From Human Intelligence to Artificial Intelligence

An exploratory study of how organizations manage adoption of AI analytics from a change management perspective

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Abstract:
Artificial intelligence, claimed to represent not only the future of technology development, but also a fundamental shift of our society, has become a hot topic among today's business, when the idea of "data-centric decision making" resulting in better firm performance is shared by more and more researchers and practitioners. However, the number of organizations who have successfully adopted AI analytics into their business is limited. Built on prior research on technology adoption and digitalization in organizations, the study combines two theoretical concepts - dynamic capabilities and three-stage of change, to understand how organizations manage adoption of AI analytics. The results confirm that both dynamic capabilities and change management practices taken at different stages play an important role in organizational AI adoption. Further, the study suggests that they exist in an interrelated co-evolving relationship, and that through the interplay of these two dimensions, organizations develop their readiness for future changes.

Keywords: Artificial intelligence, AI-driven Analytics, Change Management, Three-Stage of Change, Dynamic Capabilities

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Chapter 1. Introduction

1.1 Background

"The future is already here — it's just not very evenly distributed."

William Gibson

In the year 1947, the transistor was invented, paving the way to more advanced digital computers. In the 1970s, the first home computer appeared in public eyes. In the 1980s, computers made their way into schools, households and businesses. In the 1990s, Motorola created the first ever mobile phone, and the World Wide Web was invented and became publicly accessible. Two decades later, by 2016, nearly half of the world's population had become internet users, and by 2019, 48% of the total internet use time will be conducted via mobile phone (Kemp, 2019) This is a brief history of the digital revolution, and the introduction to humanity's digital transformation story.

Today, we live in an increasingly digital world, and whoever holds access to the information holds power in their hands. In the late 80s, less than 1% of the world's technologically stored information was digital. Less than 30 years later, the proportion was judged to have risen to 99% (Hilbert & Lopez, 2011). Today, it is estimated that there are 2.5 quintillion bytes of data created every day (Marr, 2018). With the enormous and ever-growing amount of data generated and collected, and the advancing capacity of data storage and growing computing power, it is no surprise that today's businesses are becoming more and more data centric. Furthermore, topics like artificial intelligence and advanced analytics appear everywhere from countless discussions and articles, to tabloid headlines about its effects, and marketing campaigns.

In this digital age, AI (artificial intelligence), is becoming widely discussed, with some claiming that it will be revolutionary. The technologies underlying it keep moving forward, enabling applications like self-driving cars, facial recognition on smartphones, and AI-algorithms to diagnose diseases. At the same time, it can also provide companies with deeper understandings of end markets, assist managers with organizational decision making, and potentially even predict the future state. With its constant advancement and progression, AI is expected one day to fundamentally change the way people work (McKinsey Global Institute, 2018).

BlackRock, the biggest investment firm in the United States, is attempting to develop a fully automated investment program - Robo-Advisor 4.0 (Tokic, 2018), utilizing advanced analytics and artificial intelligence, to replace human stock-pickers. As opposed to technical analytics, the goal of Robo-Advisor 4.0 should be able to conduct fundamental analysis in active investment management. Could the success of this robo-advisor could potentially lead to the replacement of human intelligence with AI in a broader industrial context? Will the rise of "Robo-Bosses" one day put many high-level decision-making managerial jobs at risk just as how we've been speculating? (Tokic, 2018). Although no one knows the exact answer to this question, some researchers propose a concept of complementary and collaborative intelligence between human and AI in future organizations. (Wilson & Daugherty, 2018; Calabretta et al, 2016; Jarrahi, 2018; Campbell, 2016).

However, although AI represents the future of not only technology development, but also fundamental shift of our society, according to Mckinsey Global institute (2018), only a handful of pioneering companies have adopted AI at scale. Bughin (2018), studying 3,000 AI-aware C-suite executives and another of 1,600 global executives, claims that more than 95% of companies have not yet embraced AI and advanced analytics to reinvent how they do business. While the potential application areas for AI are considerable, there appear to be significant forces holding back most organizations from using the technology. To present more insights on how AI analytics adoption occur on organizational level and to better prepare today's business for the upcoming future, this study will look inside organizations who have embarked their AI analytics journey and provide up-close view on how it is adoption is being managed.

1.2 Research Gap

While AI (artificial intelligence) in analytics has generated huge interest and attention in academic research in for example computer science and information management science, extant business research aims at presenting a holistic view of AI strategy, adoption and challenges spanning a complex set of AI applications. Although prior research on digitalization and technology adoption can provide a glimpse into AI analytics adoption in organizations, prior research is done on older sets of technologies in a different context. In order to understand how AI analytics is being adopted in organizations, the authors argue for the need of further research on this area

1.3 Purpose & Research Question

The purpose of the study is to investigate how "artificial intelligence" in "advanced analytics" ("AI analytics" or "AI" used in following texts) adoption on organizational level is currently being managed inside the company. The study aims at filling the purpose by examining the following research question:

How do organizations manage AI adoption from a change management perspective?

To answer this question, the authors separate the main research question into two sub questions, built on two distinct yet closely related theoretical concepts:

Applying dynamic capabilities view, the authors study what organizational characteristics are associated with successful AI adoption, by examining micro foundations, *"the organizational and managerial processes, procedures, systems, and structures that undergird each class of capability"* (Teece, 2007).

Adopting 3-stage of change model, the authors study organizational AI adoption as a change management process by analysing change management practices direct or indirectly taken by change agents, defined as "the individual or group that undertakes the task of initiating and managing change in an organization" (Tschirky, 2011) in the adoption process.

The two sub-questions are framed as:

Sub-question 1: What organizational micro foundations undergird the dynamic capabilities for AI adoption?

Sub-question 2: How do change agents support driving forces to enable organizational AI adoption?

1.4 Research Outline

To gain deeper understanding and generate new insights, the author conducted an explorative qualitative study, looking into organizational AI adoption initiatives in a wide range of organizations. An abductive approach - systematic combining, which allows the authors to go back and forth between empirics and theories, was then chosen to lead the research direction. During the research process, the issues at hand and the analytical framework are excessively reoriented when confronted with the empirical world (Dubois & Gadde, 2002).

The study is divided into two parts: pre-study, consisting of two interviews with two experts in academia and attending a two-day data innovation summit held in Stockholm, with workshops and lectures, in order to take part in the most up to date topics and discussions in the subject field before entering the research. Parallel to the pre-study, the authors searched and reviewed a wide range of related literature to identify the empirical knowledge gap and preliminary theoretical constructs to guide the authors' exploration in the empirical field. The main study was then designed accordingly, consisting of 16 interviews.

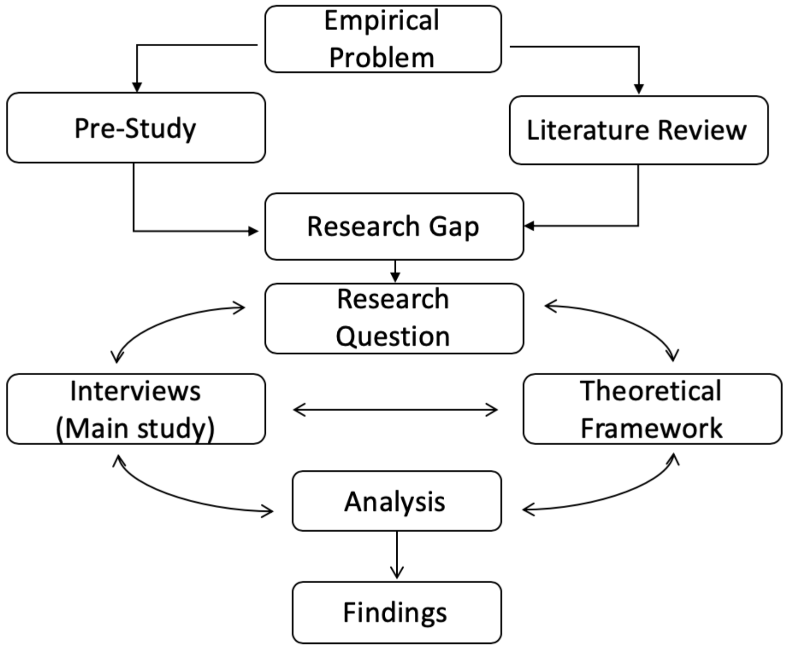

Figure 1: research outline

1.5 Delimitations

While the topic organizational AI adoption present considerable interesting areas of study, due to backgrounds in business and management and lack of technical expertise, the authors delimit the study to understand how organizations manage AI adoption from a change management perspective. Further, as AI comprises a set of complex technologies, the study is delimited to AI solutions in analytics. Due to a possible unbalance in AI adoption rates between different geographical areas, the study is further delimited to the Nordic region, where digital maturity is recognized to be among the highest in EU (Nordicom, 2018) and also where the authors are located. Moreover, as AI adoption for most organizations, is still at its very early stage (McKinsey Global Institute 2017, 2018), the study is delimited to medium and above size organizations who have started to make progresses, in a wide range of industries.

