian/dataistic logic (including associated socio-technical dynamics) as well as the design thinking foresight perspective, in order to understand how tech strategists make sense of the dynamics of strategic thinking and BD & AI in strategic decision-making. Specifically, we will use the instrumentarian/dataistic logic and design thinking foresight perspectives as a *conceptual lens* in our analysis, which allows us to interpret the generated data in order to arrive at an answer to our research question. By drawing on multiple theoretical points of departure and using them in tandem, we avoid what Walters (2013:2) refers to as 'self-contained packages'. In other words, we keep our minds open to new discoveries and refrain from pouring our participants' views into fixed and labelled containers.

4 Methodology

This chapter describes our methodological approach. The first section explains the research design employed as the guiding methodology in examining the research question and the associated nature of our study's intellectual puzzle. We have chosen a *qualitative exploratory research design* as it enables us to grasp and explore the participants' subjective voices and constructions of meaning of the researched dynamics of strategic thinking and BD & AI applications (Creswell, 2009:8). The second section discusses our method of data generation and the study's participants and material. In the third section, we outline the methodological guidelines and practical application of our conventional qualitative content analysis (C-QCA) and reflect on the choice of C-QCA as our method of analysis. In general, the aim of C-QCA is to make sense of data by drawing socially constructed connections and patterns in order to contribute to a greater understanding of a studied phenomenon. In our analysis of data, we applied the conceptual lens discussed in the previous chapter. In concluding this chapter, we discuss our study's ethical considerations.

4.1 Research Design

This study follows a *qualitative* research design. We systematically employ semi-structured expert interviews and C-QCA to understand tech strategists' sensemaking of the dynamics of human strategic thinking and BD & AI applications in the context of strategic decision-making. The epistemological basis of this study is shaped by our *constructivist* understanding of knowledge production. In other words, we understand our research inquiry as a systematic process that focuses on human subjectivity to explore various meanings ‘constructed by human beings as they engage with the world they are interpreting’ (Creswell, 2009:8). Thus, we view our research in traditionally qualitative terms insofar as we presuppose our participants as active agents of socio-technical processes. Hence, they are not ‘passive recipients’ of social dynamics, but meanings emerge from interpretations, which, in turn, influence actions (Povrzanović-Frykman, 2020). Consequently, the purpose of our qualitative research is to understand (interpret) our participants’ sensemaking (Kirkegaard, 2020a). Intrinsically then, as qualitative researchers, we constitute the ‘key instrument’ of data generation and analysis (Creswell, 2009:175).

Our qualitative research *puzzle* represents a mix of processual and experiential facets as we are interested in exploring the ‘*dynamics*, nuances, ebbs and flows’, as well as life *experiences* and encounters concerning the phenomenon in question (Mason, 2018:12, emphasis added). Our research puzzle and design represent a form of *‘interpretive’* inquiry, wherein we construct interpretations of participants’ ‘patterns of meaning’ (Creswell, 2009:176; Kirkegaard, 2020a). Participants’ meanings are often ‘negotiated socially’, similar to how our interpretations as researchers ‘cannot be separated’ from our own backgrounds and prior understandings (Creswell, 2009:8/176). Finally, in developing an interpretive understanding, our qualitative research design is rendered an ‘*emergent* design’ in the sense that initial research plans have not been ‘tightly prescribed’ and all phases of the process were bound to iterative adjustments (Creswell, 2009:175f.). These iterations occurred as we developed an analytical sense of our participants’ sensemaking towards strategically designing our methodological logic. Strategically in the sense that we can conduct an investigation of our puzzle in a way that leads to answering our research question (Mason, 2018). We discuss any research process adjustments throughout this chapter.

4.2 Data Generation

In adhering to our constructivist epistemology, we refer to the interview method as a data *generating* rather than a data *collecting* process, since generating 'does not conjure a view of researchers as neutral collectors of information' (Mason, 2018:21) that is simply "out there" in the world, detached from the researchers, ready to be extracted. As such, the interview method allows us to generate *material*, which represents the participants' answers documented as transcripts. Thereupon, we generate *data*, which denotes interpretations of the material, where through interactions with our participants as well as analysis of their sensemaking, we construct our research object. In other words, as everything in the social world has the potential to be data but *becomes* data through a method being employed (Kirkegaard, 2020a), our choice of methods of data generation and analysis shapes the knowledge we produce about our object of study. Correspondingly, we also discuss our material in this section and the study's participants regarding their selection and presentation.

4.2.1 Semi-Structured Expert Interviews

We conducted semi-structured in-depth expert interviews with tech strategists to understand their sensemaking of the dynamics of strategic thinking and BD & AI applications. Expert interviews are conducted with persons with specific knowledge resulting from their particular professional experience pertaining to a research subject matter (Gläser & Laudel, 2010:12). In our case, the interviewed tech strategists were identified as practitioners with professional experience in both strategic decision-making and BD & AI applications. As such, our participants became mediums for insight rather than being the object under study themselves (Gläser & Laudel, 2010:12). We focused on inquiring about their professional experience as strategic thinkers and decision-makers and BD & AI practitioners while also allowing space for them to share their more personal reflections as private persons to generate richer material (Kirkegaard, 2020b).

The interviews were semi-structured, following a list of topics through an *interview guide*. The interview guide was designed based on our research question and the subsequent operational questions, i.e., following the three overarching themes of strategic thinking, BD & AI, and their dynamics. At the onset of the interviewing process, we conducted three pilot interviews (included in the study) based on a preliminary list of flexible questions[12]. We revised the pilot interview guide upon testing these pilot questions for their suitability to answer our research question. A modified version of the questions guided subsequent interviews[13]. During the interviews, we posed open-ended questions, leaving room to follow new leads depending on the participants' directions of answers (Bernard, 2006:212). Following Povrzanović-Frykman's (2020) advice, we started by asking about general impressions and more descriptive questions, encouraged answers about concrete events, asked for clarifications, engaged in active listening by not constraining the participants' answer time[14], and made sure not to judge answers (non)verbally. As we gained experience in our role as interviewers, we were able to follow up more spontaneously, which often led to detours that would enrich the interview material (Bernard, 2006:212). Lastly, all interviews have been video-recorded with the participants' consent[15] and later transcribed for purposes of the analytical process.

We chose the semi-structured expert interview method since, unlike surveys that offer predetermined responses, the participants could answer 'on their own terms', thereby allowing for unscripted developments of themes (Chambliss & Schutt, 2019:264). This is often done when the 'full range of responses cannot be

[12] For the Pilot Interview Guide, see Appendix I.

[13] For the revised Interview Guide, see Appendix II.

[14] To the contrary, we would not interrupt silences so as to give the participants time to reflect and add to their answers if they wished so. This, in fact, frequently led to many elaborations on their behalf, which then enabled us to explore new leads, thereby enriching the generated material. Similarly, being open and asking for clarifications became an important part of the interviews. For instance, during one interview, we sensed scepticism in the participant's answer, so we openly asked about it specifically, which led to the participant clarifying what they intended to express.

[15] Informed consent and ethical considerations are discussed later in this chapter. For the Informed Consent Form, see Appendix III.

anticipated' or when researchers probe complex concepts, which was particularly relevant in our exploration of the participants' sensemaking (Chambliss & Schutt, 2019:100). Although interviews provide information in a designated place rather than a natural field setting (Creswell, 2009), they enabled us to explore the participants' accounts of their views and experiences with BD & AI as tech strategists. Due to the current pandemic, we opted for conducting digital interviews via Zoom. The main advantage was that both our participants and we could select our own comfortable interview environments. In contrast, there is commonly no guarantee that the expert will devote their full attention (interviewers cannot control interruptions), and interaction is often reduced to a 'purely linguistic level' (Bogner, Littig & Menz, 2009:10). In our case, no major interruptions or difficulties in understanding occurred, and the participants frequently gestured in their answers, expressing nonverbal cues for us to pick up on. However, what has been very noticeable is the factor of 'adequacy checks' common in telephone/digital interviews (Irvine, Drew & Sainsbury, 2013). The participants frequently resorted to explicit checks on whether they are answering our questions "adequately" or whether their answers are "relevant" to our questions. Considered broadly, this may pose an 'important ethical consideration' in terms of interviewees' 'lasting impression of their "performance" in the interview' (Irvine, Drew & Sainsbury, 2013:102). Keeping this ethical facet in mind, we contend that, although we did not sense any struggles of our participants in the online setting (especially since they mentioned the commonness of virtual communication in their work), such adequacy checking became central to our reflexive process, which we return to later in this chapter.

4.2.2 Selecting Our Participants

The aim was to find participants who have professional experience in the fields of both strategy and BD & AI in order to explore their sensemaking of the researched dynamics. More specifically, we searched for participants involved creating and undertaking strategies and strategic decision-making who would also possess knowledge and experience in working with BD & AI in organisations.

Therefore, we employed strategic *purposive* sampling, which constitutes a type of non-probability sampling suited for qualitative research, where researchers are obtaining deeper knowledge about a phenomenon rather than drawing statistical inferences (Chambliss & Schutt, 2019:133f.). As such, the participant sample was based on our judgment considering the sample that would be most useful for the purposes of our research (Mason, 2018:57ff.). In practice, this meant that we searched through profiles of people on LinkedIn[16], filtering our search with keywords such as “AI”, “Big Data”, and “AI strategy”. Following such an initial filtered search, we would carefully read through profile information to determine whether the person’s role and experience are aligned with the sampling criteria of at least three years[17] (approximately) of experience in contexts of both strategic decision-making and BD & AI applications. We contacted the majority of our participants directly. Four participants have been referred to us through (three) gatekeepers, i.e., persons in a field setting who are able to grant access to the setting for the researchers (Chambliss & Schutt, 2019:244). In terms of the selection, we “took every relevant participant we could get”. This was mostly influenced by LinkedIn search function possibilities and public access to profiles. And although we did not select anyone based on age, gender, nationality, or affiliation to any specific sector or organisation, the social “nature” of the fields of strategy and BD & AI is mirrored in our final sample. More specifically, given the gender gap among AI professionals (World Economic Forum, 2018), most of our participants are male; and the common university degree requirements for strategic and AI roles is reflected in most of our participants’ educational backgrounds. However, despite strategic roles being traditionally associated with “older” executives, the age reach in our participant

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[16] The LinkedIn platform provided us with easy access to potential participants as well as a way to learn about the gist of their professional roles and experiences.

[17] We opted for approximately 3 years minimum upon consideration of commonly required professional experiences for above-entry-level practitioners (Indeed, 2020).

sample is rather wide, which can be bound to the fusion with AI technology knowledge that is arguably more present among younger age groups.

Generally, our sample is not representative in terms of such selection criteria, but given our study's qualitative nature, this was not the aim. A richer female perspective could have been explored, but the gender distribution of our participants hindered us from pursuing this thread. Nevertheless, we focused on continuously examining the data *saturation* point throughout our research process, i.e., whether our sample provides access to enough material with the appropriate focus to answer our research question in the context of a 'relatively limited group' (Chambliss & Schutt, 2019:134; Mason, 2018). This has been a dynamic process guided by Rubin & Rubin's (1995:72–73) advice that to 'ensure that a purposive sample adequately represents' our studied setting, completeness and saturation should be scrutinised. That is, examining whether what we hear 'provides an overall sense' of studied meanings and whether we are gaining confidence that we are 'learning little that is new from subsequent interviews', respectively (Rubin & Rubin, 1995:72–73). During our 14 interviews, we started sensing completeness and saturation around interview 11, whereby the last three interviews confirmed our sense of saturation as noticeable differences were bound to specificities of contexts and personal nuances in sensemaking.

4.2.3 Meeting Our Participants

The final sample includes 14 participants, whom we call "tech strategists" for the purposes of this study. We define a *tech strategist* as a person with professional experience in strategic decision-making, and thus thinking strategically about organisational processes, as well as professional knowledge and experience with BD & AI applications in organisational contexts. We present our participants here in general terms to safeguard their identities in accordance with participant anonymisation in this study.

Our participants vary in age, national and educational background, and years of experience. The sample includes participants from both private and public sectors, more specifically from fields of financial, management, tech, and telecommunications consulting, finance, food processing, intergovernmental institutions, maritime, and technology. The participants are located primarily in Europe (mostly Sweden) but also South East Asia, East Asia, and North America. Two of our participants are female. The specific roles of our tech strategists vary, but they are generally middle managers or executives. Correspondingly, we minimise the likelihood of overgeneralisation through our aforementioned purposive sampling, whereby all our participants occupy the 'unique position' of a tech strategist (Chambliss & Schutt, 2019:134). Moreover, all participants were knowledgeable on the interview topics, open to sharing their sensemaking, and represented a range of perspectives.

Before conducting the interviews, we messaged with the participants to build a "relationship" and informed them about our study, which facilitated interview arrangements and served to establish a sense of genuine interest and trust. We strived to combat the typically formal nature of interview beginnings by spending a few minutes talking casually and introducing ourselves before proceeding with recording and our questions. All interviews ensued in a friendly manner; we felt that the participants were very open with us (they used colloquial expressions and frequently resorted to jokes). And although most participants are not English-natives, we did not sense any language difficulties disrupting the flow and relaxed nature of the interviews. We wish to acknowledge that every single participant came across as a caring and mature professional genuinely interested in contributing to this research.

4.2.4 Material

The interviews, which we conducted between 13 April and 3 May 2021, constitute our primary source for data. The interviews were all conducted in English, generally lasted between 1–2 hours. This resulted in a total of approximately 20 hours of material, which was transcribed in full verbatim, i.e., "everything said", including grammatical mistakes, repeated and filler words. In the following chapter, where we introduce the data (i.e., our interpretations of the material and material excerpts), such mistakes and repetitions have been corrected in the direct quote excerpts for better readability. In taking the liberty to make such changes, we made sure not to alter any conveyed meanings. Additionally, in accordance with participant anonymisation, all participants are assigned their own letter (A–N). Each letter designation is always accompanied by a number that serves to showcase how many times a given participant has been quoted. We do this to ensure transparency.

4.3 Data Analysis

In this section, we discuss C-QCA and outline its practical application as our method of data analysis while continuously reflecting on the choice of C-QCA for making sense of the generated data. We have used theory as an analytical lens, which has shaped the interview guide themes and the interpretation process of our analysis. Nevertheless, in the process of constructing our categories, we followed Lather's (in Creswell, 2009:65) recommendation that '[d]ata must be allowed to generate propositions in a dialectical manner that permits use of *a priori* theoretical frameworks, but which keeps a particular framework from becoming the container into which the data must be poured'.

4.3.1 Conventional Qualitative Content Analysis

The aim of C-QCA is to enable findings that 'make connections, identify patterns, and contribute to greater understanding' of a studied phenomenon (Glesne & Peshkin, 1992:146). As an interpretive data analysis method, it is generally used to interpret patterns of meanings from communication-centric, textual data whereby researchers 'immerse themselves into the data until patterns emerge' (Hsieh & Shannon, 2005:1279). In contrast to quantitative analysis, C-QCA does not aim to quantify a phenomenon but rather focuses on deriving socially constructed meanings and seeing the material as open to interpretation. In other words, C-QCA departs from the position that ‘simply because a topic occurs fewer times does not mean that it is a lesser topic’ (Williamson, Given & Scifleet, 2018:463). As an interpretive approach, it allows us to examine the topics most meaningful to answering our research question and is thus well suited to our exploratory design. Moreover, as opposed to directed qualitative content analysis, C-QCA avoids an over-emphasis on theory, which can ‘blind researchers to contextual aspects’ of a phenomenon under study (Hsieh & Shannon, 2005:1283). Correspondingly, C-QCA offers us a flexible approach to our exploratory inquiry as it constitutes a ‘highly interactive process’ between us as researchers and the data (Williamson, Given & Scifleet, 2018:454). Nonetheless, it follows that the process is time-consuming and labour intensive. Additionally, unlike grounded theory method, C-QCA does not intend to develop a nuanced understanding of lived experience, although knowledge generated from C-QCA is based on the participants’ unique perspectives and grounded in the data (Hsieh & Shannon, 2005:1281). Yet, concept development in terms of model building is possible (Hsieh & Shannon, 2005). This is the case in our analysis, where we offer a mental model of the process of developing a strategy in complex systems by jointly employing BD & AI and strategic thinking, which is derived from the richness of our material.