Chapter 2. Literature Review

The following chapter reviews research literature relevant to the study. It begins by reviewing literature on technology adoption in organizations in general. Next, literature on digitalisation and digital transformation is reviewed, as this is argued to precede AI adoption (McKinsey Global Institute, 2018). As the research area is quite technical, an explanation of technological terms and concepts is then provided. Finally, current literature on AI adoption is reviewed. As this is a relatively recent phenomenon, the number of studies published on the topic is limited.

2.1 Technology Adoption in Organizations

The section provides an overview of what has been written about technology adoption in organizations. As the adoption of AI is an example of this, it is relevant to review studies on the adoption of earlier technologies.

There exists a stream of prior research on organizational adoption of technologies. Particular attention has been given to IT and communication systems, as they have received a substantial portion of organizational investments for the past 50 years (Hillmer, 2009). Studies revealed that many of these implementations failed, often for reasons not caused by the technology itself (Brynjolfsson, Renshaw & Van Alstyne, 1996). More emphasis was put on technology adoption to study if the technology is being "used appropriately" (Hillmer, 2009) within the organization. Leonard-Barton (1988) argues that technology rarely fits perfectly into the user environment from the start, making an adaptation process necessary.

There exist several theories on the factors that facilitate the adoption process of new technologies. Diffusion of innovation theory links adoption to perceived usefulness of an innovation, norms within the particular social system, and communication efforts by change agents (Hillmer, 2009). Technology implementation process theory likewise emphasises the importance of "opinion leaders" within the social system, and that perceived riskiness of the technology is negatively correlated with its likelihood to be adopted (Leonard-Barton, 1983; Hillmer, 2009) Adoption of new technology is argued to often necessitate substantial changes to the organization's practices, structures, and strategy (Brynjolfsson, Renshaw & Van Alstyne, 1996).

IT adoption in particular often failed because too much focus was put on the technology and too little on the organizational aspects (Brynjolfsson & Hitt, 1996). Successful technology adoption was argued to be connected with stakeholder involvement, changing the human resource practices in accordance with the new systems, and being aware of the wider implications that the new technology would cause, in that it would likely affect many parts of the organization due to interdependencies (Brynjolfsson, Renshaw & Van Alstyne, 1996).

2.2 Digitalization and Digital Transformation

The section provides an overview of what is currently being written about digitalization and digital transformation. AI adoption is described as a next possible step after having undergone a successful digital transformation (McKinsey Global Institute, 2018), pointing to the two areas being related.

The term *digitalization* is broad, encompassing a number of different organizational changes and uses of technology. It is by Gartner (2018) defined as "the process of moving to a digital business", which is described as the "creation of new business designs by the blurring of the physical and digital worlds" (Gartner, 2018). Another definition (IDG Research, 2018) is of digitalization as a process which utilizes digital technology to "create new values and competitive advantages through new business models, offerings, and partnerships". It is not just about increasing efficiency of existing processes, instead, it has changed fundamentally how business is done and value is created (Andersson et al., 2018; Henriette et al., 2015; Bonnet & Westerman, 2015; Soule et al., 2016).

Digitalization has been ongoing for decades and has now reached all sectors of society (Andersson et al., 2018). It tends to cause wide-reaching changes to the organizations undergoing it (Henriette et al., 2015). Studies indicate that most organizations expect that digital trends will disrupt their businesses to moderate or significant extents, and that they have started adopting "digital first" strategies in response. Still, many respondents think that their companies are unprepared for these changes (Buckley et al., 2016; Grand View Research, 2017).

A number of approaches to digitalization are suggested by the literature and it is argued that there is no "silver bullet" solution for every company (Parviainen et al., 2017). Nevertheless, approaches on how to manage digitalization have been proposed, as well as common characteristics of organizations that succeeded (Buckley et al., 2016; Bonnet & Westerman, 2015; Kane et al., 2017).

In terms of the management of the transformation process, leadership support is brought up as important in order to drive through digitalisation efforts (Andersson et al., 2018; Nadeem et al., 2018), and similarly that the organization has a clear digital strategy that it is pursuing (Kane et al., 2017; Buckley et al., 2016, Fehér & Varga, 2017). As the transformation implies a shift towards a more digital organization, efforts should also be made towards building up a well-developed IT infrastructure (Soule et al., 2016).

Regarding organizational characteristics, a digitally skilled workforce is argued to be important (Soule et al., 2016; Fehér & Varga, 2017). Structures that foster high degrees of cooperation and collaboration are argued to be beneficial for digitalization efforts (Andersson et al., 2018; Maedche, 2016,), both in terms of collaboration between different functions of the same organization (Dremel et al., 2017), and outside traditional organizational boundaries (Andersson et al., 2018; Svahn et al., 2017). Some also argue that flatter hierarchical structures are desirable (Andersson et al., 2018).

Particular cultural attributes are also connected with successful digitalisation. That the organization fosters experimentation is claimed to be positive (Buckley et al., 2016, Fehér & Varga, 2017), one argument for this being that many digital systems benefit from being tried out in a small scale and then scaled up to enterprise level if they are proven to work (Dremel et al., 2017). Expanded appetites for risk taking is argued to characterise the cultures of digitally adept organizations (Buckley et al., 2016, Fehér & Varga, 2017), seemingly because many digital initiatives are highly exploratory and uncertain, and thus prone to failure.

Additionally, Soule et al. (2016) posit that as digitalization relies on technologies that are continuously changing, a truly digital organization must have “the sustained ability to rapidly take advantage of emerging digital possibilities”, which they term *digital dexterity.* This is claimed to be possible to achieve via acquiring underlying organizational characteristics (Soule et al., 2016) similar to those reviewed above, implying that there may exist organizational change capabilities related to digitalization in particular.

2.3 Current State of AI Analytics

This section provides an overview of relevant technologies and terms that are often touched upon in industrial reports and business research, in comparison of each other. The scope is adjusted to fit into this paper’s context - to answer, “what do we mean when we say AI in analytics?”

Business intelligence

Recent advances of the data technological evolution have tremendously improved organizations’ capabilities to collect, store and process unprecedented volumes and types of data and provide analytic insights over the last two decades (Kowalczyk, 2017; McKinsey Global Institute, 2017). Many business practitioners and researchers in both information system and management research have started to see organizational and management decision making as in the middle of a transition stage from instinct driven and experienced based to a progressively data centric approach (Davenport, 2010; Brynjolfsson et al., 2011).

In the early 1970s, the concept of decision support, evolving from theoretical studies of organizational decision making, gained its position as a research area on its own. In the 1990s, Howard Dresner proposed using business intelligence as an umbrella term to describe "concepts and methods to improve business decision making by using fact-based support systems”. The new term later became widely accepted and in the practical world, business intelligence is now a priority of many organizations (Power, 2007; Watson & Wixom, 2007). Although a universal definition of business intelligence does not exist, a broader and more recent definition is “the process of collecting business data and turning it into information that is meaningful and actionable towards a strategic goal.” (Logi Analytics, 2019)

Business intelligence encompasses two processes: (Watson & Wixom, 2007; Guru 99, 2019).

1. Data warehousing - extracting, transferring and organizing data for decision support. Getting data in is the core and most challenging part of business Intelligence.
2. Analysis - contextualizing the data and answering questions. Having the data is only the first step. Just like raw material, for it to become meaningful, data needs to be processed through analysis. The use of different analysis tools enables decision makers in the organization to understand data, detect patterns, identify trends and predict possible future outcomes.

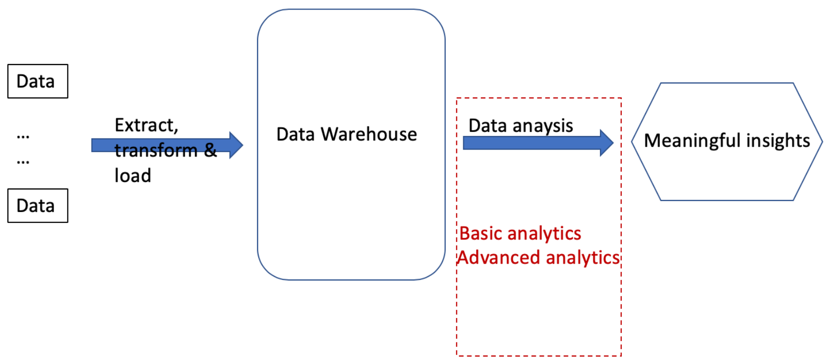

Figure 2: From data to insights

Analytics and advanced analytics

Analytics

According to Gartner (2018), analytics has become a catch-all term for a variety of different business intelligence and application-related initiatives. The definition of analytics can be taken from different perspectives and are thus unified, however in this paper, we adopt a general organizational view that it is “the process of transforming data into actions through analysis and insights in the context of organizational decision making and problem solving.” (Educba, 2019). It spans descriptive, predictive, prescriptive and AI-driven analytics (Becominghuman.ai, 2017; Educba, 2019)

Advanced analytics

Advanced analytics refers to a wide range of more sophisticated analytics tool and techniques, such as data mining, machine learning and forecasting, to produce insights that traditional BI approaches are not likely to reach. Under advanced analytics, there are predictive analytics, prescriptive analytics and AI-driven analytics (Rapidminer, 2019; Wagner, 2018; Toolsgroup, 2018).