4.3.1.1 Method Technique

Our concrete systematic approach to C-QCA primarily rests on *category coding* and *thematic analysis* of the data (Hsieh & Shannon, 2005). Our systematic approach was four-fold. Firstly, based on the three main aspects of our research question, which were reflected in the practical division of our interview guide into three discussion themes (see Appendices I and II), we created several questions for each theme as the basis for the initial coding of the participants’ sensemaking. For the first theme, coding keywords were bound to: understandings of what it means to be strategic and to think strategically, any processes and actions considered strategic and any values and norms attached to being and thinking strategic(ally). For the second theme, coding was bound to: impressions of BD & AI, essence understood, features, capabilities, limitations, effects and influences, and any norms and values attached to BD & AI. Lastly, we coded any sensemaking topics pertaining to direct connections made by the participants between BD & AI technologies and strategic thinking/being, joint necessities, challenges, opportunities, interactions, tradeoffs, and influences of strategic thinking and BD & AI.

Secondly, upon transcribing our interview material, we individually read through a first "batch" of the transcripts, making interpretative notes in the margins, and beginning to develop a list of sensemaking topics brought up by the participants based on our aforementioned initial coding criteria.

Thirdly, we continued with the remaining transcripts with corresponding margin notes, highlighting any new sensemaking topics interpreted while starting to compose groupings of all interpreted sensemaking topics under broader categories. *Categories* represent our interpretations of the sensemaking *topics*[18] at a higher level of meaning abstraction, and the final set of categories is introduced in the next chapter. At this stage in the process, the categories were fluid, more numerous and overlapping than the final set.

Fourthly, all transcripts were revisited using the listed categories, refining the categories as necessary to reflect the interpreted sensemaking topics from all interviews against the final set of categories. At this stage, some similar initial categories were merged into broader, more inclusive categories while being sensitive to context. We did this in order to arrive at a level of abstraction in terms of the categories drawn from the data, which would enable us to meaningfully answer our research question in an exploratory sense. As such, the primary purpose of the categories has been to make sense of their content later in the analysis.

Although we have discerned four stages here, the process of C-QCA functions iteratively, whereby coding cannot be reduced to a mere process of data

[18] For increased transparency, we provide lists of sensemaking topics composed under each category in our integrative data diagram in Appendix IV.

reduction. The whole analysis must be seen as a circular movement between an overall understanding and closer analysis. As such, the data analysis is not a smooth process but necessitates dealing with initial confusion and indecision (Chambliss & Schutt, 2019), which we experienced particularly mid-way through the coding of the transcripts. Correspondingly, it is worth noting that C-QCA entails elements of facet methodology, i.e., 'the idea of casting and refracting light rather than illuminating it' (Mason, 2018:45). This has translated into our analysis in the sense that our interpretations of data are contingent on how we casted light on the various facets of the data (Mason, 2018).

4.4 Ethical Considerations

The participants do not represent a particularly vulnerable group; however, all of them still occupy the same professional position from which they drew most of their experiences. Moreover, given frequent depictions of AI in the media surrounding discrimination and other types of harm, as well as the existence of many spheres of "controversial" opinions about applications of BD & AI, ethical reflections underlie our study.

As such, it is our primary responsibility as researchers, besides sound research, to protect all our participants (Bernard, 2006:26). To live up to this responsibility, we provided the participants with an *informed consent* form[19] and a two-week period for participation withdrawal. Although 'full disclosure of everything that could possibly affect a participant' as a result of their participation in a study is not possible (Baumrind, 1985:165), we included an information letter stating the purpose of our study and all related terms and conditions of participation to the best of our knowledge and ability in the consent form. Additionally, we asked the participants to express their verbal consent after we

[19] This was done at least several days prior to the interview date, already following initial communication threads wherein we introduced the study's purpose and meanings of potential participation. See *Appendix III* for the Informed Consent Form sent to each participant prior to their participation. The Informed Consent Form has also been shared with our supervisor prior to its use.

introduced ourselves and the study again at the beginning of each interview, whereby their response constitutes the very start of each video recording[20].

Furthermore, we ensure *confidentiality* by anonymising all participants, who are referred to as participants A–N. Any identifiers, such as details about their organisation, age, or gender, have been removed so as to not reveal such personally identifying information in this study. Additionally, we wish to highlight that besides ensuring voluntary participation, identity concealment, and honest communication, we placed emphasis on participant well-being (Chambliss & Schutt, 2019:261). We did this by allowing the participants to choose their best suited times for the interview, adapting to the need to reschedule, and by expressing our gratitude for their participation on multiple occasions. In seeing interviewing as a *'moral inquiry'* (Creswell, 2009:90, emphasis added) with the need to critically examine whether we have captured the interviewees' voices, we present a portion of the data through direct quotes, thereby allowing our participants to speak *before us*.

[20] As we conducted our interviews via Zoom, an automatically prompted window also appeared on the participant's screen informing them of the start of the recording and asking for their acceptance by clicking a button.

5 Data

This chapter introduces the data divided into three themes derived from the operationalised research question. The themes are further divided into categories, which represent clusters of recurring sensemaking topics that have emerged during the interviews. The discussions in each category focus on the sensemaking topics that have been identified as most prevalent and relevant to answering our research question, which has been done in an iterative process between us as researchers and the data. Although presented separately for purposes of clarity, the categories are not mutually exclusive but reinforce each other, producing an *assemblage* of our constructions of the participants' sensemaking topics. For each category, we provide a general exposition on the conveyed meanings of the categories, and we supplement this with excerpts from the material.

5.1 Realm of Strategic Thinking

In this section, we present the theme of strategic thinking explored during the interviews. Five categories have been constructed based on the sensemaking topics brought up by the participants. As mentioned previously, our coding is based on their understandings of what it means to be strategic and to think strategically, as perceived and experienced by the participants in the context of their work. Additionally, any processes and actions considered strategic and any values and norms attached to being and thinking strategic(ally) are included. In general, the overarching theme of strategic thinking is broken down into the following categories: *knowing the future to act on it today*, *necessity of adaptiveness*, *looking at ecosystems and contexts*, *reliance on data amidst human limits*, and the *pursuit of people, culture, and change*.

5.1.1 Knowing the Future to Act on It Today

In the first category surrounding strategic thinking, several sensemaking topics come into view. The participants brought up the desired ability to know the future, to position oneself favourably in it, anticipation and modelling of opportunities and risks, the ability to be preventive and proactive in the sense of being actionable on the future rather than past events, as well as inherent challenges pertaining to prioritising for their envisioned futures with limited resources.

Thinking strategically comes to entail a forward-looking, envisioning approach that centres around expectations of *preferred* versions of the future, as Participant B explained:

> ***B** (1):* '[S]trategic thinking is the way to position yourself or position your project in a way that is favourable in the future. Not thinking about here and now, but positioning yourself in the future.'

In echoing this future envisioning approach, participants emphasised the importance of understanding what gap needs to be filled to end up in a favourable position in the future, which allows for steering towards the future today:

> ***F** (1):* 'If you really understand what you're trying to achieve from a business point of view, then you can control what you're going to do.'

Such necessity of knowledge about future places to *strategically* steer actions resonated further:

> ***K** (1):* '[T]his strategical part is, of course, about understanding what we will do before we do it.'

> ***G** (1):* 'Pre-empting any risks that might come up or any issues that might come up. That's strategic thinking.'

However, in discussing the need to envision and know the future before it arrives, the participants emphasised another point referring to the strategic purpose and value attached to such knowledge of the future. In reiterating the need for a vision to work towards, contrasts between the traditional "reactive" nature of strategic thinking, where information about the future comes 'a bit too late' (N), and a different, desired “proactive” approach emerged. Participant N put this new desired approach eloquently:

> ***N** (1):* ‘I think it’s important that you can work proactively. Like when you’re doing food. If you chop up the vegetables and you have the ingredients done before you start cooking, because you know you will use some of the ingredients. You will be a lot more effective in your cooking. But when you just start doing your cooking and you understand, okay, now I need carrots, now I need a banana, now I need to chop up the meat. But then you’re not so effective in your work. […] [I]f you can predict what’s going to happen, you can also start working with the prescriptive part of it.’

What this cooking analogy alludes to is that knowledge about the future is linked to the *ability* to be actionable on it in a prescriptive sense, which is understood to bring further strategic benefits:

> ***N** (2):* ‘[Y]ou can get the analytics part, the reporting to actually design your business strategy. Rather than just supporting it. […] I mean, if you can predict, then you know what actions you should take. […] You allow yourself at least to be flexible. You allow yourself to be able to react on the future. Not to react on the past.’

In agreeing with the utility of such predictive and prescriptive strategic thinking, Participant J also expressed the expectation of having knowledge of the future for control, as well as frustration if such proactive strategic thinking is absent:

> ***J** (1):* ‘Sometimes, we do have the data, or we do receive the data, but we do not capitalise on it. […] There will be employees resigning. There will be machine equipment failing. So why the hell do we not do anything about it until after?’

5.1.2 Necessity of Adaptation

In the context of discussing the meanings and requirements of strategic thinking, the participants highlighted the need for adaptation. The forms of adaptation they spotlighted revolved around the necessities of experimentation, learning, and feedback loops.

The importance of this necessity of being increasingly more capable of adapting to change was succinctly explained by Participant M:

> ***M*** *(1):* 'It's all about learning now. Which I think, it's maybe the thing that we compete on most now is the data learning. […] I mean, applying strategic thinking now, it's a lot about execution to get to the rate of learning. Whatever it takes to sort of increase the rate of learning, and how this might be done today and then also be adapted in the future.'

In drawing their emphasis on increasing future adaptability to uncertainty through learning, they added:

> ***M*** *(2):* [T]o be sure that we are adaptable, and flexible, and modular, and much more aware of the tech stack that we have and the tech stack that we need. That is to me strategic thinking.'

What this addition also shows is the coupling of strategic thinking with the *prioritisation* of necessarily limited resources. The general interconnection between the necessity of adaptation and the desire to know and act upon an uncertain future was echoed in the participants' reasonings:

> ***B*** *(2):* 'Now that we are moving in a fast-paced changing market, everyone needs to adapt and everyone would like to get ahead over each other, of course. And try to leverage, try, I would say, new ways of working.'

Building on this link between new fast-paced change and the associated higher need for better (i.e., quicker) adaptation, the element of *newness* in this interconnection was further accentuated as Participant C discussed how monolithic promotions (such as on TV and radio) are no longer powerful as they once were and digital platforms take on:

> ***C*** *(1):* 'So suddenly, the individual consumer has a voice in a way they didn't before and you can see the trends. You can predict trends very quickly now. […] You have to be more agile and quicker, more dynamic. The Big Tech majors are good at it.'

Adding onto this perceived shift in the (higher) need for adaptation to a fast-paced, changing environment and the importance of learning, the participants also commented on the current inadequacy of strategic actions to meet these needs:

> ***H*** *(1):* 'When you don't predetermine and predestine people to certain jobs, then you give them a better chance for them to adapt throughout their careers to new jobs and new ways of working. And that's to me the fundamental change that needs to happen. It's also training people for skills and increasing their level of resilience and

adaptability to external environments. And like that then you create the future innovator. It's being able to take advantage of new contexts.'

5.1.3 Looking at Ecosystems and Contexts

Another cluster of meanings emerging from the interviews centred around the frame of better ways of navigating complex environments. The participants addressed the need for an ecosystem level of strategic thinking that focuses on seeing interconnections between problems and takes into account external factors, which play variously pivotal roles (such as regulatory influence). They also addressed the need for creativity, critical thinking, and value-based judgment in the sense of continuously re-evaluating strategic directions through different angles and stakeholder implications, which are perceived as necessitated by the world's interconnectedness. Particularly foregrounded was the relationship between such strategic, holistic, systems thinking and the need for contextualisation and needs-based strategising. Participant F's statement begins to illuminate:

> ***F** (2):* '[W]hat we need to understand is: Are we trying to change something locally, are we trying to change something at your departmental level, are we trying to change something within your entire universe, corporate universe? […] [A]nd this is the strategic part, am I going to solve one problem or is this going to be the first step in order to try and solve many problems within a corporate level?'

The notion of seeing *connections* between problems as part of the strategic ability to think about and subsequently act on the future was mirrored in other interviews. In discussing the need to tackle one of the biggest global challenges today — the tech-talent shortage, spatial and temporal dimensions of the importance of accounting for interdependent problems when thinking strategically emerged:

> ***L** (1):* 'To support the children, you need to support the teachers. Then you need to run the training programmes for the teachers there. And that's something like a connection. So if you will not do the job well with the teachers, probably in 10 years from now, we will not have that many experts as we would need to have. […] So trying to pick up a real challenge that people have. It's not only about the business part.'

This awareness of the need to not only acknowledge but *strategically* work in an ecosystem problem-solving way resonated further. Participant M put this need poetically:

> ***M** (3):* 'More moving away from ego to more eco. Understanding how things… what happens around you.'

However, the participants further highlighted during the interviews that a mere focus of strategic thinking on holistic interconnections is not enough. A simultaneous *interplay* of ecosystem knowledge and contextualised knowledge in strategic thinking practice is necessary:

> ***F** (3):* '[I]t's to develop *your* own methodology or your workflow, based on your own business, on your own capability. […] [T]he key here is to understand what you're doing throughout a methodological process that covers everything *you* need to tackle.'

The role of contextual knowledge in thinking strategically, drawn from organisational drivers and needs, became more evident as participants continued to stress how specific organisational needs and gaps drive strategic actions, especially in the context of highly limited resources and need for prioritisation:

> ***I** (1):* '[T]he coordination on the need level, like what they really need. […] So the information has to be tailored to the need. This is where the design thinking or the good thinking comes, because we have… Lack of funding, resources, lack of access. There's a lot of lack. So you really have to go spot on in what you need.'

5.1.4 Reliance on Data Amidst Human Limits

During our interviews with the participants, a specific meaning tangent materialised in discussions on strategic thinking in relation to creating strategies and taking strategic decisions. The participants portrayed data as an essential basis for strategic work. In this sense, the ability to defend one's strategic decisions on the grounds of numerical data and patterns was highlighted in contrast to undesirable human bias.

The participants brought up connections between strategic envisioning and acting upon the future and the role of data therein:

> ***D** (1):* '[W]hen you're talking about putting together a strategy, you typically do that on the basis of data, right. You expect that the market will develop in a certain way. So it's a lot about forecasting. […] [U]sing data science, you can objectify your decision-making much more. You can ground your decision-making on data. […] Decisions that are being taken today are grounded in real truth! In data! Similar thing with the COVID pandemic, right. […] The way that governments are able to react in strategic decision-making on who to quarantine and where to roll out medication and whatnot, is very very different! The basis of strategic decisions has changed. We have data now.'

As the passage suggests, a pivotal *shift* in the role of data for strategic thinking and decision-making is perceived wherein proactive, and thus prescriptive, strategic foresight is enabled through data on a higher level than perceived in the past. Other participants voiced parallel perceptions:

> ***B** (3):* '[T]o be able to set your strategy, you need to know the risks within the environment that you are in. […] So, I mean, in all risk assessment, even if you don't think that you use data, you always use data. I mean, if you were to quantify risk, you need data.'