Descriptive analytics

Descriptive analytics is the basis of all analytical activities. It uses and examines historic data or content, often performed manually, to answer the question "what happened". It is used to summarize or turn data into relevant information and is characterized by traditional BI and visualizations (Educba, 2019; Tohamy, 2018) The focus of descriptive analytics is to provide insights into the past (Halobi, 2019).

Predictive analytics

Just as its name entails, predictive analytics is used to forecast what might happen in the future. It involves advanced statistical, modelling, data mining and one or more machine learning techniques to look beyond the surface of data and determines whether a result is viable. In its nature, predictive analytics is probabilistic (Educba, 2019; Halobi, 2019).

Prescriptive analytics

Prescriptive analytics is one step forward from predictive analytics. It aims to quantify the effect of future decisions in order to give advice on probable outcomes before the decisions are actually made. In its best, predictive analytics can give insights to what will happen, why it will happen and even give recommendations on actions to best take advantages of the prediction. Prescriptive analytics uses a combination of analytic techniques and tools such as business rules, algorithms, machine learning and computational modelling procedures (Educba, 2019; Halobi, 2019).

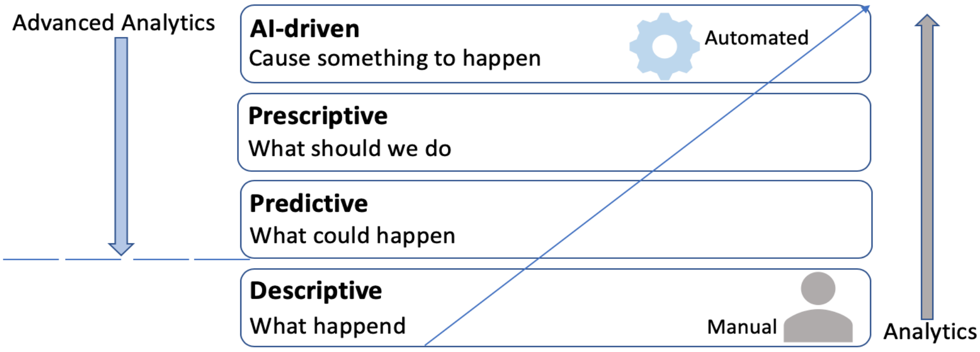

Figure 3: level of analytics

Artificial intelligence and AI-driven analytics

According to Gartner (2018), artificial intelligence "applies advanced analysis and logic-based techniques, including machine learning, to interpret events, support and automate decisions, and take actions." More broadly, It is seen as a set of technologies that seeks to simulate human intelligence - the ability to draw conclusions from data, to understand complex concepts, to make interaction with human in humanly manner, and find recommended actions without explicit human interventions (Wagner, 2018; Becominghuman.ai, 2017). AI driven analytics is the most leading-edge of advanced analytics. It spans machine learning, deep learning, natural language processing. What then sets aside artificial intelligence from traditional predictive and prescriptive analytics are 1. Its self-learning ability and 2. Its' ability to process natural languages. It makes possible the automation of knowledge acquisition in systems that aims to emulate the human decision-making process (Toolsgroup, 2018).

But will it one day replace human intelligence? A stream of AI researchers argues otherwise. They propose instead a concept of complementary and collaborative intelligence between human and AI in the context of organizational decision making (Wilson & Daugherty, 2018; Calabretta et al, 2016; Jarrahi, 2018; Campbell, 2016) The analytical capacity of artificial intelligence makes it more suitable for supporting rational decision making than intuitive decision making. But on the other hand, compared to humans, it is less viable in environments characterized with high uncertainty and unpredictability (Brynjolfsson & McAfee, 2012; Wilson & Daugherty, 2018; Kolbjørnsrud et al., 2016; Campbell, 2016). Gartner (2018), made the distinction between augmenting decision-making - to assist in the process by generating insights and recommended actions, and automating decision-making - to also execute decisions without or with minimal human interventions. Areas like order fulfilment, production planning and demand forecasting can be ideal candidates to increase automation, while areas like risk management remain a better fit with decision augmentation with the involvement of human intervention.

However, Davenport (2016) pointed out that humans may still be ahead of artificial intelligence when it comes to strategizing and decision augmentation, but that we should not be too complacent. Although a single system won't be able to handle all strategic decisions. Promisingly, in the future, advanced analytics will be more used in decision automation, due to advancement of technology, enhanced data quality and increased organizational openness (Gartner, 2018).

2.4 State of AI Adoption in Organizations

This section gives insights from current industrial reports and research literature about the state of artificial intelligence adoption worldwide. It starts with AI's strategic importance, business potential, adoption rate, and challenges that hinder successful adoption. It ends with characteristics and practices connected to successful implementation.

The implementation of analytics has become a hot topic among today's business when the idea of data-centric decision-making results in better decisions and thus better firm performance is shared by more and more researchers and practitioners (Arnott and Pervan, 2014; Pfeffer and Sutton, 2006; Davenport et al., 2010; LaValle et al., 2011; Brighton & Gigerenzer, 2015). Now, with the participation of artificial intelligence and cognitive insights, it is even possible to predict future outcomes with improving accuracy and some decisions in the organization can be automated or semi-automated (Gartner, 2018) As a consequence, AI and other smart machines are seen as the turning point of an unprecedented wave of automation, specifically the driver for the transformation of decision making (Frey & Osborne, 2017; Parry et al., 2017; McCrory et al., 2014; Davenport 2016). Further, it's argued that the diffusion of AI would follow an S-curve, meaning it can speed up dramatically and leap into another phase over the coming years and thus leave companies who are insufficiently digitized in the dust (Bughin, 2018).

Many business leaders have high expectations for these technologies, and AI is now situated at the top of Gartner's hype cycle (Panetta, 2017). According to a study by McKinsey Global Institute (2018), AI has the potential to create 40% of the total value created across sectors, with the biggest impact on industries in travel, high tech, and insurance; and on functions in sales and marketing, supply chain, and manufacturing (McKinsey Global Institute, 2018).

Although hopes for AI appear substantial, they do not yet appear to have been realized. Just 20% of companies are claimed to use any AI at all, and 61% have an AI strategy in place (McKinsey Global Institute, 2018). In a recent survey, for those who are deploying some sort of AI technology, over 95% were not using Artificial Intelligence technologies to "reinvent the way they do business", but mainly as a method to automate labour or cut costs (Krogue, 2017; Brighton & Gigerenzer, 2015).

There exist studies aimed at revealing the obstacles and challenges facing successful implementation of AI technologies. Recurring findings and conclusions in them are - lack of trust (Davenport, 2019; Michelman, 2017), need for significant employee retraining (Bughin, 2018), lack of top leadership support or understanding (Ransbotham et al., 2017), the need for cultural changes (McKinsey Global Institute, 2018), and scarcity of AI competences (Ross, 2018). In additions, there are other researchers who argue that AI is being wrongly regarded and communicated as a method to automate work and cut labor costs, which supposedly can cause fear, whereas AI in reality may be more useful for augmenting and upgrading jobs than replacing them (Ross, 2018; Kirby & Davenport, 2016).

What then characterizes the few companies who are leading the game and have implemented AI at scale (McKinsey Global Institute, 2018), on the other hand, is that they are claimed to have developed and implemented sound data strategies (Bughin, 2018; McKinsey Global Institute, 2018) and invested heavily in AI-competences, providing artificial intelligence systems with the resources needed to generate value (Krogue, 2017). An article by Ransbotham et al. (2017) claim that “AI Pioneering” companies are characterised by high degrees of top management support and organisational understanding of AI.

2.5 Concluding Remarks

In the previous section, the authors reviewed extant literature surrounding, but constrained to AI adoption in organizations. It spans subjects including technology adoption, digitalization, state of AI analytics technologies, and AI adoption in general.

To conclude, research on technology adoption, digitalization and AI adoption pointed out a set of challenges and requirements, in the form of for example organizational capabilities for organizations to successfully achieve respective goal and suggested that there must be a strategic and cultural fit between the technology adoption and the organization itself. Interestingly, technology adoption research pointed out that a common reason for failures in adopting new technologies, especially IT technology, is not too little focus on technology, but too little on people. Further, it highlighted the role of change agents and change management in the technology adoption process in organizations. However, AI analytics, as a newer form of technology imitating human intelligence, has not generated enough academic research around it and most of existing business AI literature is rather normative and prescriptive and focuses holistically on a wide range of AI applications. Therefore, inspired by technology adoption research, the authors argue for the need of studying organizational AI analytics adoption from a change management perspective, as prior research based on context of older technologies may not still hold true in the field of AI analytics.

Chapter 3. Theoretical Framework

To explore organizational AI adoption from a change management perspective, the authors draw on dynamic capabilities theory, which depicts organization's' ability to alter itself proactively in the light of changing external environment, and the three-stage model of change, which focuses on forces that drive change through three different stages. Note that in line with abductive research approach, the theories that are best fit and final theoretical constructs derives from the constant matching between empirical world and theories and evolve gradually with the case. To conclude, the author's choice of theories is based little on prior literature review (which provides understanding of the field), but rather lead by interesting and novel findings in the empirical field. Combined together, these two theoretical concepts give the authors the opportunity to look into the organizational environment AI adoption is embedded in, as well as the change management practices in the adoption process.

The following chapter is structured into three sections:

(1) A review of dynamic capabilities theory
(2) A review of change management theory and lewin's planned approach
(3) Synthesis of theoretical framework

3.1 Dynamic Capabilities Theory

Dynamic Capabilities is a management theory which is centred on the drivers of organizational change and refers to the processes within an organization that lets it alter its resource base in light of a changing external environment (Eisenhardt & Martin, 2000). These capabilities have been defined as "the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments" (Teece et al, 1997), and are envisaged as routines or behaviours that may exist within an organization. In order to comprehensively describe Dynamic Capabilities, it may be appropriate to first contextualize the theory with the earlier theory it is argued to be an outgrowth of (Teece, 2007).

3.1.1 Background - The Resource Based View

The theory of Dynamic Capabilities is closely connected with the Resource Based View (Teece, 2007). The latter theory posits that different organizations hold different bundles of resources that can be applied to gain a competitive advantage (Grant, 1991). I had been found that differences in profitability between firms in the same industries were significantly greater than the differences between different industries (Grant, 1991). Thus, presenting a need for theories that could better explain why certain firms in the same industry were more profitable than others, even over extended periods of time.

The theory seeks to explain why certain organizations have competitive advantages over others by looking at their internal rather than external factors (Barney, 1991). The theory hence envisions a company as a set of *resources,* which then give rise to certain *capabilities,* which then may or may not confer a competitive advantage (Barney, 1991; Grant, 1991). Resources are described as "inputs into the production process", whereas a capability is the "capacity for a team of resources to perform some task or activity" (Grant, 1991).

3.1.2 Emergence of Dynamic Capabilities

The Resource Based View became scrutinized for its perspective on competitive advantage as generated by a seemingly static asset base of resources and capabilities. In a paper by Teece et al. (1997), it was argued that the view does not adequately capture the conditions for organizations in environments of rapid change (Teece et al., 1997), and places too much emphasis on their current asset stocks, which could become outdated quite quickly (Wang & Ahmed, 2007). Simultaneously, it was observed that even in rapidly changing markets, certain organizations performed better than others over time (Eisenhardt & Martin, 2000). Consequently, a new stream of theories inspired by evolutionary economics (Teece, 2007), proposed the existence of another kind of internal organizational advantage - *dynamic capabilities.* These refer to the processes within an organization that lets it alter its resource base in light of changing external circumstances. Whether that is by acquiring new resources, shedding old resources, integrating resources together, or recombining them in order to form new value creating strategies (Eisenhardt & Martin, 2000).

Dynamic capabilities theory is hence inspired by the older Resource Based View (Wang & Ahmed, 2007). The dynamic capabilities themselves are by Eisenhardt and Martin (2000) described as "antecedent" to the resources in the resource-based view, hence functioning like an additional dimension that explains how the resources and capabilities that make up an organization change and why. A distinction is thus made between ordinary capabilities from the resource-based view, that refer to the organization's standard operations (Teece, 2007), and the *dynamic capabilities* that generate renewal and reconfiguration of an organization's resources (Wang & Ahmed, 2007). The unit of analysis in dynamic capabilities is processes or routines (Eisenhardt & Martin, 2000).

Dynamic capabilities are by Eisenhardt et al. (2000) described as being heterogeneously distributed across organizations, being constrained by specific processes, asset positions and path dependencies (Barreto, 2010). The latter refers to change and learning tending to be incremental, and thus affected by the investments and processes a firm has had in its past (Teece et al., 1997).

3.1.3 Categories and Underlying foundations of Dynamic Capabilities

Teece (2007) presents a framework that identifies three main subcategories of dynamic capabilities, called *sensing, seizing* and *reconfiguring.* These three capacities are responsible for one dimension each of the routines that comprise dynamic capabilities:

Sensing: The ability of the organization to sense, filter, shape and calibrate emerging opportunities and threats. This involves the organisation scanning, searching for and exploring potential opportunities across technologies and markets (Teece, 2007).

Seizing: The ability of the organization to effectively address emerging opportunities that have been identified. Involves the organization's strategic decision making, investment, and execution skills (Teece, 2007).

Reconfiguring: The capacity of the organization for enhancing, combining, protecting and reconfiguring its own asset base, structures and processes. The ability of the organization to stay agile and continuously change itself (Teece, 2007).

These capacities are by Teece (2007) argued to form dynamic capabilities. Significant emphasis appears to be placed on the organization's leadership as a source for these capabilities, although they are not stated to be exclusive to them.

Additionally, research has been conducted on the underlying organizational characteristics that lead to the creation of these capacities. Eisenhardt & Martin (2000) propose certain processes and routines that potentially give rise to them, and Teece (2007) refers to these as *micro foundations*. He defines them as *"the organizational and managerial processes, procedures, systems, and structures that undergird each class of capability"* (Teece, 2007). He presents a framework with sets of these for each of the three capabilities but adds that the list of potential micro foundations is large and that his framework is not meant to be comprehensive. Furthermore, his proposed micro foundations are meant to form an umbrella framework for the effects of dynamic capabilities in any changes an organization can make to stay competitive. Rather than the adoption of AI in particular.

Nevertheless, Dynamic capabilities describe an organization's capacity to successfully transform itself according to external changes, and the proposed subcategorization into sensing, seizing and reconfiguring capabilities increases the depth of the theory. Likewise, for the concept of micro foundations that in turn undergird these three capabilities.

It appears possible to make a connection between the successful adoption of AI in organizations and a theory that aims to explain the causes of how organizations spot opportunities and manage to change their capabilities accordingly. Thus, the concepts described above could provide a theoretical lens for analysing and identifying if there are particular underlying characteristics, or micro foundations, that affect the capability of organizations to manage successful AI adoption.

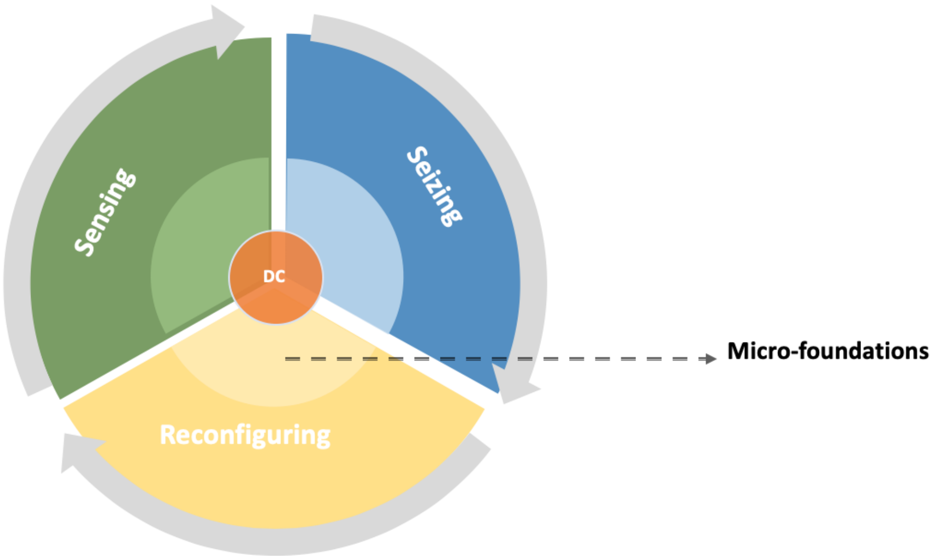

Figure 4: Dynamic Capabilities theoretical framework

3.2 Change Management Theory

Change management has been defined as "the process of continually renewing an organization's direction, structure, and capabilities to serve the ever-changing needs of external and internal customers" (Moran & Brightman, 2001). It is argued that change is an ever-present feature of organizational environment and organizational change and strategy cannot be separated from each other (Burnes, 2004). Although there is no consensus on a framework of organizational change management, different types of and approaches to changes that are present in organizations have been mapped by researchers (By, 2005).

Based on Senior's (2002) three categories of changes, in "change by how it comes about", there is the "planned change", "emergent change", "contingency model" and "approach of choice" (Bamford & Forrester, 2003):

1. **The planned approach** to change was initiated in 1946 by Lewin to distinguish "change that was consciously embarked upon by an organisation", as opposed to "unintended changes such as those that might come about by accident" (Burnes, 2004). It emphasises that organizations proactively identify where the change is required, and then evaluate the opportunity to initiate change.

2. In response to the planned approach, **the emergent approach** started to gain ground (By, 2005). It emphasizes that change should not be seen as a series of linear events, but rather as a continuous, open-ended process of adjusting to changing situations (Burnes 2004; Burnes, 1996). Most suggested sequence of actions by emergent approach scholars are rather abstract and hard to comply with. However, there are some researchers who offer more practical guidelines e.g. Kotter's eight step model to change (Burnes, 2004; Kotter, 1996; Kotter & Schlesinger, 1979).