The excerpts also allow for an understanding of the nature of the data highlighted. The possibilities of "objectifying" and "quantifying" demonstrate quantitative bases of proactive strategic thinking. In reiterating this desire to become data-driven and gain the ability to be proactive on the future, we also heard about the challenges in such data-driven strategic approaches in practice:

> ***N** (3):* '[B]usinesses today should use data and analytics to form and design their strategies. They shouldn't just look at what happened yesterday. Because you have the data, you can just apply the models and you would be able to take a lot better decisions. However! There is some courage that needs to be here as with most data, if you predict the future, you cannot be 100%. […] What you need to do is to base your facts on the highest possible probability.'

Although scepticism was tied to thinking in terms of probabilities, the participants frequently drew comparisons between reliance on data, probabilities, and patterns and on past human experience:

> ***J** (2):* '[T]he intelligent enterprise relies on data, not on humans. We're not stupid. […] [We] neglect signallings and indications of things actually happening because we have feelings and experiences, but don't have it all. Only personal ones and those are limited. […] [M]emory capacity is not a problem for computers. While it is for

> humans. And computing is also a problem for humans. We're not great in computing. The computer is much better than us.'

Additionally, our participants explained that the reasoning behind such reliance on data in strategic decision-making also arises from another strategic use of data:

> ***D** (2):* 'If, later on, it turns out that the decision was wrong, there will be a need for the board members to explain themselves to shareholders, to stakeholders, and whatnot. And if they know during the decision-making process, that if, if it goes wrong, they can point to those facts, and say: "Look at that! That's what I was presented with at the time of making a decision, it's not my fault!". The possibility to say "it's not my fault" is a huge game-changer in boardroom decision-making.'

Despite the general resounding emphasis on the necessity of relying on data in strategic decision-making, of safeguarding one's grounds of prescriptive visions of the future, one interviewee came to question whether such a strategic approach will be sustainable as organisations become more aware of ecosystem interconnections:

> ***H** (2):* 'I think even thinking strategically will change to a certain extent as we start going into operation that's more feedback, dynamic in nature, rather than linear. […] [F]or many, many years, the strategic skill very much referred to the ability to predict outcomes based on a set of data. I think we will move to something much more creative in nature. Being able to anticipate behaviours of systems.'

In a friendly open conversation with one of our participants that followed after their answer to our last question, the participant pointed to the capacity and role of individual agency in on-the-ground realities of strategic decision-making:

> ***I** (2):* 'I'm always surprised that… You think of [organisation name], you think of like companies, they're just people doing their job! From this point of view, including something, if you really want, is very easy. […] Decisions, most of the time, are individual decisions.'

The last two excerpts signal the influential capacity of human intuition *even* in environments where strategic thinking is grounded in numerical data understood as *truth.* We revisit this role of human "gut feeling" initiatives in our last theme in the context of the participants' perspectives on BD & AI and human augmentation dynamics.

5.1.5 Pursuit of People, Culture, and Change

Our last constructed category under the theme of strategic thinking surrounds the participants' notable emphasis on people and change in strategic endeavours. The participants discussed the role of communication, collaboration, nurturing talent, supporting interdisciplinary skills and social ideation, and the importance of leadership for empowerment and change.

In inquiring about the meanings and necessities of strategic thinking, communication was spotlighted by the participants as a prerequisite for strategic thinking/being:

> ***K** (2):* '[C]ommunication for me is key when it comes to strategic thinking. Because, as I see the strategic part is to align on what is the vision, what is the value add, and to be able to do that you need to have clear communication with the other stakeholders who are part of this whole solution building. […] [F]or me, the strategic aspect of building solutions and being ahead of yourself and defining what you should do and how to create value, that is purely about communication and alignment and setting a direction basically.'

The intrinsic role of communication in strategic thinking that is conveyed here builds on the strategic need to anticipate and proactively prepare for futures, whereby a strategic value in alignment is put forth. The idea of *alignment* in (re)thinking strategically envisioned futures was echoed by other participants through the prism of associated skills:

> ***M** (4):* '[P]eople skills, it's a new type of skill that should be incentivised. So more, you know, critical thinking, problem-solving. Maybe that's been around for a while, but re-imagining, be more, you know, asking questions rather than always provide the answers. Admitting that you don't understand what's going on. […] And try to engage people to solve problems.'

As the participant reiterated the connection between communication and engaging people in problem-solving as important people skills, which also enable future adaptability and resilience, they highlighted the link between the desire to (re)imagine preferred futures and necessary "culture work". The necessity of continuous alignments in mindset/culture, which is bound to strategic thinking and endeavours, resonated in other interviews:

> ***G*** *(2):* '[M]y objective is to get people to change their behaviour. […] [I]f you have the tools and technology and you have the process of the procedures and policy. But if the people and the culture are not there, it's useless! So, it needs everything. So we call it change management. […] It's changing the culture, changing the mindset, changing the way people work, operate. And being able to just, you know, take tough decisions. […] [G]etting people to to add value where they do best. […] [I]n terms of the background and mindset and attitude, that's good to have variation.'

Calls for collaboration and diversity were mirrored in other participants' responses, whereby the realm of strategic thinking acquired an additional dimension as one participant talked about the environment where strategic thinking is bred:

> ***D*** *(3):* 'Everybody knows what everybody else is doing. All the time. So, if, for example, an [organisation name] AI employee has a great idea and they go work on it, that's likely to be dinner conversation a week later, somewhere. And other people go: "Hmm, you guys are doing this, let's think about this!" […] So that's the basis for what I would say a great many of the ideas. We simply talk.'

What this passage suggests is that strategic thinking can be seen as something that happens in various *microcosms* where ideas are socialised, evolved, and supported. It points to a much more informal and *organic* side of strategic thinking that is inextricably bound to and shaped by its ecosystems. Building on this notion of microcosms, other participants discussed the importance of spaces of ideation for envisioned futures and how their success depends on how well ecosystems are supported outwards:

> ***L*** *(2):* 'It's very important to get talents that are interested in this field. […] And that's why we are supporting our Bachelor, Masters, and PhD students, helping them facilitate their particular thesis, because then I can give them the real business challenge we have. […] And then the talent is prepared after the universities.'

But also inwards:

> ***L*** *(3):* '[I]t's very important that you show the direction where they [employees] can grow. The people having boring work without growth, they will change it. […] You need to show the vision to the people. You need to have their personal growth for the team, it's just mandatory, you cannot not do that.'

This emphasis on not only acknowledging but actively *nurturing* organisational ecosystems was echoed by other participants while pinpointing a desire for change in leadership for the future. An empowering leadership that can shape microcosms towards flexibility, modularity, adaptability; that embraces complexity; one which enhances:

> ***G*** *(3):* '[T]he ability to take chances, give people freedom, and not set the parameters of what they're trying to achieve, how long they can take, how much money they should spend, what quality to be reached. These kind of things are important.'
>
> ***H*** *(3):* '[T]he leaders of tomorrow should start thinking of changing their mindset. […] [S]top hiding behind complexity, which was the case for, and is the case, for so many! […] That's where I would see the new leaders, the real leaders of tomorrow.'

Thus far, the data highlights that strategic thinking entails an understanding and reflection on what is, at present, and what is needed to support one's capacity to adapt in a future (preferred) place/space. Strengthening adaptability through learning is viewed as important to be able to navigate new contexts. However, strategic thinking is also associated with recognising moments when execution needs to be set in motion, while later being adapted. Strategic thinking also comes to involve an interplay of ecosystem and contextual knowledge dependent on engaging people. Rooted in the acknowledgement that problems do not occur in isolation, the interpreted meanings mirror notions of complex system dependencies associated with the perspective of designing and communicating about futures with and for others. Lastly, underlying strategic thinking, the data suggests an association between a perceived necessity of knowledge about future (preferred) places and the ability to act on such knowledge proactively. This necessity becomes accentuated through "frustration" with currently felt obstacles to such "better" ways of thinking strategically, i.e., proactively and prescriptively towards visions of preferred futures.

5.2 Realm of Emerging Tech

In this section, we will present the theme of emerging technologies (Big Data and Artificial Intelligence) explored in the interviews with our participants. We have constructed four categories emanating from the sensemaking topics raised by the participants. Coding under this theme is based on their impressions of the technologies, the understood essence of BD & AI, the features, capabilities, and limitations, as well as influences. Moreover, any norms and values attached to BD & AI were coded. Broadly, the overarching theme of these technologies is split into the following categories: *new omnipresent value potential*, *new capability of predictive data processing*, *"just" single problem "tools" for holistic use*, and *recognising the path of uncertainty*.

5.2.1 New Omnipresent Value Potential

The first two categories surrounding BD & AI are bound together in the sense that the meanings conveyed by the participants resonate around the new possibilities perceived vis-à-vis the capabilities of AI. Nevertheless, certain sensemaking topics emerged as "pre-understandings" of others. Hence, these "pre-topics" are discussed in this first category, which the following constructed category of meanings builds upon.

In conversations around first impressions, understandings, as well as later in follow-up conversations, the participants explained that these technologies inherently bring along various new opportunities for value creation. New abilities of efficiency, enablement of more focused human work, the removal of tedious work, and collateral value generation were highlighted, along with past and present comparisons of machine and human capabilities.

These new opportunities for wide-ranging value creation were foregrounded during the interviews:

> ***B*** *(4):* 'I see a big opportunity in like, basically anything can benefit from the use of Big Data, and the use of Artificial Intelligence or Machine Learning. And I mean we are only just scratching the surface here.'

> ***F*** *(4):* '[I]t's a business revolution enabled by technology. Many of the ideas that we had 20, 40 years ago that we were not able to address because of the lack of technology. Right now, we see the capability to achieve them. From a cultural point of view, it [BD & AI] only enables or it only gives a way of execution to ideas that, most of the time, are not new.'

As the participants elaborated on their reasoning for seeing these technologies as new value and problem-solving enablers, the *nature* of this value became more apparent:

> ***J*** *(3):* 'First of all, there is nothing artificial in Artificial Intelligence. The better term is amazing innovation. […] Amazing innovation is, of course, fantastic, if you can do things that are transformative and changing things in a simple go. And that is basically what AI is doing. […] And maybe, most importantly, is that we can take away those tedious things from people that they're doing.'

> ***H*** *(4):* '[H]uge opportunities because we haven't been in this situation in the past to have the ability to turn everything into information and store so much knowledge that it gets to a point where we were not very good at doing something with it. And actually, not just being very good at doing something with it, but also being overwhelmed with the volume and the pace of this information coming towards us.'

Depictions of value mostly revolved around possibilities and (in)abilities. Possibilities in being supported by technology in new, more efficient ways. The contrast between machine ability and human *in*ability to deal with fast-paced volumes of information flow. The abilities of accessing and storing knowledge, removing tedious tasks, and thus allowing space for tasks perceived as more deserving of human time. And correspondingly, the desirability of easily transforming an organisation — a capability bound to adaptation in fast-paced, interconnected environments.

Throughout our interviews with the participants, the contrast between machine and intrinsically human capabilities became more apparent:

> ***M*** *(5):* 'So, [thinking about] where we can use machines to make it better for humans. So that humans can focus on maybe the more creative, or the more innovative, or the more fun, or the whatever stuff that the human does better.'

This desired focus on and attached importance to human capabilities was echoed in different ways. One participant highlighted the value of more time for human interactions enabled by the technologies:

> ***L** (4):* 'AI increases the performance of the work. […] [I]f you have it automatically done most of the things, then you can focus on the part of talking with people about results, about the growth, and focus on the people part.'

Although wide-ranging value potentials were discussed, a sense of frustration and annoyance about the common (mis)portrayal of the value of BD & AI was voiced by the participants:

> ***I** (3):* '[O]verrated, that's my perspective. So, I think there is little knowledge about AI, little knowledge of what AI can do. I think even [organisation name] is doing a mistake when there is a problem and they say to put AI on it. Overrated and there is a total misconception of what AI is really.'

> ***L** (5):* 'Even within research, it's a lot harder to sell the term Machine Learning than Artificial Intelligence. Because Machine Learning, business is afraid of, and Artificial Intelligence is easier.'

In seconding this nuisance and building up to the following category of meanings surrounding the new capabilities of BD & AI, one of our participants emphasised:

> ***M** (6):* '[T]o me, it's more like a state of mind or a way of thinking about problem solving. That's what AI and also Big Data, I would say, is about.'

5.2.2 New Capability of Predictive Data Processing

The participants further unfolded the implications of the aforementioned new opportunities. Reasonings revolved around the ability to draw insights for better decision-making, the enablement of predictions and pattern recognition for optimising decisions, problem-solving capacities of AI and how AI can drive strategy, as well as how BD & AI are necessitated for organisational sustainability and survival.

When asked to provide their understanding or explanation of these technologies, Participant K highlighted:

> ***K*** *(3):* 'We are generating information everywhere now, right? In everything we do. We're so connected nowadays. […] All of this is like data. And that's Big Data because it's generated so fast, exponentially generated. And the Big Data is all about like how do we make sense of this and how can we provide value out of this data? […] [T]he data is the ground. The basics of it. […] I would explain AI to people, I would say how can we find patterns in data to take better decisions? How can we improve predictions on what's going to happen without us knowing about it in advance? So basically use historical data to make predictions of the future.'

This passage succinctly illustrates the strategic aspiration associated with these technologies. That is, the aspiration of *leveraging* these technologies to tackle human inability to deal with large volumes of data in order to derive value, which is tied to the strategic ability of knowing and acting upon the future. Additionally, perceptions of the volumes of data simply "being here and available" for extraction towards value generation resonated further as findable patterns for actionable insights were highlighted:

> ***C*** *(2):* '[T]he AI, if you like, component of that is using Machine Learning and Deep Learning or other data science techniques like knowledge graphs to effectively understand what that data means, to find patterns hidden in that data, and actionable insights to personalise the journey and interactions of users to improve the customer experience.'

> ***A*** *(1):* 'The basic point of Machine Learning, which is again the predictive modelling, is using trends from historical data, and there's another branch of it, which is creating dashboards so that someone can, at a glance, see comparisons of different groups or see different trends and visualise those, so that a human can make a better decision.'

Another participant compared this strategically valuable connection between pattern finding and the possibility/ability of forecasting to scientific endeavours:

> ***D*** *(4):* 'And really the aim is to find some sort of coherent pattern in the data and present that using a mathematical equation. […] Effectively, Artificial Intelligence is the conversion of a large dataset to a mathematical equation that will calculate something of use to me. So it's very similar to physics!'

In emphasising that AI as a field entails various mathematical methods and use cases, the participants also pointed out the wide-ranging and collateral value of AI use in strategically optimising processes taking into account limited resources:

> ***C** (3):* 'Every one minute of unplanned downtime, cost them $22,000 on average. Now you can use predictive analytics. […] [Y]ou can try and prevent that before it actually occurs by adjusting the machine. So you prevent the outages, the undesired, unplanned outages, which A: reduces your business interruption, your lost time and B: extends the asset life of those expensive equipment. You can also use, to reduce costs and optimise energy consumption, and also try and schedule production when energy prices are lower.'

Another participant put the bottom-line of such AI value succinctly:

> ***M** (7):* '[B]eing more data driven and using vast amounts of data in a way to *superpower* your existing processes. I think that's where we are now, for the most of it.'

In discussing the value, the participants highlighted that such strategic "super-powering" through AI is tied to the function of being actionable on the future in order to *modify* it, to mould it towards a preferred future of value:

> ***D** (5):* '[I]f for some reason we conclude that, you know, we're not able to really modify the market dynamics, then the project is worthless and will be discontinued. And the reason that these projects are not discontinued is because we find that we, in fact, can influence your behaviour!'

Another participant echoed this actionability while relating to the strategic need of seeing interconnected future problems:

> ***F** (5):* '[I]f you're just trying to understand what happened in the past, then you can stop here. […] But that's not the point. […] So, understanding that we can predict the future, and allow me to say this, but we can have predictive power, we can act on something. And then you can decide: "Okay, I know that maybe, this asset is going to freeze in a month. So am I able to address all these kind of reparations, or can I prioritise, can I address all the things that I need in order to reduce my cost, save money, make money, and so on.'

As such, the participants accentuated the ability to *extract* data, *predict* futures, and consequently make strategic decisions designed through these data- and AI-driven processes. Such strategic *super-powered* thinking discussed by our participants was further portrayed as more and more necessary for not only better strategic decisions but for organisational survival in interconnected and increasingly digital environments:

> ***B** (5):* 'I am having a hard time seeing that they [organisation] would even exist on a global market if they didn't use the advantages they have from using both AI and Big Data.'

> ***E** (1):* 'So I think we are taking a very good step forward. Integrating the digital feature aspects in our assets. […] I think that's one of the things for competitive strategy we could have to survive in this industry.'

AI for future organisational survival, nonetheless, depends on an organisation's understanding of its own context:

> ***F** (6):* 'You need to understand that although you want to undergo a digital transformation, and this is something very very important, you need to understand that maybe your business is not about data, it's not about the digital. […] You need to understand, is this going to really empower your business model, or are you doing something that is not related? Although I can digitalise it, is it really digital?'

5.2.3 'Just' Single Problem 'Tools' for Holistic Use

During our interviews with the participants, their depictions of the perceived value of BD & AI invariably led to an emphasis on the flip side of the imaginary AI coin. Throughout our discussions, they continued to stress the mere "tool" nature of BD & AI, its "thinking" limitations in contrast to human strategic thinking about problems, the need for holistic AI implementation where problems should be sliced, broken down, and AI project scaling ensured. In this context, the participants pointed out that although "all-purpose" (General/Super) AI applications currently do not exist, misconceptions and corresponding strategic failures in AI use are widespread.

Statements from participants I and F illustrate this overarching "tool" sensemaking:

> ***I** (4):* 'It's like a screwdriver, it's just a tool. I think it's just a tool that is trying to do what the human is doing. In some specific area for now.'

> ***F** (7):* 'These are tools. This is a means to an end. This is a technological revolution that is helping us change our reality or shape our reality.'

In a follow-up discussion, when we asked directly if they see any areas where AI is influencing strategic thinking, Participant I continued:

> ***I** (5):* 'So for instance, I don't know, if I'm asking you what's the strategy thinking combination with Excel or Word? I mean it's just a tool, right? And you're like, what's the impact of Microsoft Windows in your strategic thinking about policy? I just open and write. That's how I perceive it.'

What this elaboration shows is that although strategic value was highlighted and exemplified by the participants, we can see that BD & AI are made sense of as a means to an end. Coming back to the cooking metaphor excerpted earlier, BD & AI are made sense of as a knife, spatula, or cooking spoon that serves its purpose and brings about value *as but one part* of the cooking (strategy) process. In echoing this sentiment to a similar question of whether AI is influencing any strategic thinking processes, another participant appended:

> ***G** (4):* 'Not enough. So I don't think, no… I think people just always think: "AI, it'll solve all my strategy problems.'

This sense of common misconceptions resonated in other discussions, which the participants also pointed out in explanations of how AI needs to be thought of holistically but realised in insular applications given AI's essence:

> ***D** (6):* '[AI] supplies numerical answers to numerical questions. Period. So you better ask the right questions. And most of the time, what I see, is hitch-hikers guide to the galaxy. You know, the CEO asks the question of universal life. Two months later, I send the email with 42. And then comes the board meeting. Right. W-T-F. Haha. "Why did you send me 42? What's the point?" Right. So if you include AI in strategic decision-making processes, you have to be aware that you need to ask very precise questions. And you're going to get a precise answer to exactly that! And not a question that is similar to the one you asked. No, no, no, no, no. It will be exactly the question you asked.'

Another participant similarly highlighted the *insular* nature of AI within *holistically* thought-through strategic processes by telling us about the contrast between human and machine capabilities, and thus roles, within such processes. They began by explaining that the role of the human is to know and understand organisational processes in terms of a bigger picture:

> ***A** (2):* 'There is a part where a human knows A influences B, but I don't know the exact mathematical formula for how it does that. That's the place where AI fits in. […] AI is very good at that sort of narrow prediction problem. But then if you said: "What's the broader structure of the problem? What should I do to achieve to maximise the amount of revenue we make for this quarter?" AI wouldn't have been able to say: "Hey, you haven't thought about competition dynamics, you need to also think of that".'

The need for *co-leveraging* processes resonated throughout conversations with our participants, whereby contrasts between injections of human capabilities and BD & AI value were drawn, with a prevailing need to simultaneously emphasise misconceptions about such co-functioning processes.

5.2.4 Recognising the Path of Uncertainty

The last constructed category in this second theme builds on the sentiments conveyed about the other side of the AI coin — the participants' acknowledgement of limitations bound to these technologies at this day and age of AI maturity. Acknowledgements revolved around working with historical data in dramatically changing environments, challenges associated with designing and deploying responsible AI, explainability, ethics, and trust in AI applications with associated considerations of different contexts of potential harm, as well as AI regulation and control.

The innate proximity and interplay of the two sides of the coin were explained by Participant H:

> ***H** (5):* 'A huge opportunity but also crossroads. […] We don't really know much about this technology, and that's both positive and negative. That's where the big opportunities come from. It's the fact that we are dealing with something that's quite novel and has a promise to solve some of the problems humanity has. But also, at the same time, it's because we don't know it, we are unprepared to deal with something as novel as those intelligent agents. […] So we need to start thinking differently, the way we approach creating those artefacts and allow ourselves to rethink the way we operate.'

In being aware of these uncertainties brought about with BD & AI applications and the perceived accompanying need for re-thinking processes, the participants echoed these challenges through personal experiences. One participant told us about a situation wherein a retail client was using pre-COVID data for an AI model to determine future stocks of school supplies in stores for 2020 when many schools did not re-start, and the issues arising from the use of (historical) data in changing environments:

> ***A** (3):* '[I]t's frequently called train test drift or concept drift. I was aware of it, that's the idea that I mentioned earlier like the world is changing, so whatever you learned from historical data might mislead you in the future.'

The sentiment of challenges and uncertainties in working with BD & AI prediction technology based on historical data patterns in *qualitatively* changing complex environments resonated in further interviews. Moreover, the participants often returned to their emphasis on machine/human capability contrasts in the context of these challenges and uncertainties of BD & AI use in strategic processes. In exemplifying uncertainties of AI through an analogy of how a doctor telling a patient about their MRI scan would not only state that there is a brain tumour, but would continue with a reasoning process explaining the situation, Participant D pointed out two main AI challenges:

> ***D** (7):* 'Explainability and AI ethics. […] So explainability has the purpose of not just giving you the output of the AI model but also explaining why that makes sense. The other branch is AI ethics, which really asks: Is it ethical to do whatever it is that you're gonna do. […] I think, if we have an ethical way and an explainable way to use AI, then the public has at least a better chance of trusting us to get things right.'

These were echoed across interviews:

> ***K** (4):* 'We have seen situations where we have gone a bit too fast in developing a solution that we might not have asked ourselves: Is this the right thing to do? And then, at the end, it has turned out to be unintended consequences coming along with those solutions, which is, of course, challenging.'

> ***E** (2):* '[T]o make sure you test almost every aspect you can do, that's very critical. That's why we are inferencing many things as much as we can. Make sure that things always reside in our expectations, not beyond our expectations. Logics doesn't work at this moment. Because as I said, it is almost a blackbox.'

In stressing the necessity of acknowledging and working on these uncertainties, Participant E added another necessity in the process of using these technologies strategically, i.e., *holistically* for value *across* problems, as opposed to in an *ad hoc* manner without addressing organisational needs and ecosystem stakeholders:

> ***E*** *(3):* 'We call the model "very beautiful garbage". Haha. Because it's very hard to believe! […] The obstacle is there is a lack of confidence upon the application of the AI model. […] We have to put some trust and confidence upon those models. […] So I think that has an implication on decision-makers I guess.'

The aspect of *trust* was invariably portrayed by the participants as both a necessity and challenge due to on-the-ground realities of misconceptions and lack of knowledge about these technologies; but also given differing *contexts*, which, in turn, determine different levels of such necessity:

> ***D*** *(8):* 'Let's say you like watching action movies on Netflix and it suddenly recommends this romantic comedy to you, right. Complete wrong suggestion. But what's the damage done? But if the AI system is responsible for choosing the right kind of concrete for the next bridge project that you engineer and build, if it gets that wrong and the bridge collapses and a few thousand people die, then, that's a different level of damage.'

The combination of human trust and contextualisation was further depicted as an even greater factor than the perceived capabilities of BD & AI:

> ***E*** *(4):* '[M]aturity level doesn't really have an impact on the application, because the AI model is a blackbox model. You have no idea how it works inside. So that's a very inherent limitness. Because every aspect, which requires very solid safety, it's really hard, even though it's very matured.'

By and large, the data suggests a relationship between the wide-ranging new potentials of BD & AI and human incapability to make sense of volumes of data flows, which bear insights valuable for improving decisions about the future. The statements dovetail the instrumentarian logic through an emphasis on data extraction in order to enable better predictions and thus actionability towards a preferred vision of the future. Such super-powered decision making is viewed as increasingly necessary for organisational survival. Nevertheless, perceived levels of necessary knowledge of AI, the manner of its applicability, as well as inherent limitations are low. The participants emphasise commonly widespread misconceptions undermining various types of enablement AI is understood to offer. The data generally accentuates the “tool” nature of AI, whereby it is understood to be offering new problem-solving capabilities in fitted, narrow ways, which, however, need to be thought through holistically to generate sustainable value.

5.3 Realm of New Dynamics

Turning now to the third theme, we will present three last categories that have been constructed based on the sensemaking topics derived from the interviews. Our coding here is based on direct connections made by the participants between BD & AI technologies and strategic thinking, sensemaking of joint necessities, challenges, opportunities, interactions, tradeoffs, and effects. In general, the overarching theme of these interactions and co-functionings is broken down into the following categories: the *need for joint augmentation processes*, *real world limitations of human+tech symbiosis*, and an additional all-themes spanning category of *time*.

5.3.1 Need for Joint Augmentation Processes

The participants emphasised the need for a “*symbiotic*” relationship between humans and machines in strategic processes. In highlighting reciprocal effects, they accentuated functions of human judgment in these processes. Additionally, they built on the tensions introduced in the last theme as they illuminated several challenges of having human (judgment) in the loop.

During the interviews, the participants discussed how BD & AI are sparking society-wide ripple effects, often remarking that we are getting more and more accustomed to the presence of these technologies. When asked how they see BD & AI in relation to strategic thinking, Participant G explained:

> ***G*** *(5):* 'Assisting humans. How do you put AI alongside a human being where they don't even know they are there. […] That's how you change people because they don't realise it's happening, but it happens slowly, over time.'

Discussions with other participants mirrored this envisioned relation:

> ***M*** *(8):* 'Striking that balance and working on the interaction, how human and machine can sort of be better than *only* humans, or *only* machines!'

> ***L*** *(6):* '[T]he successful combination is not by putting AI here, and a super human there. The success is from the combination.'

Adding to this perceived necessity of combining humans and AI, Participant L further explained the value behind such a symbiotic approach where "simple" parts of strategic work are processed by AI, whereas:

> ***L*** *(7):* '[t]he complex, that's where the people's experience is needed. That's where they learn from it, grow from it. That's where we see the big value of keeping the human part, right. Then if you learn from that, you will definitely bring a lot of new perspectives for yourself. And you also get different training.'

The possibility to *augment* the value of human judgment when combining human thinking and BD & AI applications, whereby AI processes large datasets, defines patterns, and provides actionable predictive insights for a human to judge and act upon, resonated throughout the interviews. In follow-up conversations on this perceived relationship and limitations of BD & AI, the participants expressed the necessity of incorporating holistic human judgment into strategic processes leveraging BD & AI:

> ***C*** *(4):* 'But you still have a human analyst decide: "What does that mean? What is the best way to leverage that?"'

> ***I*** *(6):* 'The idea is to move it to a more human in the loop approach. So, you basically have the AI that does the pre-processing, all the easy detection, and a human will validate the results. […] A human in the loop process where everything is marked as AI-generated. Still a human will validate that.'

In discussing these joint processes — whereby human strategic thinking is augmented by AI-generated BD pattern insights and machines are augmented by human (sensemaking and ethical) judgments and holistic problem-solving; certain *grey* areas of this functioning emerged as the participants described various influences:

> ***B** (6):* 'In most cases, the strategy process, I wouldn't say it's an adhoc process, but part of it is based on adhoc-ness. Or gut feelings in some cases and whatever it might be.'

To better understand such influences, we inquired about the meeting points of data-based and adhoc gut-based strategic thinking:

> ***B** (7):* 'The adhocness and the data, or the more structured way of analysing things, where they meet, that could be on basically all levels. […] Of course you can add your own flavour to this. […] With the same dataset, you could probably tell a million different stories. Based on how you present it and how the audience perceives your presentation. […] Of course some gut feeling or stuff like that could also be included at the board level. Most of the people there are there because they have huge experience in whatever field they operate in. So their gut feeling is probably a good gut feeling.'

The capability of influencing data-driven insights for strategic decision-making through communication, suggestions in meetings, and ways of graphically portraying such insights, was also mentioned by other participants. In further reflecting on the symbiotically augmenting process of humans *plus* machines, several participants illustrated why *critical thinking* on the part of the human is necessary for the success of the process:

> ***A** (4):* 'Most people in the field are able to do work that looks like what they have seen before but are not ready to think about it in a really critical way. […] They do some tasks in a very mechanical way, but are not great at figuring out the strengths and weaknesses of the approach or how to improvise, to think analytically or critically about what you are doing.'

> ***I** (7):* 'The world is biased, so AI is biased. It's not the fault of AI, it's a screwdriver. So again, I know that the dataset is biased, the quality is sometimes not great, I know the limitations of AI. So I am opening up a conversation and pushing to have policy.'

5.3.2 Real World Limitations of Human+Tech Symbiosis

Conversations around the envisioned augmentation of humans through "injecting" BD & AI data processing into strategic practices consistently returned to perceived misconceptions and comparisons between what happens "in theory" and in "real life" practice. The participants talked about the challenges caused by the current lack of BD & AI knowledge (about meanings, successful applications), which is perceived to have implications on organisational life.

Misconceptions associated with BD & AI applications in "real" practice resonated throughout all interviews as a multitude of *underestimated* requirements:

> ***D** (9):* 'When you mine for metals, you have maybe 10% metal and the rest is garbage. So data is like that. […] And that's something that most people underestimate. The amount of work it takes and the amount of data you have to throw away until you get to a valuable dataset is enormous.'

> ***F** (8):* 'You really need to take into account everything that goes from quality, to data governance, understanding where the data is coming from, how good it is, how reliable, how can I work with it, how can I make sure that everything matches.'

The commonly underestimated data and validation work tied to successful injections of BD & AI into strategic processes was discussed as but one part of on-the-ground struggles. The participants also highlighted challenges related to more ecosystem bound strategic thinking, which becomes difficult in technically practical terms:

> ***I** (8):* '[G]etting a human in the pipeline, it's hard. You have to put more protocols to include the human in the loop. […] While we are designing the pipelines, we're also designing the way and the policy on how the human will be integrated in order to protect the human. Technically it's hard.'