3. **Contingency or situational model** brought up by Dunphy and Stace (1993) argued that there is no best one approach to all changes. It was founded on the contingency theory that organizations' structure and performance are dependent on the situational factors they are faced with, and that one should vary change strategies to achieve "optimum fit" with the changing environment (Dunphy & Stace, 1993).

4. **An approach of choice** was then advocated by Burnes (1996), suggesting that organizations do not necessarily need to adapt to their external environments, and instead of being forced into certain directions, they can exercise some choice over the change issues. However, on the one hand, organizations can have influence on and control over the circumstances in which they operate through the changes; on the other hand, they can encounter decline and stagnation through an inability to control and unsuccessful approaches to change (Burnes, 2004; Burnes, 1997).

Driven by an abductive research approach, to reach the matching between the empirical observation and theories, the planned approach is selected to guide further field exploration. The authors argue and stress the proactivity of organizations´ search for change as part of organizational life and initiate change not only in response to the changing external environment, but also to actively and purposefully develop competitive advantages to stay relevant in the market. Although it may hold true that selection of change strategies should take into consideration the organization's unique situational factors, the author believes that they should also comply with some ground principles that deal with the nature of change.

3.2.1. Lewin’s Planned Approach

The work of Kurt Lewin has dominated the theory and practice of change management for over 40 years (Burnes, 2004). Lewin’s Planned approach to change is based on four mutually- reinforcing concepts - Field Theory, Group Dynamics, Action Research and Three-Step model, the combination of which is argued to bring about effective change (Burnes, 2004). It emphasises the different states which organizations have to go through under change process (Bamford & Forrester, 2003) and proposes that in order for change to move forward, the previous practices and behaviours have to be discarded (Burnes, 2004; Burnes, 1996). The three-step model of change, or the “unfreeze-change-refreeze model” is widely regarded as the fundamental or classic approach to change management, and is still argued to be highly relevant in today’s environment, with its focus on change by changing group behaviours (Burnes, 2004; Cummings et al, 2016; Kritsonis, 2004; Kaminski, 2011).

3.3.1.1. Field theory

“An approach to understanding group behaviour by trying to map out the totality and complexity of the field in which the behaviour takes place” (Burnes, 2004). Group behaviour is seen by Lewin an intricate set of interactions and forces that influence both the group structure and individual behaviours. Consequently, changes in the behaviour stem from changes in the forces within the group environment or “field” (Burnes, 2004; Lewin, 1941; Burnes & Cooke, 2013)

3.3.1.2. Group dynamics

Group dynamics stresses that the focus of change should rather be on group behaviour than that of individuals. A single individual is always constrained by group pressure to conform. Hence, attempts to implement change by focusing on individual behaviours are likely to be ineffective (Burnes, 2004).

3.3.1.3. Action research

Action research stresses that change requires action and successful action is based on matching the most appropriate solution to the situation at hand. And in order for change to be effective, it must happen at the group level and must involve all of those concerned in a participative and collaborative process (Burnes, 2004).

3.3.1.4. 3-stage model of change and force field analysis

Building on top of the other three elements of Lewin’s planned change approach, the three-step model of change views behaviour as a dynamic balance of forces working in opposing directions, with “driving forces” pushing into the direction of change and “restraining forces” working to decrease the driving forces and making it difficult to change or move forward. In order for change to happen, the status quo, or “equilibrium” must be upset. The goal of the change agent(s) is to support the driving forces to move beyond equilibrium and outweigh any restraining forces. This provides support in moving through the unfreezing – changing – refreezing stages of change. (Kritsonis, 2004; Kaminski, 2011).

Step 1: Unfreeze

According to Lewin, the first step in the process of changing behaviour is to unfreeze the equilibrium or the status quo (Kritsonis, 2004). Only by doing so, old behaviours and practices can be discarded before new ones can be adopted. Unfreezing is necessary to overcome the strains of individual resistance and group conformity. It is in this stage when the organization is being prepared to accept that the change is necessary (Burnes, 2004; Kritsonis, 2004; Kaminski, 2011). Key to this stage is uncovering and convincing the reason why change is needed.

Step 2: Change

The second stage of change is where people begin to look for new ways of doing things that are more productive than the old ones. People start to believe and act in ways that support the new direction. Here, the iterative approach, embedded in action research enables a trial and error process of research, action and more research which moves individuals and the group from a less desirable to more desirable set of behaviours (Burnes, 2004; Kritsonis, 2004). Support is need at this stage to help people transit from a set of older behaviours to new and desirable ones.

Step 3: Refreeze

The last stage of change seeks to stabilize the group at a new quasi-stationary equilibrium in order for the new behaviours to stay in place over time. Unless group norms and routines are also transformed, changes to individual behaviour are unlikely to be sustained. Refreezing often requires changes to organizational culture, norms, policies and practices and an important aspect of it is to make sure that the new behaviour must be, to some extent, congruent with the rest of the organization (Burnes, 2004; Kritsonis, 2004; Kaminski, 2011). Also, it is important to note that in lewin's three-stage of change, he saw social settings as being in a state of constant change. Not as a planned move from one stable state to another, but as a complex and iterative learning process where stability was at best quasi-stationary and always fluid, involving the balance of complex forces. Therefore, refreeze should not be seen as the end of change, but rather as a new quasi-equilibrium where forces are only temporarily balanced.

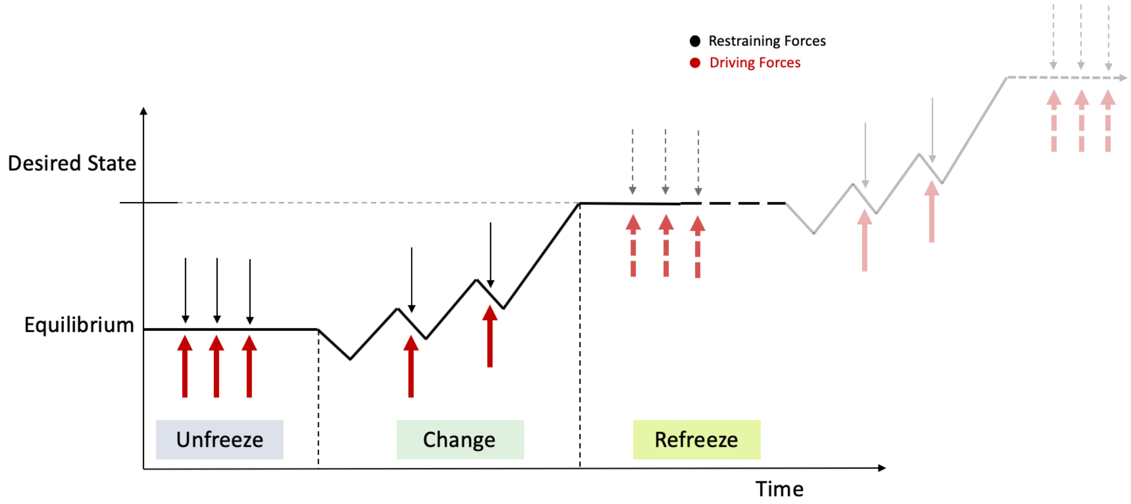

Figure 5: 3-step of change theoretical framework

3.3 Synthesis of Theoretical Framework

The preceding theoretical concepts were selected to help answer the main research question: ***"How do organizations manage successful AI adoption from a change management perspective? "***

In order to show the interrelatedness of the two chosen theoretical concepts and their relevance to organizational AI adoption, the authors constructed the following theoretical framework (See figure 6). An organization's dynamic capabilities: sensing, seizing and reconfiguring, each consisting of a set of micro-foundations, are at the centre, to depict the intrinsic characteristics of the organization as well as the change environment AI adoption sits on. Then the three-stage of change model, consisting of unfreeze, change and refreeze, are placed in the outer circle to capture the AI adoption change process. Arrows represent assumed relationships between each dynamic capability and its related change stages.

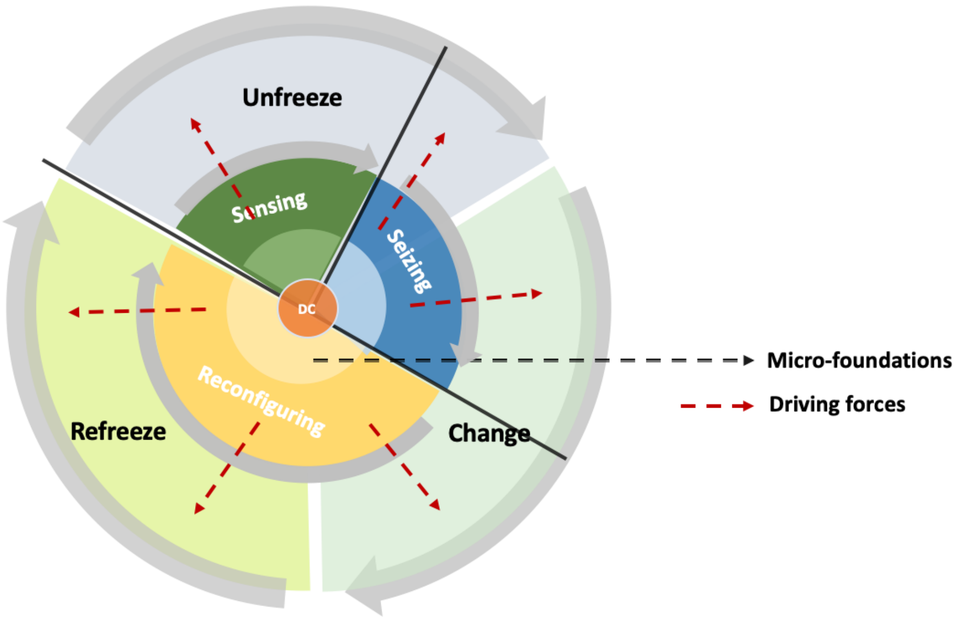

Figure 6: Synthesis of theoretical framework

Applying dynamic capability framework, the author studies how organizations leverage dynamic capabilities to sense, seize the AI opportunities and reconfigure themselves to achieve value realization, and aims at answering *sub-question 1:* ***What organizational micro foundations undergird the dynamic capabilities for AI adoption?***

To study how companies manage the change process, the author apply the three-stage of change model and force field analysis to examine what drives and retrains AI adoption and what actions are taken in response. This part aims at answering *sub-question 2:* ***How do change agents support driving forces to enable organizational AI adoption?***

Chapter 4. Methodology

In the following chapter, the authors argue for the choice of conducting a multi-case qualitative study to investigate the research questions. It then presents the research design, research process, choice of data collection and data analysis method, and ends with a discussion of research quality.

4.1 Methodological Fit

Based on the literature review, the authors conclude that there is limited research, existing empirics or formal theorizing on the subject of organizational AI analytics adoption. With the state of prior work and theory specifically for AI analytics in a nascent stage, the choice qualitative method provides the authors an opportunity to approach the issue at a close distance and interact with subjects being investigated, which enables a deeper understanding of the issue and its' embedded context (Bryman & Bell, 2015, Edmondson & McManus, 2007).

4.1.1 Research Approach

An abductive approach refers to a creative inferential process aimed at finding the best explanation to a phenomenon from a set of observation and generation of new concepts and development of theoretical models based on surprising research evidence (Flick, 2014; Dubois & Gadde, 2002; Timmermans & Tavory, 2012). Systematic combining, grounded in abductive logic, is defined as "a process where theoretical framework, empirical fieldwork, and case analysis evolve simultaneously". It emphasizes the search for suitable theories to an empirical observation (Dubois & Gadde, 2002).

Adopting systematic combining means that the authors constantly go back and forth between the empirics and theoretical framework. The original framework will be successively modified, both as a result of unanticipated empirical findings and theoretical insights gained during the research process. Hence the researcher should not be unnecessarily constrained by having to adhere to previously developed theory, as the main concern is related to the generation of new concepts and development of theoretical models, instead of confirmation of existing theories. (Dubois & Gadde, 2002). According to Strauss and Corbin (1990), the researcher enters the research situations with some background in what they call 'technical literature', and as the empirical fieldwork runs parallel to the theoretical conceptualization, the need of theory is created in the process.

4.1.2 Research Strategy

Aligned with the research approach, the author pursued a case study method in order to investigate and understand complex issues in real-world settings (Flick, 2014). A multiple-case research study was then chosen to allow for more in-depth understanding and comprehensive exploration of research questions and theory development, through comparing and contrasting findings deriving from each individual case (Bryman & Bell, 2015; Gustafsson, 2017). By understanding the similarities and differences between the cases, the authors can therefore generate stronger and more reliable evidence and clarify if the findings are valuable or not (Gustafsson, 2017).

4.2 Data Collection & Analysis

In this research, data was collected through interviews in the main study, conducted by the two authors together. Collected data was then sent back to the interview participants and discussed. Multiple cross-validation build on the authors' acquired knowledge and ensure high credibility in collected data.

4.2.1 Pre-study

To broader and deeper authors' knowledge of the issue at hand and its' embedded context (Bryman & Bell, 2015), a pre-study, consists of two interviews with AI and data analytics experts in academia, was conducted parallel to the search of relevant literature. It reconfirmed identifies research gap and helped form initial research questions and analytical framework to enter the study field.

4.2.2 Interview Sample

The selection of the interview samples was guided by "theoretical sampling", which aims at arriving at an appropriate matching between reality and theoretical constructs (Glaser and Strauss, 1967). Thus, sampling became a continuous process overlapping with data analysis and evolves during the study, based on both leads from previous interviews and the authors' desired knowledge outcome (Dubois & Gadde, 2002).

A total of 16 interviews, lasting from 30-90 minutes, were conducted in the main study, either via skype or in face to face setting (See appendix 1). Prior entering the main research field, insights generated in the pre-study showed that organizations who have invested and made progresses in adopting AI analytics generally acquiring services from consulting firms. And due to the imbalance in knowledge and resource consolidation, highly assorted consulting firms become experienced experts in this area and have a really wide client portfolio. Consequently, the authors decides using consultants as the interview sample and study AI adoption in their client organizations.

The authors' decision on the initial interview samples derived from the authors' judgement and insights from pre-study about who have the most knowledge about the adoption of AI & advanced analytics in organizations. On the basis of theoretical ideas and concepts revealed in the previous stage, further sampling was conducted on a continuous basis until reaching theoretical saturation (Flick, 2014):

1. In stage one, at the very beginning of the main study, IT consultant was judged to be the on the ground practitioner who drives AI adoption in the organization. Through LinkedIn search and authors' own network, the author established contacts with 4 experienced IT consultants and completed initial data collection and analysis.
2. In stage two, more and more information emerged pointing to that the biggest hurdle in the adoption process was not technology itself, but rather the "human" problem. Management consultants who work side by side with IT consultants in AI & advanced analytics projects were then selected to be the authors' interview targets.
3. While the overlapping data collection and analysis continued, the authors expanded the interview sample search from only management consultants with years of experience, to former consultants who joined client companies later on, in the end to experienced change agents who have extensive knowledge of the whole adoption process on both technology and human side. The title or position of the interviewee were of less focus than his/her actual rich experience and deep knowledge in the field.

4.2.3 Interview Design

Expert interviews, applying semi-structured interviews, were chosen in the study (Flick, 2014). Semi-structured interview setting made it more likely that the interviewees express their subjective viewpoints, compared to a standardized interview or a questionnaire (Flick, 2014).

An interview guide (See appendix 2) was prepared prior each interview and was modified throughout the study to fit into evolving theoretical constructs and personalized according to each interviewee's background. In general, each of the interviews were introduced by an open question; additionally, theory-driven questions were asked; and ended by a confrontational question (Flick, 2014).

4.2.4 Data Analysis

All interviews were recorded and transcribed into structured texts to facilitate the researchers' understanding. The data analysis was conducted iteratively in parallel with the interviewing and guided further continuous sampling (Lincoln & Guba, 1985). Thematic coding was applied as a multi stage procedure (Flick, 2014), which involves identifying texts that are linked by a common theme or idea allowing the researcher to index the text into categories and therefore establish a "framework of thematic ideas” (Gibbs 2007). Driven by an abductive approach, the generated themes were consistently re-evaluated against the theoretical background. As the data was analysed by two researchers, there were occasional disagreements regarding how particular statements should be interpreted and coded. In such cases the matter was discussed until the researchers reached a consensus, in accordance with the advice on how to handle such situations (Gioia et al., 2013). A table of codes is provided (See appendix 3).

4.3 Quality of Study

Measuring the quality of research conducted by qualitative methods is difficult, and there are a number of different criteria that are being proposed for doing so (Flick, 2014).

4.3.1 Dependability

Dependability refers to the “stability of findings over time” (Bitsch, 2005) and if an evaluation of the study finds that the interpretations and recommendations therein are supported by the data (Anney, 2015). Or whether a similar study carried out on similar respondents in a similar context would find the same results (Cohen et al, 2011). The study aims to ensure its dependability by providing an *audit trail*, which is the transparent disclosure of the research process, activities, and materials (Flick, 2014). The researchers have provided descriptions of how the data was collected, coded and analysed, and the original interview transcripts have been made available to an external supervisor.

4.3.2 Credibility

Credibility is the degree of confidence in whether the findings of the study match the truth (Korstjens & Moser, 2018). It can be compared to internal validity in quantitative research (Lincoln & Guba, 1985). In order to increase the study’s credibility, a number of methods were used. One was triangulation, referring to the usage of different researchers, methods, and data sources (Korstjens & Moser, 2018).

Investigator triangulation was used by having two researchers analyse and interpret the data, *method triangulation* by combining the interviews of the main study with pre-study data as well as written reports, and *data triangulation* by gathering data from different types and levels of people as well as comparing and cross-checking them.