As well as due to commonly linear approaches to strategic thinking:

> ***G** (6):* 'It's a constant learning process. And I think that's also a challenge that people don't realise. Just because you have this version doesn't mean it's the last version. But that requires investing time and patience.'

In reasoning about the roots and implications of technical and cultural misconceptions, Participant A explained one of the greatest challenges perceived in achieving successful human+AI symbiosis:

> ***A** (5):* 'I think that there's been to date a huge division between the people who do AI and the people who do strategic thinking or design thinking. […] I think AI today is almost exclusively used where someone starts with a very narrow view and doesn't think very deeply about how that gets used in decision-making or how the decisions around affect our carbon footprint or profitability or customer experience. I just think that those are happening in *two separate worlds*.'

The challenge of combining the world of AI prediction model building and that of organisational domain knowledge was echoed in all interviews. The participants stressed the increasing necessity of addressing its root cause — an amalgamation of insufficient tech literacy, lack of mutual understandings and cross-functional collaboration, and static cultures of silos. The need for *translating mindsets* traversed all conversations in various forms:

> ***C** (5):* 'Make sure that your data science team and your business team are aligned. That they're speaking the same language. […] Because the data scientists talk very technically, in AI terminology. And the business team thinks AI is some magic out of the box, Skynet, or I Robot that is just going to magically do everything.'

> ***D** (10):* 'The most important job in an AI project is the job of translator. Everybody might speak English, but they speak different vocabularies. […] Somebody needs to play the role of translator between these groups. And that's really the critical piece. That's the bottleneck of the project.'

In adding onto this need of *bridging* data science mindsets and business domain expertise ways of thinking, the need for increased data *literacy* that would translate into organisational cultures was raised:

> ***E** (5):* 'The world is changing but they [legacy organisations/executives] have no idea. […] There has been no change. So I think starting from university, it has to be intertwined with the curriculum, that will be a starting point. Then they can understand each other and start reducing the gap.'

> ***N** (4):* 'Senior decision-makers, they don't understand AI. They don't understand how to use data. They think that it's an off-the-shelf product. The shareholders, they don't have the resilience, patience to see it through. They don't understand that this is a big journey.'

As such, poor change management, lack of education and translation were depicted as the most influential factors determining BD & AI project success or failure. Correspondingly, the participants shared their suggestions for tackling change management successfully. As they exemplified ways of addressing education, translation, and cultural structures based on their practical experiences, the *empowering* nature of such shifts unfolded:

> ***M** (9):* 'The way we build companies traditionally is with large IT platforms, very centralised, very monolithic. You need that to be done in a very decentralised way to create value and to be fast and adaptive and to be able to scale these things up. […] You need governance that incentivises democratisation.'

Empowerment through the democratisation of knowledge and access, further enabling adaptability, as well as through recognition of the need for cross-functional collaboration were voiced as desired and necessary steps to be undertaken for human+AI symbiosis, which brings about new opportunities and value. Nevertheless, even here, challenges were spotlighted as Participant I explained that existing societal inequalities could be reinforced with increased data literacy and access to these technologies. For instance, with the democratisation of knowledge (only) in the Global North:

> ***I** (9):* 'If you think about democratising access to AI in the terms that you teach everybody to code. And we don't have like the North coding on the South. It's relevant when you talk about biases, when a researcher in the Global North has total access of your data, and then applies the data to you, and you have no right to say no, for instance. So if you deploy a model to a poor community that has no knowledge of AI, no knowledge of the data they are producing.'

5.3.3 Time

Our last constructed category pertains to a factor, which has been predominant in all interviews in various ways, spanning across all themes — the multifaceted factor of time. Since some of the sensemaking topics around time have been tied to the previous categories and are thus embedded therein, we briefly summarise the main highlights here and further flesh out additional reasonings.

The participants discussed the *effects of time constraints*, such as the need to prioritise and do the "best" with time available, pointing out that strategic thinking is two-dimensional in the sense of looking at what one wants to achieve and how long can one spend. They highlighted how time constraints affect the feasibility of "injecting" human judgment into AI workflows and how time-induced biases occur when humans get attached to solutions after considerable time spent. Time constraint effects were also depicted as bound to different levels of time constraints held by organisations within ecosystems.

Correspondingly, they suggested that time is a strategic resource, which needs to be handled in a certain (strategic) way by discussing ways of *"better" use of time*. Resonating throughout answers, the participants talked about the ability to free up time through AI for different tasks, to optimise previous time "wasted" on defending decisions and reactive ways of working. They expressed frustration about commonly spent time on AI projects "without a purpose", thus in a non-strategic way.

The aspect of *responses in time* was accentuated in conversations. Besides noticeable reductions in possible response times of decisions today, the participants raised the importance of strengthening feedback response times and considering that the actual feasibility of certain response times will be restricted in specific settings, as Participants G and I illustrate:

> ***G** (7):* 'When Disney develops cartoons, they send the artist to Africa to see how the wildlife interacts and then model that on a screen. So access to the time with your customer is an important resource, having that visibility, not working blindly.'
>
> ***I** (10):* 'In disaster response, are you going to receive feedback from the ground? If your adaptation technique is based on response from the ground, might be impossible. Are they spending time to give you feedback for your model? Things are flowing. I don't think that is a reasonable plan.'

Another recurring topic revolves around *time horizons* in strategic thinking. Emphasis was placed on acknowledging that strategic processes are never "finished", that data is never finished, and thus a corresponding need to think strategically in such broader horizons. Conveying regret about the traditionally short-term horizons of most strategies, participants emphasised the need to think strategically in longer horizons, especially when incorporating BD & AI into their strategic work:

> ***D** (11):* 'Companies generally don't want to do anything that's more than a year or two out. That's why certain ideas that are good but are a bit too long-term, companies always stay away from that. […] And so there is a danger because companies are oriented to quick wins, to things they can do in a couple of months.'

Such a need for longer time horizons was also argued for in relation to *time for reflection*:

> ***H** (6):* '[It's] not really a resource but more of a trait of leadership. To be patient. […] I think we need to keep a balance in between how much we want to change the current structure before we break things up.'

The need for reflection and longer time frames, as well as considering which *values and priorities* are embedded into strategic processes, influences how time is allocated. One participant reflected on the experienced challenges today when it comes to allowing for and incentivising reflection time on values, especially when working with AI:

> ***K** (5):* 'You are encouraged to estimate how much time it will take. If that's the only parameter that you are kind of measured on, then it's very easy to say: "Yeah, I will do this in 10 hours". But is that really the key measurement? To complete the solution, yes, I need 10 hours. But in order to do the analysis and really evaluate if I've done it correctly or if I have added all these parameters and if I use the reflection time. When it comes to AI, that's a huge threat! Reflection is the core.'

How time is allocated is based on values. In this context, our participants frequently criticised the value underlying such time allocation, which is, at the moment, determined mainly by commercial interests:

> ***D** (12):* 'I think they [future applications] will be mainly driven by commercial interest. […] I wish it weren't so! I wish that AI were developing more in the direction of providing goodness for humanity as a whole. But I predict that there will always be this undercurrent of profit-making.'

During our conversations with the participants, the need to acknowledge reciprocal relations in complex (eco)systems as an important part of thinking strategically became apparent. In this context, an accentuated emphasis on being aware of reciprocal “push and pull” effects of data and strategy was conveyed in relation to a perceived shift in time:

> ***B*** *(8):* ‘Even before we started talking about Big Data or any of the technologies, it was the same type of interplay. Between basically reality and your strategy. But now we can model and draw *more* insights from our reality than we could earlier. And that, of course, affects the way we plan and strategise for the future. You have your data that you use for inputting into your risk assessment. That’s like the *push* thing. With this type of data, you push your strategy in one way or the other based on historical value or projections into the future. And then you have your strategy, we are aiming for this. Then you basically have a *pull* effect, you influence your environment, the future, you basically pull that environment towards your strategy. And, of course, that will affect the data or the outcome.’

Conclusively, the data suggests that a symbiotic relationship between humans and AI in strategic decision-making and other organisational processes needs to be leveraged. The success of the symbiosis is seen in a well-informed combination of AI’s analytical capabilities and raw data processing power, and human judgment and critical thinking. However, the participants underscored that the currently perceived low levels of data and AI literacy, clashing mindsets, and cultural structures need to be addressed in order to benefit from the potentials of the relationship. Finally, the data presents time as a (strategic) resource, which feeds into the symbiotic process as both a constraining and enabling element, the necessary prioritisation of which is underpinned by varying values in different contexts.

6 Analysis

This chapter analyses the “vignettes” of data through our conceptual lens. It is organised into four sections. The first three correspond with our operational questions: How do participants characterise BD & AI? How do participants characterise strategic thinking? And, how do participants perceive and envision the relationship between strategic thinking and BD & AI? The fourth section reflects on the relevance and applicability of our conceptual lens — comprising of instrumentarian/dataistic logic (including associated socio-technical dynamics) as well as a design thinking foresight perspective. Finally, in this last section, we offer a mental model grounded in the data, which aims to depict the generalised coalescence of strategic thinking and BD & AI in strategic decision-making.

Before we start delving into the analysis, we wish to highlight that underlying all conversations with our participants, and therefore this analysis, is a transcending emphasis on *contrasting* the *past* with the *present/future*. Correspondingly, rather than specifically discussing these contrasts in particular, we have woven them into the analysis itself.

6.1 How do the participants characterise BD & AI?

Our participants generally characterised BD & AI as new and exciting emerging technologies with a wide-ranging potential of use cases. The sentiment that benefits can be seen virtually in any sphere ties into the understanding that we are witnessing a constant, omnipresent generation of digital footprints. However, the participants drew a stark difference between Big Data and Artificial Intelligence. In contrast to the past, volumes of data can now be captured, aggregated, and leveraged in any sphere — the data is “simply here” ready to be used. But it is AI that truly embodies the contrast to the past as it signifies the *new ability* to make sense of the enormous growth in data and enable a way to use it. More specifically, our participants expressed that data by itself is rather "boring" and "nothing new at all". What makes contemporary practices exciting and novel is what we can now do with it. There is an *actionable* capacity associated with AI. By drawing forecasts from historical trends and patterns and creating probability maps of the future, it is now possible not only to understand what quantities of data mean as hidden patterns are made legible with AI; we can figure out what the impact of different (strategic) decisions would be. Through AI, we can approximate future knowledge; we are aided in *how* we can think about the future.

In this knowing, however, it is not dataism's almost religious sanctity of data that guides strategic thinking with AI. It is overshadowed by *instrumentarian* logic, which surfaces in our participants' portrayals through its two imperatives. Data and the corresponding extraction imperative are seen as necessary, but data is simply here for the taking. The discussion does not revolve around whether data should be extracted; the more relevant questions are rather how it should be used, how we can/should make sense of data. As our participants discussed, extracting data is only necessary because we want to be addressing needs, solving problems, improving decisions. Data is not valuable per se; it *becomes* valuable through being *acted upon*. The second imperative, that of prediction, is what constitutes the active force that our participants elevate. Through AI's predictive capabilities, we are enabled to draw insights about the future, which leads to our *ability* to address needs and solve problems. And it is in connection to this knowledge and ability, underpinned by the instrumentarian logic, that our participants contrasted the notions of "reactive" and "proactive" ability. Reacting to information, markets, developments is seen as an inefficient decision-making approach of the past, whereas what the participants stress is the need to be *proactive* on the extracted data by using AI to approximate future knowledge. The novel shift brought about by the presence of AI is precisely that of moving from reactive to proactive strategic thinking to leverage the AI-bound possibility of *moulding* the future in alignment with one's *own* strategic vision.

As such, the socio-technical objectives mediated by AI are made visible in how our participants highlighted the various types of value *attached* to this shift. On the one hand, by leveraging AI-enabled predictive modelling and forecasting, we can streamline processes, which can even bring about collateral value that was perhaps not primarily intended (e.g. not only lowered costs but a positive environmental impact through optimisation of energy consumption). Thanks to the incorporation of AI, resources can be used more efficiently and effectively. On the other hand, since AI can remove (i.e., automate) tedious tasks previously done by humans, there is value in how "unnecessary" tasks are "automated away". This is understood to free up human time that can now be used more for interacting with other people, employing human judgment in weighing decisions, and thinking holistically and creatively about processes and strategic visions. Several participants built on the value of more time made available by suggesting that as AI processes large volumes of data and explores patterns that might not have been visible to analysts, people can explore new perspectives emerging from the patterns and learn from this for their own personal growth. Similarly, as more time is freed, people can focus on leveraging their "human" strengths of seeing connections between problems and asking more first-principle-based questions. The new value here crystallises in how humans can develop new ideas on how to use AI to make processes not just slightly more efficient but completely redesigned and exponentially improved.

AI provides raw analytical power and combines it with strong pattern recognition and broad reach of use. Strategists can more easily observe and monitor a multitude of data points and get digested outputs. Humans are limited in this capacity, and it is unlikely that we will observe a change in human nature. However, with machines, we observe a radical change, as they now have powerful analytical capabilities at higher speed. Moreover, dovetailing the dataistic idea that data is grounded in "real truth" untainted by human subjectivity, several participants pointed out the value of using data analytics to stress the need for something in decision-making as well as defend one's past decisions more "rigorously".

Generally, however, the key value of AI boils down to *augmentation* and *enablement*. Augmentation of humans who can now make better decisions and afford more focused, creative, and people-oriented work. Enablement in the sense that proactive thinking and acting on data that was not possible in the past is now feasible with AI. We can super-power processes in terms of being actionable on the future, not only to inform strategy but also to design it. New, stronger analytics and other AI functionalities can give way to the execution of ideas that previously could not have been carried out. Herein, with AI's inherent dependence on data, such discussions on AI-facilitated enablement can lead us to consider how AI not only enables problems to be solved — as an object that is used; but in what ways does it also come to *define* the problems we solve, the objectives it thereby enacts, and how it can shape what we understand as problems to be solved. In this light, AI can be made sense of as a state of mind, as a way of thinking about problem-solving, highlighting precisely the Objectives facet of AI.

In the context of this oscillation between Object and Objective, the participants generally emphasised the nature of AI as a "*tool*" that can only solve very defined, narrow problems. Coming back to the emphasised value of saving human time and augmenting humans in their work, what materialises is the understanding that human time is a resource that should be used *differently.* And thanks to AI, it *can* be used differently. In this regard, the perception that human time needs to be saved to be allocated elsewhere, differently than it has been, and the perception of AI as a tool, signal a shift in socio-technical imaginaries. AI can be seen to be enabling humans to reach their *full* potential. Without this enabling and augmenting tool that AI is understood to be, humans are rather incapable of implementing solutions to complex problems. However, what becomes particularly insightful in this context is that inventiveness and the very use of tools can be seen as an innate human quality. AI, as a tool, thus comes to constitute an *extension* of what it means to be human.

Taken together, extraction and storage of data seem a natural given, data is there for transformation, which AI makes possible, and thus the normality of collecting, calculating, and storing is established. With the greater speed of change in the world, there is less clarity into what the future may hold, fuelling the desire to gain future insights. In this regard, reliance on AI is established in connection to what it makes *possible*. Nevertheless, such reliance on AI is not only bound to AI's presence and the possibility of use; reliance on AI is increasingly tied to its *necessity*. More widespread use of AI renders it a (strategic) resource that "inevitably" becomes more interwoven into organisational settings and practices. The participants' modality phrasings of possibility in connection to modality phrasings of necessity can be interpreted as creating socio-technical imaginaries where AI's necessity becomes increasingly *axiomatic*. In other words, we can start seeing how the normalcy that is increasingly embedded in the possibility of using AI today renders the *need* to use AI also increasingly self-evident and normal. As our participants highlighted, super-powering one's organisation with AI is gradually necessary for organisational survival and strategic flexibility in an interconnected, fast-paced, digital world.

Moreover, our participants also associated more demand for AI adoption today, and the axiomatic necessity, with the above ability of proactive decision-making. In an era of (fast-)changing markets, a sense of anxiety is felt in non-action or mere reactivity — or rather, non-*adaptability*. It is not only when one can "keep up" with the complexity and adaptiveness of our world, but when one can better *anticipate* developments and proactively *act on* these insights, that strategic thinking and organisations can truly thrive. In pointing out that embracing a "tech mindset" together with one's business knowledge is necessary today to leverage BD & AI for augmentation and enablement, the participants also conveyed how they see AI as being needed essentially "everywhere" in the future. AI becomes a cultural movement that will inevitably continue impacting our lives.

As such, these logics suggest that AI possibility and necessity are no longer distinguishable. The possibility of AI use is no longer an option, or an alternative luxury — possibility becomes necessity. In this blurring of boundaries, we can recognise instrumentarianism's mutually reinforcing imperatives. The logic of possibility is consumed by the instrumentarian drive, which supports the never-ending growth of possibilities, whereby possibility itself no longer constitutes a different pathway one can take; it becomes a necessity to follow such a path. Put differently; once AI starts being used, it *has to* be used to stay relevant as an organisation. In our understanding, part of the reason why the participants stress the usage of AI and emphasise that it is a tool for narrow, targeted application — that AI needs to be "plugged into" more holistic strategic endeavours to bring about augmentation and enablement — is the aspiration to plug AI more, in better ways, to make AI more widely applied.

The understanding that the leveraging of AI's potential is "not yet there" echoed throughout discussions. However, what became visible in this context is that the primary obstacle to experiencing more of the growth of possibilities does not revolve around the technical limitations of AI. Although our participants vehemently expressed the need to be aware of the flip side of the AI coin (stressing challenges of AI explainability, data bias, heavy computational, financial, and other requirements), they would often quickly shift their sensemaking focus. Most of our participants transitioned from these limitations and spent more time discussing the *people* involved in AI projects, the people not involved who should be, and issues arising from colliding mindsets and understandings. In essence, it is not AI that necessarily needs to evolve so that we can reap its potential. What is more hindering are the current common misconceptions surrounding AI, which are seen to stem from the lack of data and tech literacy, especially among executives in most organisations. Correspondingly, this suggests that what is "possible to be possible" does not apply equally to all organisations. Our participants' accounts advance the issue that there are many organisations and strategists who lack an understanding of the movings and logics of the AI environment of possibility and necessity, leading them to be left behind or struggling in the cultural rift that is at play.

At the intersection of AI knowledge and proactive strategic thinking for future adaptiveness, our participants' problematisations reveal a literacy gap not only in terms of being able to understand how the world of AI functions but ultimately a literacy gap in understanding how businesses can and need to function. Additionally, being more "tech-savvy" and possessing knowledge of and experience with using AI is seen to allow decision-makers to better grasp both sides of the AI coin. By extension, then, those more capable of grasping the intersection will be able to work with AI more strategically, i.e., more sustainably towards their preferred strategic visions of the future. Conclusively, what our participants' characterisations of BD & AI depict, above all, is the socio-technical coupling between their sensemaking of BD & AI and that of people and changing environments where certain types of knowledge, objectives, and ways of thinking are elevated.

6.2 How do the participants characterise strategic thinking?

The journey to answering this question has been a cloud of ambiguity. Since our first interview and persisting throughout all conversations, we could recognise that strategic thinking, in and of itself, is far from being a uniform concept. The notion that there is no one way of going about thinking strategically and no unambiguous, straightforward framework to follow strongly resonated in all interviews. Any clear answers in our participants' responses or direct illustrations of what (their) strategic thinking precisely is generally eluded their characterisations. They largely drew from the (changing) conditions and needs within their organisational environments, which suggests that if we want to understand how strategic thinking works, we necessarily have to consider *the environments it takes place in*. However, for most participants, straightforward characterisations of their organisational environments were as elusive as concise depictions of strategic thinking. Permeating all discussions, we can discern the sentiment that strategic thinking is something that does not necessarily *need* to be described and pinpointed. Instead, it becomes more useful to see it as something that *simply happens* in practice as we navigate complexity in order to better position ourselves in the future.

However, in piecing together various depictions, we can start understanding our participants' characterisation of strategic thinking as inherently constituted by and constitutive of its context and preferred vision(s) of the future. Strategic thinking comes to entail processes of *reflection* on current positions and desirable future places in order to support one's capacity to take adaptive decisions towards these places. It is bound to taking a *broad* view and developing an *understanding* of needs and forces at play in being able to satisfy those needs through strategic actions. It is also associated with recognising moments of execution — moments of deciding what to "bet on". Some participants also highlighted a focus on thinking more practically in operational terms. That is, associating strategic thinking not only with envisioning future outcomes but also the journeys to achieving certain goals.

In making sense of the varied assemblages of our participants' characterisations, bound to their recollections of situations where they recognise to have "thought strategically", we can argue that what transcends all participant accounts is a spectral nature of strategic thinking. It can be seen as a *spectrum of questions* about needs and gaps, tools and resources, driving forces and ecosystem (inter)connections. Correspondingly, "good/better" strategic thinking relates to one's *ability* to fluidly and adaptively move along this spectrum, answering varying questions at different spatially and temporally relevant points of the process. However, what makes strategic thinking "strategic" is the ability to answer the questions (i.e., make certain decisions) in a way that will approximate the overall spectrum towards one's preferred vision of the future. As such, we can come to view strategic thinking as a process whereby we need to be able to think about how these partial decisions will affect other outcomes and relations on the spectrum, how the scales will tip in a certain direction — how partial decisions will influence the bigger picture of the future we are trying to create. Ultimately, with this inherent recognition of complexity and adaptiveness, strategic thinking becomes a *microcosm* of spectral decision-making and balancing.

In this context, strategic thinking *oscillates* between functioning as a telescope and a microscope. It involves the need for understanding what is happening in one's surroundings through a more holistic, wider lens while contextualising insights into one's organisation. However, our participants stressed the simultaneous need to continuously align with others — mirroring the design thinking foresight perspective of designing and communicating about futures *with* others. This is ever more pivotal in today's globalised world, where decisions will, to a certain extent, affect the broader environment more quickly and extensively than in the past. Strategic thinking thus creates boundaries and ensures feedback loops within the ecosystem. Strong feedback loops and ties to the wider environment serve a risk-averse function, for example, as unintended negative consequences can be detected more quickly. However, they also constitute an opportunistic mechanism whereby new ideas can be socialised and developed through interactions with broader ecosystems; and future reciprocal benefits can be ensured when ecosystems are supported and engaged already today. As strategic thinking is understood to be tied to the viability of solving *multiple* problems rather than a single, isolated issue, adopting a wider lens also happens within a specific context.

What becomes particularly insightful is that another type of oscillation is embedded in strategic thinking. Our participants generally stressed the importance of a rigorous basis in data for making decisions, spotlighting the need to become more data-/AI-driven, mitigating human "messiness" and decision-makers' personal biases and limited perspectives influencing decisions. And although strategic thinking finds its ground in data, drawing on numerical insights, more "human" elements — intuition, human judgment, experience — play a major role in various parts of the strategic thinking process. The participants described how they engage their "gut-feeling", for instance, in the coding process, building and thresholding AI models, allocating time as a resource, or assigning employees to projects. The non-tangible human element of intuition mostly finds its useful place in supporting strategic thinking where AI fails. What AI currently cannot contribute to the microcosm are answers to certain transcending questions on the spectrum, as one of our participants (F) elucidated, where human judgment is necessary to answer:

> 'How do you know that you have a problem? How do you know when the problem is solved? How do you understand if you no longer have a problem? How do you know if you can move on? Am I okay with this? Am I doing the rights things?'

Ultimately, strategic thinking entails dealing with and balancing within a microcosm of decisions in an effort to approximate a future where strategic goals align with the future landscape; or where decisions have been balanced in a way that makes adaptation more easily feasible. There is an associated dual oscillation — between holistic and contextualised lenses and between reliance on data and intuition.

6.3 How do the participants perceive and envision the relationship between strategic thinking and BD & AI?

Building on the understanding of strategic thinking as constituted by and constitutive of the environment in which it takes place and how AI processes (and learns through) data from its environment, it becomes particularly illuminating to look at our participants' sensemaking of the current landscape. We are wrapped in a globalised web of connections between networks, organisations, individuals amidst a digital saturation of reality. Together with new technologies such as AI, not only is the speed of change heightened, perpetual change is here to stay. Correspondingly, the possibility of leveraging facets of the digital world to aid strategic thinking and be innovative is dethroned to a *standard*. Acknowledging, accepting, and embracing change is the new *norm*, superseded by the need to work with the ability of adaptation in novel, more enabling ways.

What our participants envision under this new approach is a *symbiotic* relationship between humans and AI. Symbiotic in the sense that it is *mutually* enabling and augmenting. On the one hand, AI provides raw data processing power and analytical capabilities; it enables humans to work with already pre-processed insights. But besides augmenting the quality of decisions, AI also possesses the capability to augment human judgment as humans can enrich their perspectives through "unexpected" patterns in data. On the other hand, "injecting" human judgment and critical thinking at various “checkpoints” in the process is seen as necessary to address parts of the microcosm requiring more “imaginative” input. Judgment and intuition complement AI applications as humans embed AI in a specific context, where AI’s capabilities can be used in order to approximate a preferred strategic outcome that also acknowledges the wider context. Human judgment augments AI by giving it feedback to learn from. It also enables the potential of AI when, drawing on specific domain knowledge, problems and/or needs are identified, which are then addressed using AI. Moreover, it safeguards AI’s value by recognising and mitigating layers of ethical implications in the context of wider ecosystems. Humans are also needed in the symbiotic process to keep *imagining* what else can be automated, what else can be enhanced and improved through AI. In this respect, accounts of the necessity to start with an identified (business) need, a specific problem to be solved, led to descriptions indicative of AI’s influence on problem-solving and decision-making. AI is seen to be pushing for a problem-solving approach that is more first-principle-based — ‘we start with a blank piece of paper’ (Participant A) and imagine an ideal vision of the future.

In combination with their accentuation that ‘using these technologies needs to be very strategic’ (Participant M), holistic, and critically reflective, we can come to understand strategic thinking as *shifting* towards a more imaginative and creative nature. Moreover, this imaginative focus weaves into the perceived transition ‘from a linear way of running organisations into something that is more dynamic’, more aware of and interactive with ecosystems. Essentially then, strategic thinking as human imagination is to be synthesised with AI output, whereby this synthesis is seen to happen at various points of the strategic process in acknowledgement of ‘machines’ dependency on us and [our] dependency on AI' (Participant H). As such, we can observe the need to focus on building towards “Humans *plus* AI” rather than versus.

In returning to our participants’ depictions of the current landscape as that of fast change and interconnectedness, this *reciprocally efficient* relationship between humans as strategic thinkers and AI *embodies* the called-upon novel way of better adapting amidst perpetual change and future uncertainty. Along with the conveyed sentiment that human time should be saved to be used differently, and AI thus representing an extension of what it means to be human, the envisioned symbiosis innately epitomises a *socio-technical relationship*. As the human being is elevated to the role of a supervisor, as being human is made inseparable from being creative and imaginative, the idea that technology is something neutral, merely a means to an end, is contested. As the vision of humans plus machines enters social life, so do corresponding visions of not only *what* is attainable through this symbiotic relationship but also *how* strategic processes ought and ought not to be approached and understood.

Moreover, these newly 'imagined forms of social life' (Jasanoff & Kim 2009:120) that shape 'deeper normative images' (Taylor in Jasanoff, 2014:10) of human capacities also invoke the question of: *Who* are these AI supervisors, these creatives, the humans with access to this new symbiosis? In this sense, what resonated strongly in the interviews is the socio-technical dual functioning of knowledge and power. Firstly, through the possession of certain knowledge, access to this symbiosis — the ability to imagine, create, and shape futures is made possible. Secondly, in understanding that 'it's humans trying to improve the life of other humans, it's not technology that is going to do this for us' (Participant F), it also becomes pronounced that it is not necessarily the technology itself that is changing forms of social life, but rather its use *through specific Humans*[21] that brings about certain constructions of reality. In this sense, possession of knowledge is tied to the agency in determining the 'conditions of possibilities for the social' (Jorgensen & Phillips, 2002:13–14). In other words, humans with certain knowledge become *the* Humans in Human+AI — determining the field of possibilities of the symbiosis and, consequently, determining which possibilities are turned into necessities.

However, our participants underscored that currently (perceived) low levels of data and AI literacy, clashing mindsets, and cultural structures need to be addressed in order to leverage the potential of Humans+AI augmentation. Greater

[21] The word "Humans" with capital "H" refers to people possessing the knowledge (data/AI literate) who work with these technologies and are, therefore, part of the symbiosis.

democratisation of access to the symbiosis is envisioned, which is understood to strengthen the symbiosis further as not only diverse opinions but diverse intuitions/mindsets enter the stage and more intense cross-collaboration between humans is stimulated. With this envisioned route towards democratisation, there is a recognisable sense of frustration as the desire to see more widespread Human+AI symbiosis, especially in more socially beneficial fields like healthcare, to engage more people and intensify collaboration, meets limitations of the current "real world". This frustration can primarily be traced to a perceived lack of literacy, largely derived from traditionally monolithic organisational structures and set-ups whereby legacy cultures and processes "of the past" now hinder the envisioned augmentation. In this regard, legacy cultures and data/AI illiteracy collide with the kind of socio-technical dynamics that AI calls forth — there is an inherent clash between the dynamic, webbed, democratised social ordering that is imagined with AI and the normative imagery of the past.

Consequently, what the sense of frustration and normative clash suggest is that there are certain values associated with the use of AI in a socio-technical sense. Emerging in a mutually constitutive manner, aspirations of "letting loose of the leashes" of traditional values of monolithic environments and being able to be creative, to engage in the symbiosis, are bound to the field of possibilities of AI as a technology. A field of socio-technical imaginaries engaged in (co)shaping "what can be" and "how it should be". Ultimately, these socio-technical imaginaries embedded in the Human+AI symbiosis are taken further as AI is seen to be sparking society-wide ripple effects. That is to say, as everyone gets more and more accustomed to the presence of these technologies and data literacy becomes a key basic skill in almost all professions, necessarily incorporated into all curricula of future education.

6.4 Revisiting the Theoretical Framework: Towards Re-Imaginations of ‘Human + AI’ with *Strategic Processing*

At this point, we wish to return to our theoretical framework to reflect on its relevance in making sense of the participants’ characterisations, experiences, and understandings. To reiterate, we have chosen to adopt such a conceptual assemblage given the absence of a uniform theory that would provide us with an understanding of the dynamics between strategic thinking and BD & AI in a more experiential sense that would be indicative of people’s sensemaking of such dynamics. Upon our analysis, the assemblage of dataistic and instrumentarian lenses underpinned by socio-technical dynamics, as well as the design thinking foresight perspective, jointly embedded in a complex systems framework, proved a useful lens in answering our research question; and getting a deeper understanding of the tech strategists’ sensemaking. However, through our analytical interpretations, certain logics of the conceptual assemblage were more explicative than others, itself a predictable outcome given the sheer complexity of the layers of various reinforcing logics involved and lack of a uniform pre-existing theoretical framework.