The study also made use of *prolonged engagement* (Korstjens & Moser, 2018) in that interviews were of sufficient length and the subjects were asked to elaborate on their answers until a satisfactory degree of understanding was reached. Furthermore, enough individuals were interviewed in the study for saturation in responses to be reached. *Persistent observation* (Korstjens & Moser, 2018) was also used by the researchers iteratively reading and rereading the interview data and adjusting the theories and concepts according to this.

4.3.3 Transferability

Transferability refers to the extent of which the results of the research can be transferred to other contexts or settings (Korstjens & Moser, 2018). The transferability of qualitative research is somewhat disputed, but methods have been proposed for improving it (Denscombe, 1998). Accordingly, the study made use of *thick description* (Bitsch, 2005; Lincoln & Guba, 1985), which is to comprehensively convey the details regarding the study participants and research process, so that the reader may assess whether the results are relevant to his or her own setting (Korstjens & Moser, 2018). Through the usage of p*urposive sampling* (Bitsch, 2005; Yin, 2011) by interviewing individuals who have worked with AI & analytics across multiple settings, the transferability of the results to different contexts should be improved.

Chapter 5. Empirics

The following chapter presents empirical findings from the main study and is structured into the following five themes, each consisting of a number of sub-themes. Due to the business perspective of the study, the latter three themes presented below are in focus, and provide richer empirical findings:

(1) Quality data as the AI foundation
(2) Technology solutions that fit into the context
(3) Aligning the business side as the starting point
(4) People as part of the AI transformation journey
(5) Change management as the enabling force

Then, the relationships and correlations between different themes are identified and presented in a separate section.

5.1 Quality data as the AI foundation

The findings support that for an organization to be able to leverage AI and advanced analytics at all, it is paramount that it has stored sufficient amounts of data and has an adequate digital infrastructure. This forms the foundation for looking into uses of AI. Without that, it is not possible to do much with the technology.

"Data is important. We need to have data with high quality. That is very important. Without data, all of these solutions will not work..." (Kanda Kumar)

Proper data warehousing was emphasized, meaning that the data is collected and stored in integrated formats. Furthermore, if this data management is lacking, the process of reorganizing it to be sufficient for AI applications could be difficult.

"...the decommissioning of legacy systems is extremely time consuming, a lot of work and extremely costly as well, and the problem is that in many cases they have the mainframe systems, so a mainframe that was built I think in the 90s that is extremely costly and the people who built it, they're not part of the corporation anymore." (IT Consultant 1)

Low quality data could also be a hurdle to overcome. AI applications make data-driven decisions, and the data thus needs to be of sufficient quality for these to be correct. Several interviewees bring up examples where poor-quality data has impeded projects. Here too, the process of cleaning the data to be good enough could be challenging.

"...So what is happening is that the modelling took us about three weeks, but we spent almost ten months trying to clean up the data and understand how everything was interconnected, talking to the legacy systems, and get the data quality we need. We don't need 100 % quality, but we need good enough quality that we believe in what we are seeing. It took ten months." (Nils Kristensen)

The governance and ownership of data is also mentioned by respondents, such as whether different stakeholders in an organization are willing or able to share data with each other or not. Without that, securing access to the quantity or variety of data the AI applications might need could be difficult.

5.2 Technology solutions that fit into the context

While technology itself is not focus of the study, some findings should be noted. The first is the necessity for technical expertise as a prerequisite for adopting the technology, as the systems in question can be highly complex.

"...And here, when we are talking technology, it is very important to get sharp specialists. I think we have survived with a lot of generalists. But now it is really important to have hardcore, you know, very edgy technology people." (Niclas Hansson)

Another aspect mentioned is the importance of having a solution that fits the organization's specific needs and context. This relates to how the technology development itself should be handled; whether AI should be developed in-house, co-created with a partner, or bought from a vendor.

5.3 Aligning the business side as the starting point

5.3.1 To link AI adoption with business value creation

The empirical findings suggest that effective AI deployment has to be connected to the organization's very core business and understanding of the mechanisms and pain points. At times when technology development and quality data are present, the next big question is "*Does it make business sense to do it?"* (Christian Guttman). Yet often, what happens in organizations is that the agenda is set in the board and pushed down to the enterprise without a clear vision of what AI will do to the business.

"Only knowing AI or automation or data analytics is not going to help unless you know where you are going to apply it." (Kanda Kumar)

AI adoption rarely works by having technology people telling you “this is the newest technology that we are capable of and let’s do it”, but rather by involving the business side to really think through what we do, how we are doing it, what the challenges are and how it can be improved with AI and analytics. As stated by Nils Kristensen:

“You need to focus much more on the actual drivers for success, you need to focus much on more the pain that they are seeing and how we can alleviate those pain points by using advanced analytics, automation and sort of think it outside of the box than what they are doing today. But it’s very difficult to make people think in that way.” (Nils Kristensen)

Simultaneously, the empirics demonstrate the cruciality of understanding what deploying AI means for the organization and business. Nils Kristensen says:” *this is business transformation; it is not just to spot machine that will break down.*” Consequently, companies will need to rethink the competences needed, ways of working, partnership relations to its business model, and the entire process.

“I*f you really build up advanced data capabilities and AI machine learning on any scale in your operations, it will require a totally different way of doing IT. It will change the way everybody is looking at the company!*” (Reinhard Seifert)

5.3.2 To get end to end commitment from the top management

The most significant characteristics of leadership which enables organizational wide AI adoption, as demonstrated by the empirics, is to be able to sense the changes caused by technology in other areas of the world and life and internalizing it into how they want to change their business.

“Yes you need to have top management that sees the changes and understands that this is going to bring value, you need to have sort of future oriented management” (Nils Kristensen)

In addition, to initiate the change, the leadership team needs to set out a vision and strategy, and most importantly, gives continuous commitment and support to avoid distraction from other parts of the organization and to not deviate from the path of - *“continuously improving and to making sure that you are always working on whatever you set out to do.* (Nils Kristensen)

“The main challenges are the managers, the company, the people making the decisions.” (Adrien Vetterli)

"What will be required is full commitment from the business side, also to set to remove any kinds of hinders, from the technical, IT stakeholders' side inside the company..." (Reinhard Seifert)

Although adopting AI requires high technological advancement, the empirical findings also show that successful AI initiatives rarely come from the technical side of organization, with the underlying reason that AI, although having its' technical nature, touches and impacts more than merely the technical level. And in order to make it relevant and feasible, the change initiatives need to come from the management, the business side.

"I have seen some minor projects and also resistance stories and the technical side trying to push from a technical perspective. The point is it will change, and it will touch a lot. A lot more than the technical side. So if it does not come from the business side, if it does not come from the management, it will not be feasible and it will probably be efficient and irrelevant, it will have no impact. You waste at least a hundred thousand euros and you will not have impact." (Reinhard Seifert)

5.3.3 To prioritize and allocate resources

"They see this as important; they know they need to do this. They can see that on the competitive level, "we win in the market if we do this", but they haven't got the people, they haven't got the technology, they haven't got the priorities set up correctly. Because they have too many legacy things that they need to do. They have too many operational issues that are going on everywhere. They can't really prioritize this." (Nils Kristensen)

Another major point pointed out by the empirics concerns organizations' resource allocation and balance of competing priorities. On the technology side, very often, AI has to compete with other technology initiatives; on the business side, as always, there are too many strategic and operational issues spread out everywhere with pressing deadlines. So, really, it is a matter of prioritization and allocating resources accordingly that determines AI projects life or death. As Peter Beronius puts it:

"I'm not saying organizations are naive, but it is a way of how you prioritize your resources." (Peter Beronius)

5.3.4 To combat structural barriers in the organization

Another recurring theme in the empirics concerns some (especially large) organizations' structures, which are often characterized as old, overcomplicated, disjointed between different departments and bureaucratic; and processes, which are critically pinned down as slow, messy and too fixed. Together, they pose major barriers to organizations' AI or change initiatives in general. Respondents in the research often describes that in such organizations, the mandate to decision is scattered and collaboration is minimum, as a result, they have to go through multiple channels and back and forth to get access to even one minor thing.

*"This is something that is still so mind boggling for me, how few companies have good collaboration, communication between departments or even people within the departments. They use different systems and buy different tools, and the systems don't talk to each other, and it is absolutely mind boggling! "(*Vince Guidotti)

"There are so many different decision layers, there are so many stakeholders because the decisions are so scattered across the company and across the world. So, it is a lot about finding the right people, communicate to the right people, getting the right approvals at the right time from the right people…" (Milap Patel)

5.4 People as part of the AI transformation journey

5.4.1 Knowledge and awareness

Data literacy

The concept of data literacy is a recurring theme in the empirics. It is described as a desirable trait for all members of organizations that aim to implement AI, and essentially means having a decent grasp of how to understand and work with data. Along with knowledge of core concepts and technologies. It does not necessitate in-depth understanding on the level of actual specialists. It may be particularly important for management, even people on the operational level, in order for them to manage and evaluate the technical applications.