More specifically, the tech strategists’ sensemaking is not as intimately tied to the dataistic notion of the sanctity of data and data extraction for extraction and calculation sake as the dataistic “religion” maintains. Instead, it is the inherently associated, but in the context of the participants’ sensemaking, notably *different* logic that is more prevalent and socio-technically constructive. The instrumentarian imperative of (AI) *prediction* for modification — for the ability to be *proactive* on the future towards a preferred view of the future, is more actively present in their sensemaking; and further illuminating of the relationship with thinking strategically — i.e., thinking and acting proactive(ly). Similarly, the adopted perspective of strategic foresight underpinned by a design thinking mindset, which elevates the need to facilitate deeper connections with the environment in which futures thinking takes place, was helpful in making sense of the discussions behind a need for stronger ties and feedback loops. Finally, the lens of socio-technical imaginaries led us to engage in analytical interlacing of our interpretations, providing insightful ground to discuss the implications of our findings, to which we turn in the next chapter.

Our participants' sensemaking of what they do, how they understand and relate to BD & AI and strategic thinking resonates with our conceptual lens; however, when they explained all these logics and narratives, how they drew from their *practice-oriented*, on-the-ground perspective became insightful in an additional way. Although not initially intended to be a product of this thesis, we have developed a mental model based on such practice-bound sensemaking. This form of "added value" was primarily sparked by the richness of the material and the discussions we encountered during the research process. This model is by no means complete; it is rather an attempt at understanding what happens during the process of strategy development whereby BD & AI and strategic thinking are incorporated symbiotically. As such, the model can be seen as a step towards "translating" the heavy-weight, expert field of tech strategists as Humans to other humans.

We term this approximating attempt the *strategic processing* model. We chose to introduce the new term of "processing" upon recognising that the socio-technically shaped symbiosis of Humans+AI is constructive of new realities. Hence, merely combining the term "strategic thinking" with "AI" may render the intermingling of logics oversimplified, especially if presented as a mental model, i.e., a simplified visualisation of 'certain aspects of a phenomenon that matter, while keeping away distracting noise' (Schühly, Becker & Klein, 2020:127). As such, processing designates both the *processing* of data/information that is done both through AI models and human strategic thinking, and indicates that strategy development is a *process*, with iterations and loops.

In essence, then, strategic processing can be understood as the process of developing a strategy in complex systems by jointly employing BD & AI and strategic thinking. It functions as a continuous iterative cycle — a microcosm of decision-making, where the reciprocal push and pull forces act on various parts of the process. Combining both perceived strengths of Humans and those of AI, such a strategic processing approach aims to constitute a more adaptive approach to navigating complexity strategically in the context of decision-making. As such, this approach is only bound to incorporating AI for data analytics and use for predictive insights. The model itself consists of ten (iteratively re-visited) "phases" and can be seen below. For a more nuanced understanding of the necessary considerations in each phase, we offer a detailed version of the mental model in Appendix IV.

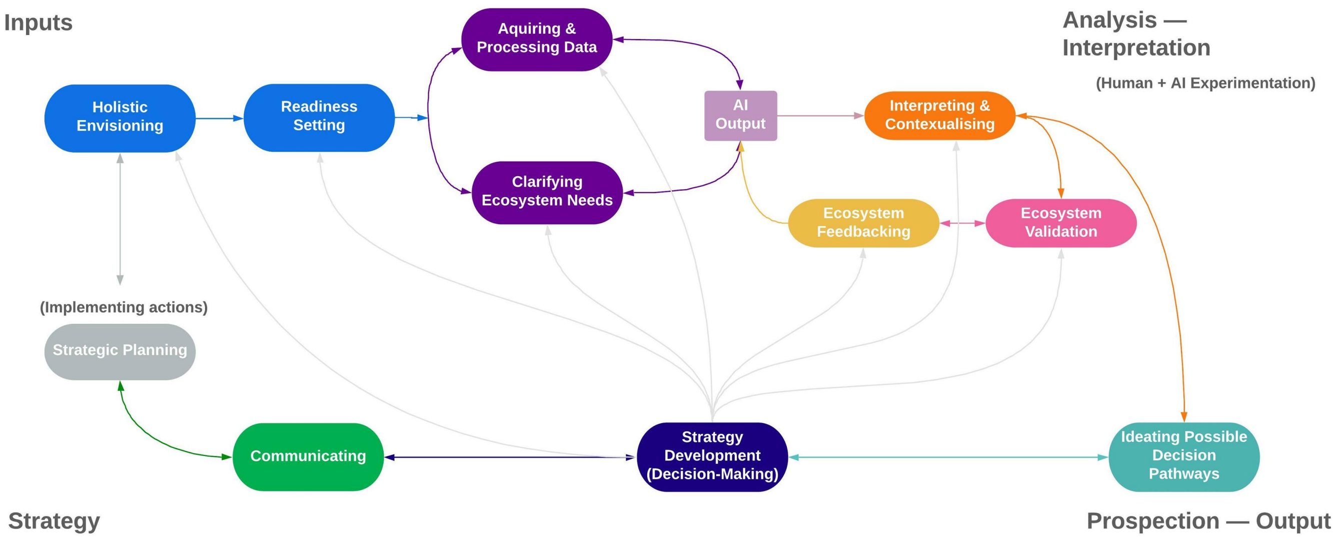

Fig. 5: Conceptual Model of Strategic Processing

7 Concluding Discussion and Remarks

On account of our analysis, we conclude that tech strategists make sense of the dynamics of strategic thinking and BD & AI in strategic decision-making based on, firstly, BD & AI are characterised by their wide-ranging potential. However, it is AI that is associated with a novel, *actionable* capacity through which knowledge of the future can be approximated and acted upon *proactively*. The key value of AI lies in this proactive capacity that opens up possibilities for augmentation and enablement, which are rendered a strategic *necessity* in our fast-paced, globalised, and datafied world.

Secondly, strategic thinking is characterised by how it is constituted by and constitutive of its context and preferred visions of the future. It entails dealing with and balancing on a *spectrum* of questions about needs, gaps, tools, resources, and ecosystem (inter)connections; while *oscillating* between holistic and contextualised lenses as well as reliance on data and intuition. In other words, strategic thinking constitutes a *microcosm* of sub-decision-making in an effort to co-shape and move towards a future, where the outcome(s) of previous spectral decision-making is aligned with the future landscape or is conducive to adaptability.

Thirdly, the relationship between strategic thinking and BD & AI is marked by its embeddedness in today's digital saturation of reality where acknowledging perpetual change is the new norm and more enabling ways of working (strategically) are perceived as required. This is envisioned through a *symbiotic* relationship between human strategic thinking, as imagination, and AI. Such a Humans+AI symbiosis is understood to carry great *potential*; however, major *obstacles* are perceived in most organisations today to leveraging this envisioned and necessary potential.

Lastly, several socio-technical imaginaries permeate the tech strategists' sensemaking of the dynamics. As visions of Humans+AI rise to prominence and fields of possibility are not only imagined but increasingly established and *merged* with fields of necessity, certain visions of what is attainable and how it ought (not) to be attainable enter social understandings. Through the association with the *enablement* of proactive adaptability and *augmentation* of human work and judgment, AI's field of possibilities is socio-technically expanded to constitute a tool that not only co-shapes problems(-olving) but what is perceived as more innately "human". However, the *enactment* of the (expanded) field of possibilities of AI brings about changes in social life, not merely through the use of this tool. Rather, through the use of this tool *in the pursuit of* certain normative images of the future — through Humans possessing and thus co-creating knowledge of AI's field of possibilities.

So what? First and foremost, our thesis provides a *humanised* view of the field of BD & AI by giving voice to experts from this field. Generally speaking, it provides *insight* into how such experts, as human beings, think and feel about the(ir) world(s) of strategic decision-making with the lens of BD & AI. In the context of the perceived bordered, divided, and misunderstood worlds of BD/AI/technology and of strategic management/business, this study can be seen as a step towards better understanding what is going on by offering a look into "on-the-ground" perspectives, narratives, and sensemaking of those who experience both of these worlds in their own contexts. By providing insight into these two worlds at their intersection, the relevance of this thesis also lies in its contribution to *bridging* the perceived gap in understanding. Given our participants' aspirations of democratising the world of AI, bringing in more mindsets, and intensifying collaborations, our thesis functions as a stimulus to this desired dialogue between Humans and humans.

Furthermore, through the specific findings we have drawn, this study raises *awareness* of the socio-technical functionings of technology. As such, we deconstruct the stereotype that technology is a mere "tool", a neutral "object" devoid of effects in the realm of the social. Rather, we explore how our engagement with technology comes to influence fields of (im)possibility in how we think about the world, how we engage in reciprocal relationships with technology, and ultimately, how we construct our reality.

Finally, and by extension, this thesis raises *questions* about what kind(s) of *knowledge* are being produced through these socio-technical imaginaries and functionings and the corresponding power dynamics bound to knowledge (and lack thereof). As Humans engage their intelligence — their imagination to envision preferred futures, to be proactive on the future, the kinds of questions they (can) imagine come to define the agendas of their thinking, and thus, determine the information they seek. Our participants discussed that as we become faster in perceiving the world around us with AI, we can spend more time reflecting on the "so-what(s)" of our decisions. However, similarly to this discussion on the implications of our findings, the positions we take and the worldviews we hold will shape the so-what(s) we draw and deem worthy of consideration and debate. Correspondingly, we need to look not only at the kinds of knowledge that are being produced and used but the *power* dynamics stemming from asymmetries in knowledge.

Thereupon, we suggest future research that could take these conversations further. For instance, an anthropological study of intra-corporate communication could be explored to obtain a nuanced understanding of the everyday workings and struggles in AI projects. Additionally, drawing on our participants' frustration about the obstacles to more democratised knowledge and access to the Human+AI symbiosis in traditionally monolithic organisations, ethnographic studies could shed light on how legacy structures constrain or effect "action from below".

On a final note, as technology solidifies its role in the fabric of social life and as questions of: Who knows? Who decides? Who decides who decides? come to define knowledge and power in our time; it becomes clear that these questions cannot be answered by one Human or one thesis, but rather as a result of *dialogue*.

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Appendix I.

Pilot Interview Guide

Based on our research question and theoretical framework, we developed an initial pilot interview guide. The following list of topics guided the first three interviews and was subsequently revised to generate material that would better enable us to answer our research question.

Big Data & Artificial Intelligence

- Immediate thoughts and impressions of BD & AI
- Describing BD & AI on a higher level
- Main features, functionings, and value
- Own use of BD & AI in terms of application workflows
- Meanings of BD & AI in own work
- Perceptions of BD & AI by colleagues in organisation
- Effects of BD & AI on own professional role

Strategic Thinking and Decision-Making

- Describing features of own organisational environment
- Describing requirements of organisational context for own role
- Processes of strategy making
- Features, resources, and challenges for successful strategies
- Changes and uncertainties in own organisational environment
- Strategic thinking meanings, processes, and experiences
- Challenges in thinking strategically

Intersections and Dynamics

- Role of BD & AI in strategic processes / decision-making
- Perceptions of strategic dynamics of BD & AI and humans
- Experiences of roles of humans and BD & AI in strategic processes / decision-making
- Perceptions of human and BD & AI functionings in strategic processes / decision-making
- Perceptions of future BD & AI applications

Appendix II.

Interview Guide

Following our three pilot interviews, we revised our initial pilot interview guide in order for the questions to better generate material in pursuit of answering our research question. The following list of topics guided our interviews with room for variation and adaptation depending on the participants' professional role(s) and their answer directions during the interviews.

Big Data & Artificial Intelligence

- Immediate impressions of BD & AI
- Explaining BD & AI
- Experiences with use cases, workflows, practicalities
- Perceived enablers and blockers in adoption
- Perceived changes

Strategic Thinking and Decision-Making

- Perceived features of own organisational environment
- Perceived strategic resources in organisational environment
- Perceived challenges and opportunities in navigating organisational environment
- Strategic thinking meanings, processes, and experiences

Intersections and Dynamics

- Perceived effects of BD & AI on strategic processes / decision-making
- Characteristics of problem-solving with BD & AI in strategic processes / decision-making
- Perceived considerations of BD & AI in strategic processes / decision-making
- Perceived roles and functionings of humans and AI
- Perceptions of future developments of BD & AI in strategic processes / decision-making

Appendix III.

Informed Consent Form

The informed consent form sent out to the participants prior to their participation in the study included an information letter, terms and conditions of participation, as well as contact information pertaining to both the researchers and the thesis supervisor. The entire form is attached below:

Informed Consent Form

Project Title:

Master Thesis: Leveraging and Being Leveraged by Big Data and Artificial Intelligence

Researchers:

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Level: Master

Information

Veronika Wilhelmová and Woo Seung Shin are studying Management at Lund University, writing their Master thesis with this study. They are supervised by Programme Director and Senior Lecturer, Ph.D. Stein Kleppestø.

Big Data and Artificial Intelligence are terms constantly permeating discussions in our contemporary digital world, be it discussions about technological innovation, the economy and new types of stakeholders, platforms of education, business investments, ethics, or social change. The applications and far-ranging effects of these technologies are increasingly present in academic articles and discussions; nevertheless, research exploring the dynamics of these technologies and strategic thinking as experienced on-the-ground is scarce. This study humbly aspires to explore this research gap, contributing to a conceptual understanding of these dynamics.

The purpose of this qualitative study is to explore how strategy-involved practitioners make sense of the presence and practices of Big Data & AI in the context of VUCA environments (i.e., under complexity, uncertainty). To this end, the study aims to create a conceptual understanding of the experienced dynamics of Big Data & Artificial Intelligence and strategic thinking in the context of our world. In order to investigate this phenomenon, we conduct a series of 1–2 hour semi-structured interviews with strategy-involved practitioners experienced in working with Big Data & Artificial Intelligence in their organisations.

The number of participants is expected to be approximately 10. The study will take place from January to June 2021. Anonymity and data safety are guaranteed for the participants and their identity will not be exposed.

Please read the following terms and conditions of this study designed to ensure fully informed consent.

I hereby agree to the following:

- I…………………………………..voluntarily agree to participate in this research study.
- I understand that even if I agree to participate now, I can withdraw at any time or refuse to answer any question without any consequences of any kind.
- I understand that I can withdraw permission to use data from my interview within one week after the interview, in which case the material will be deleted.
- I have had the purpose and nature of the study explained to me and I have had the opportunity to ask questions about the study.
- I understand that participation involves an interview, which will serve as data in a Master thesis for the Management programme at Lund University, Sweden.
- I understand that I will not benefit directly from participating in this research.
- I agree to my interview being video-recorded.
- I understand that all information I provide for this study will be treated confidentially.
- I understand that the recorded material will be discarded after the completion and evaluation of the research project.

- I understand that in any report on the results of this research my identity will remain anonymous. This will be done by changing my name and disguising any details of my interview, which may reveal my identity or the identity of people I speak about.
- I understand that disguised extracts from my interview may be quoted in the Master thesis of Veronika Wilhelmová and Woo Seung Shin, which may be uploaded on the electronic platform, Lund University Publications [LUP] (www.lup.lub.lu.se).
- I understand that if I inform the researchers that myself or someone else is at risk of harm, they may have to report this to the relevant authorities – they will discuss this with us but may be required to report with or without my permission.
- I understand that signed consent forms and original video recordings will be retained in the researchers' personal, secured hard disks in Malmö and Lund, Sweden, and that only the two researchers themselves will have direct access to the raw data.
- I understand that a transcript of my interview in which all identifying information has been removed will be retained by the researchers.
- I understand that the transcribed material will be discarded after the completion and evaluation of the research project.
- I understand that under freedom of information legalisation I am entitled to access the information I have provided at any time.
- I understand that I am free to contact the researchers to seek further clarification and information.

Researchers:

- Veronika Wilhelmová, Management Master student at Lund University / E-mail: ve3034wi-s@student.lu.se / Phone: +420 733649930
- Woo Seung Shin, Management Master student at Lund University / E-mail: wo7774sh-s@student.lu.se / Phone: +46 769110589

Supervisor:

- Ph.D. Stein Kleppestø, Senior Lecturer at Lund University / E-mail: stein.kleppesto@fek.lu.se

Signature of research participant

I hereby submit my consent to participate in this study

Signature of participant

Date: ______________________

Signatures of researchers

I believe the participant is giving informed consent to participate in this study

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Signature of researcher
(Veronika Wilhelmová)

Signature of researcher
(Woo Seung Shin)

Date: ______________________

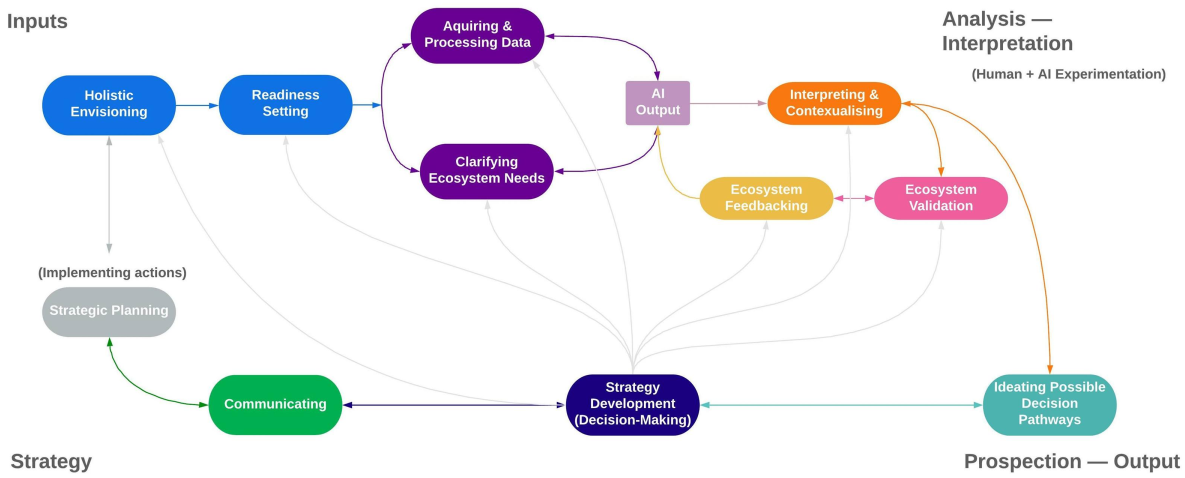
Appendix IV.

Data Connections: Integrative Diagram

Fig. 6: Integrative Diagram of Research Data

THEMES – CATEGORIES – TOPICS		
Realms of Strategic Thinking	**Realm of Emerging Tech**	**Realm of New Dynamics**
Identified based on anything that relates to being strategic, creating or executing a strategy, any processes considered strategic, meanings and understanding of anything strategic, actions understood as strategic, values and norms attached to strategic meanings and actions.	*Identified based on necessities involved, challenges and opportunities involved, connections/relations involved, co-functionings and interactions involved, various dynamics, trade offs, effects and influences.*	*Identified based on impressions of the tech, essence understood of the tech, what it is and is not, features of the tech, capabilities and limitations of the tech, effects and influences of the tech, norms and values attached to the tech.*
Knowing the Future to Act on It Today	**Need for Joint Augmentation Processes**	**New Omnipresent Value Potential**
Forward-looking, envisioning approach towards preferred future	Need for symbiotic co-functioning between human & AI	New opportunity for value creation
Knowing the future positioning favourably for the future	Natural phenomenon towards the digitalisation due to keen necessity of it to survive in the environment	Strategic upskilling required for accelerating adoption of BD/AI and embracing continuous change of the technological development
Vision and pathway to goal setting	Pursuing Human In the Loop in AI	Differences in how people understand tech, debated, spectrum from buzzwords
Modelling opportunities	Balancing quantitative and qualitative validation	Frustration for not being able to embrace the technology and see benefits
Anticipating risks	Combining first principle thinking and empirical approach with BD/AI	People haven't realised they can benefit from AI use cases
Pre-emptying risks that might come up	Strategic leadership (purely at human's realm) required when working with AI projects	Value of AI depends on value for whom
Rather than merely prediction, more about understanding gaps, needs, how to deliver the most value	Ethical consideration (purely at human's realm) required when working with AI projects	Typology of AI models depending on suitability to problem
Being reactive vs. Preventive/Proactive	Human connecting the dots and taking course of action out of the narrow AI result	Opportunities for our whole ecosystem
Being actionable and practical	Human judgement / involvement depends on time available	BD= boring vs. AI value
Dealing with limited resources, prioritisation and trade-offs	Different levels of human injection required depending on the characteristics of the problem to solve	BD containing meanings
Dealing with time limits and horizons	Human contextualising and interpreting the AI result for making decisions that make sense	AI is conversion of a large dataset to a mathematical equation that will calculate something of useful
Having open mindset, embracing new perspectives (Not jumping to assumptions)	Need of human role for storytelling	BD & AI for seeking opportunity
Tendency to compare yourself to what other people are doing	Influence of communication in AI projects	BD & AI are in symbiotic relationship
Understanding what to bet on under uncertainties	Leveraging BD & AI for humans to exercise more of creative thinking	Rationalist vs Empiricist approach to BD & AI
	Ripple effects of AI	BD & AI being able to turn data into information
Necessity of Adaptation	Humans add their own flavour to the data set for preferred decision/strategy making process	Anything can be leveraged by BD & AI
Future is nonlinear		BD & AI can make a "Change"
World is fast-paced and changes happens fast with accidental effects and impacts (adding to complexity nature)	**Real World Limitations of Humans + Tech Symbiosis**	Insights allow humans to transit from reactive to proactive decision making
Increasing future adaptability to cope with uncertainty	Challenge of perception AI is ready-made food	BD & AI enables faster decision making for reaching targets proactively
Prioritisation of necessary limited resources	Underestimated AI requirements	Processing mining helping business to improve by looking at more holistic view from data perspectives
Knowing that there is a lot of information flow requires us to adapt to the trend	Huge amount of work for AI	Novel technology offering positive and negative sides
Desirability to be able to predict	High demand of change management	Seeing potentials but unprepared for the unknown
Being risk-averse and opportunistic	Requires long term vision and patience	AI removes tedious work
Necessity of experimentation and learning, and self-reinforcing cycle	Under-recognised crucial role of culture, mindset, and change management	AI is a way to react to different circumstances and make decisions based on data
Knowing what resources are required for upskilling	Data as metal - 10% is useful, the rest is garbage.	New ability to be more efficient
Being as modular as you can	Necessity of data cleaning	Pursuing AI for good
Necessity of adaptation capability to change	Needs for covering the gap between business needs and technology	Leveraging data for the better quality of humanity
Being responsible for sustainable future orientation	Starting with defining use cases, needs, values, and consequences the technology would bring.	AI as a methodology trying to mimic humans.
Strategy being formulated through at all levels	Providing and communicating concise information and exact needs.	BD & AI Leveraged by financial value (aiming for cost reduction and revenue generation)
Setting up boundaries for manageable (digestible) operations	Top down digital leadership approach for facilitating the AI deployment needs	BD and AI as essential asset to stay competitiveness in the market
	Necessity of tech justifications	Excitements around AI developments in the healthcare sector
Looking at Ecosystems and Contexts	Domain knowledge employed at the project scoping and during the validation process.	Constant generation of digital footprints
Ego to ecosystem thinkings	Start with low hanging fruit and demonstrating meaningful change possible with BD & AI usage	AGI future far away
Small decisions tied to bigger decisions	Necessity of digital resources, infrastructure and trade-offs within available resources	
Interconnected problem-solving approach	Silos, legacy systems = unhealthy	**New Capability of Predictive Data Processing**
Need for creativity in strategy	Necessity of testing, verifying and tradeoffs within available resources	New ability to draw predictive insights for decision-making
Necessity of critical thinking	Necessity of balancing time	Processing real-time evolving and updating data
Need for human judgement and intuition in balancing decisions	Thinking like Big Tech (Technology embracing mindset - focus on revenue generation through tech, than cost reduction)	AI enables predictions = desirable
Understanding and tailoring to own context and needs	Cross-collaboration = necessary	Dealing with complex systems will be possible
Need-Based / Problem-Based Strategy	Coordination as critical needs	Enabling optimisation of decisions = desirable
Regulatory influence	Emphasis on practicality of AI (implementation possibility)	AI drives strategy, differences between companies, past vs. present + AI for problem-solving
	Diversity of thinking and opinions = challenge and combination opportunity	AI unrelated influence on strategy
Reliance on Data Amidst Human Limits	Translation necessary	AI for organisational survival
Strategy based on data	Need for diversity	Insights allowing us to transit from reactive to proactive decision making
Objectifying decision-making	Necessity of involving stakeholders	BD & AI leveraged for adapting to the complex environments
Ability to defend oneself with data	Mindful BD & AI usage in consideration of ESG	
Limitations to human complexity navigation capabilities	Necessity of experience in contexts and deployment in practice	**'Just' Single Problem 'Tools' for Holistic Use**
Humans can't work as efficient as a computer can	Data quality important over volume	AI is just tools
AI being able to crunch huge datasets	Access to data is challenging	Overrated BD & AI
Undesirability of human bias	Constant learning for enhancing AI confidence level	Disillumination & hyped expectations on what BD and AI can do (especially from the senior management)
Computing is not a problem for computers but is for humans	Necessity of human's mitigation efforts in between the blackbox model	AI cannot think = limitation
Humans tend to be messy	People unaware of tech impact	Insular nature of AI
	People without understanding are afraid, fear	Realization: not simple one-size fits all answer
Pursuit of People, Culture, and Change	Inherent limitation on not explainable AI	Need for holistic AI implementation and balancing resources holistically
Necessity of collaborative and learning culture and mindset	Achieving convincing standing of AI Explainability.	Slicing up problems = necessary
Necessity of talent and interdisciplinary skills	The obstacle is not high or low AI maturity but lack of competence of application of AI model	AI project scaling = desirable
Empowering "missionaries" not "machineries".	Desire to become data-driven organisations but face difficulties to adopt it successfully	Different use cases exist
Having data science team and business team aligned	Most companies struggle	
C-team taking ownership of AI and promoting it throughout the company	Resistance to change is a challenge to AI adoption.	**Recognising the Path of Uncertainty**
Importance of human feelings in decision-making	Less focus on value identification due to limited time and resources	Less reflection on purpose of the BD & AI usage (Why and for whom we are using the AI)
Empathy as an important skill	Knowledge power limitations in terms of whose foresight	Historical data can potentially mislead us for prediction (Uncertainty aspects)
Strategic cornerstone is up-skilling resources	Lack of (management) knowledge about tech	Historical data limitation under change
Data literacy as key in environments	Generational knowledge gap on AI technology	Data quality important over volume
Socialising for ideation and collaboration	Importance of learning, education, upskilling to work with data	Access to data is challenging
Importance of leadership for empowerment and alignment	Seeing benefits / values = more use, need to see results, buy-in	Need for avoiding biases + Setting human values into AI = challenge
Effective communication to align people to execute vision	Divide between We Tech vs People Non-tech = Perceived as issue by We Tech	Controlling the tech is necessary
Consideration of stakeholders, and greater society	Democratisation of tech knowledge / use has impact, need for accessibility	Trusting/Embracing the tech is necessary
Decentralised way to scale value creation		Need for responsible AI
	Time	Need to anonymise data
	Effects of time constraints	Considering Safety and harm influence
	Optimising tasks needed	Necessity of XAI
	Strengthening feedback response time	Thinking about ethics
	Measuring required time = challenge	Desire of AI for good
	Time allocated based on values	New (and unknown) dynamics and forces
	Time desired for reflection	
	Time-induced biases	
	Reciprocal "push and pull effects"	
	Endless strategic processes	

Conceptual Model of Strategic Processing



Inputs

Holistic Envisioning

- Understanding the capabilities and limitations of BD&AI;
- Understanding present surroundings and own organisation's relations to it;
- Envisioning mid- to long-term objectives to position oneself favourably and sustainably for the future;
- Identifying needs/gaps (problems) for future positioning and adaptability;
- Engaging in first principle thinking about identified problems;
- Envisioning how the gap between present and preferred future can be bridged in practical terms, incl. reasoning how and why envisioned tools are suitable for that purpose (incl. BD&AI);
- Risk assessment of multi-layered consequences of tools used (incl. BD&AI);
- Prioritising objectives based on available resources.

Readiness Setting

- Nurturing a culture of interdisciplinary learning and collaboration, and supporting the development of interdisciplinary skills, data literacy for individual empowerment and organisational adaptability;
- Aligning teams on vision of preferred future (esp. data science and business teams);
- Ensuring top down buy-in from executives;
- Democratising access to data, decentralising architectures, breaking down siloed structures;
- Opting for an initial low-hanging fruit approach to explore future possibilities;
- Identifying necessary resources (incl. digital assets, human resources, finances, etc.).
  - Understanding how digital assets will be sourced, aggregated, synthesised, incl. data governance and data ethics.

Acquiring & Processing Data

- Collecting and fine-tuning data;
- Translating organisational structure into a computational format;
- Developing own methodology and building AI models suitable for envisioned objectives;
- Feeding appropriate (in consideration of necessary quality, volume, source diversity) data into AI models.

Clarifying Ecosystem Needs

- Re-evaluating appropriateness of used datasets to identify potential new data sources and improvements to AI models.

Analysis — Interpretation

Interpreting & Contextualising

- Initial judgment of AI output: inferencing on results (identified patterns) by scrutinising correlation and causality;
- Contextualising insular AI output with reference to domain knowledge;
- Incorporating diversity of judgment (opinions, mindsets, backgrounds, etc.);
- Scrutinising applied judgment (intuition);
- Allocating time for reflection;

Upon reiteration, before moving onto ideation: compromising on point of "sufficient enough" quality of interpreted and contextualised output in order to proactively respond (i.e., to move towards ideation and decision-making).

Ecosystem Validation

- (Re)defining testing boundaries;
- Constant re-evaluation of AI trustworthiness, incl. over-reliance on AI output;
- Compromising on possibilities for human intervention and judgment based on problem complexity and necessary speed of response;
- Re-evaluating validation processes and considering possible improvements to validation;

Ecosystem Feedbacking

- Feedbacking AI to enhance confidence level, based on human judgment of meta-questions, e.g.:
  - "Does the model solve the problem (desirably)?"
  - "How will the solution relate to/influence other problem (solutions)?"

Prospection — Output

Ideating Possible Solutions

- Engaging in divergent and convergent thinking on output to create value (i.e., imagining decision pathways and relating them to wider ecosystems)
- Turning insights into possible actionable decision pathways that would increase future adaptiveness;
- Acknowledging ecosystem interdependencies and tailoring decision pathways in consideration of ESG;
- Embracing lack of future certainties during ideation of decision pathways.

Strategy Development (Decision-Making)

- Selecting preferred decision pathway in line with holistic envisioning (i.e., strategic decision-making);
- Recognising push and pull effects of such undertaken decision pathway on future strategic processing(s).

Communicating

- Engaging in storytelling on developed strategy to stakeholders;
- Alignment on vision and decisions within each phase of the process;
- Socialising on additional ideas within each phase of the process.

Strategy

Fig. 7: Conceptual Model of Strategic Processing (detailed)