"Data literacy is like reading literacy. It's like an education. Understanding of the technology and understanding of the data. What is information, how do I gather information, what can I get out of the information. It is needed in the leadership. They need to understand how to make sense of information…" (Reinhard Seifert)

Knowledge of AI

In addition to an understanding of data, the empirics also support the notion that people should have a decent understanding of AI and related technologies. It can help non-AI-specialists identify potential application areas for the technology in their own domains.

General knowledge of AI is described as limited, particularly because the information that individuals can get from reading mass media is often misleading. This lack of knowledge can manifest itself either as scepticism or fear of AI that may hinder its adoption, or as over-optimism that leads companies into having too high expectations.

"...I still believe that people need to have some basic knowledge of the fundamentals of what goes... Like they go some online course, so they understand what AI can do and what the principles are underneath it. That will help them first to understand how AI can help them, and secondly so that they can identify the area within the team where AI can help them." (Vik Li)

5.4.2 People's reactions that hinder the change

Fear

Fear is described as a common reaction that people have in organizations that initiate AI projects. More specifically, it tends to be a fear that the new systems may put them out of their jobs.

"...In a lot of companies, they will think that the AI or automation machinery will be replacing them, and they will have to find a new job or get retrained or something. So it can be as simple as that." (Vince Guidotti)

Lack of trust in the technology

The respondents also mention that individuals within the organization may not trust in the information or decisions provided by AI applications. This lack of trust in the results may be compounded by the fact that AI can make mistakes. As Christian Guttman describes a hypothetical situation:

"...It does it very quick, and often much more accurate than humans. But it is still something where you need to set yourself, you need to understand this, and the risk involved. And you need to start developing a certain trust in this sort of, the same with self-driving cars, or robots that start stitching people together right. So, you need to have certain trust in that." (Christian Guttman)

Not seeing the need

An additional common reaction is that people within the organization simply do not see the need for AI or advanced analytics technologies. This may be because they are happy with the kinds of data they are receiving at the moment and do not see any need to improve it. It may also be simple unwillingness to change their existing ways of working.

Resistance

"I'd say what I have seen mostly, is that the resistance to change prevents the deployment. You know it's in human nature that people don't like to change things." (Reinhard Seifert)

Supported in the empirics, resistance to change is a common challenge facing AI or any type of organizational transformation. And in terms of why, some respondents explained that it is in our human nature to dislike change. Change causes a mental lockdown at the first glance. And on top that, some people have really just been in the business for too long to see the benefits of moving forward. The legacy people, who sit centre in the organizational network, can pose the biggest hurdle to change. Lastly, the complexity of AI technology and insufficient knowledge about what benefits it can bring make people hesitate or even see it more as a threat than an opportunity.

5.4.3 New competencies and new roles

Multidisciplinary teams

A finding strongly supported by the empirics is the necessity for different types of competencies when adopting AI: mainly technology expertise and business expertise. For adoption of AI to be effective, technical expertise needs to be combined with domain expertise about the business, and how AI can be used to provide business value and impact on it. As high level of business understanding is often described as missing among technology experts, it is important to have multidisciplinary teams with both technology and business expertise.

"*So just having pure business people won't do, because then you don't understand how tech can enable it. And pure tech people you can't have because then you won't understand the value, or business impact if you like. So you need to have the right team around you that can talk from a business perspective, a strategy perspective. And then you need to have people that have technical expertise, that can talk from an operational perspective."* (Milap Patel).

A further type of related competence alluded to in an ideal team is someone who knows enough about both the business side and the technology side to function as a bridge between both groups.

Change agents

Another theme found in the empirics is “change agents” - Individuals who have the willingness and ability to build support in the organization for the AI initiatives, and thus make them possible to enact in practice. Said change agents may be necessary both for convincing the top management to see the need for AI and thus devote resources to the projects, as well as to manage resistance from stakeholders and other people in the organization. Several respondents mention that AI adoption may bring large changes to how organizations look and function, which then makes the competence of change management particularly important for its success.

“.... you need to start at the top and say that this is something that we need to do. Because you need to bring together the business side, the data modelling side and the technology side. That means you have to have a mandate to put all of those together and you need to sort of have someone within, preferably not buying them from outside, a burning desire to do this. Because this is something that you need to drive through, because it will change the way you work in, it will change the operating model really.” (Nils Kristensen)

Experience and guidance

The empirics shows also that AI stands in the very front edge of technology and societal development, few organizations have had actual experience adopting AI at large scales to successfully transform their business. Consequently, methods such as industrial benchmarking and bringing in outside expertise, which not only lead the direction but also contribute to organizational learning, are widely applied in companies who have embarked AI journey.

“So I think it was not the lack of resources but more the lack of guidance and being able to talk with somebody who has done it in the past.” (Peter Beronius)

New roles and capabilities needed in the organization

The respondents predict an increased overall need for technical competence in organizations as a result of AI adoption. There will be a need for people who understand the complex data modelling, algorithms, and other tools that will be components in organizations that make use of these advanced technologies. The creation of new roles that are highly technical in nature, and thus mainly open to data scientists and data engineers, can be expected.

The findings also support the growth of non-technical job roles, however. Respondents predict organizations increasing head counts in more customer facing or creative functions at the same time as their needs for workers in back-office functions decrease.

Competence building in the organization

The shift in demanded competences is stated to pose a challenge. Organizations may need to invest in competence development to re-educate and upskill their current workforces to both meet their needs for necessary skills and reduce the number of employees that have to be let go.

"But you can also see changes in how it affects the white-collar workers. They need to be re-educated, or they need to learn to use the new technology at a greater rate than they have done in the past. Or they will simply be outdated and not relevant anymore." (Peter Beronius)

5.4.4 A shift to AI culture

Much of the empirical data regarding the traits an organization should have to succeed in AI adoption relates to cultural characteristics. Adoption of AI is also often described as a cultural shift than just a technology revolution.

Tech savvy culture that trust data and machine

To utilize AI solution, the organization needs first adequate level of trust in its data and algorithm. It is also a change of mindset, from "human first" to "machine first".

*"But then if we use a strategy that is "machine first", then first I will find a way for machines to do this, and then I will put the people ... "(*Kanda Kumar)

The empirics show that companies whose core business is technology or are pronouncedly tech savvy, have an upper hand when it comes to adoption of AI. With the possible reasons being they have for one the base, second, the interest, third, the courage and openness to try out new technologies.

"And take a technology organization like Ericsson, TSC, Accenture as example. For them they are driving AI across the whole organization, because they are tech savvy. They have been doing technology things and it's not a new phenomenon for them to try something new..." (Richa)

Agile culture that emphasizes learning

Brought up constantly, agile is key to how organizational culture moving forward. The empirics suggest that in the context of deploying AI, agile culture includes: crossfuntional collaboration, transparency in communication, customer focus, and flatter hierarchies with clearer and less lengthy processes.

"So like the change we are going through right now is also a massive cultural change where we throw away this whole hierarchy thinking, and we start thinking as a network. It is all about looking at opportunities and creating those opportunities on the run. That is a cultural change, so instead of looking at your boss like "what do you want me to do boss?", you look to the side. You look like "customer says they want AI for something significant - fraud detection". And then you get this request, and you look around the organization like who can help me get that, address the need of the customer..." (Christian Guttman)

AI is often described as an iterative process with experimentations and unpredictability. Time to value realization may be very long and failures may occur along the process. Consequently, companies need to have a learning culture that is open to change and uncertainty.

"it's a learning curve that you have to go through as an organization. So you have to have a little bit respect for that process overall. So if you have an open mindset, it will go well. Because this is something you learn and adapt from." (Fredrik Holmgren)

5.5 Change management as the enabling force

*"Digital transformation is about business, technology, and human. And, the perfect harmony exists when you have a total balance between these three. And too often, the human bubble is being overlooked. "(*Niclas Hansson)

5.5.1 To drive an organizational wide vision

The empirical findings reveal that often there are many ongoing analytics projects scattered throughout the organization. They are not part of a joint strategy and one solution will not be talking to another. Also, as marginal and incremental changes may be easier to adopt, companies run the risk of missing the disruptive potential by AI.

" Yeah you can do plenty of simple things which are marginal, which also are somewhat useful, but are having marginal impact on the business, and certainly you are missing the point or the big picture…" (Christian Guttman)

To go forward, respondents stressed that driving AI should not be project based, but start with an organizational wide vision, with all the key stakeholders engaged and all the sub initiatives part of the overall strategy. Then to sustain the change, the organization drives more of it, so that it becomes part of the organizational life going forward.

5.5.2 To support an open mindset and future orientation

Another finding touches upon the mindset organizations need: be open to uncertainty and see it as a learning process. And this is often difficult in companies that are very outcome and target oriented.

"Eventually, you do not realize the benefit of AI solution in another year or two. It takes time. Then what is it in there for them to invest in it? It's not always money, it's not always about actually realizing the benefit, it's about being part of the future…" (Richa)

"You need to try to maximize learning rather than maximize money in the first instance. So it is not about making the fifty million euro in this year, but about trying to find out what are the structures and processes that need to be in place…" (Christian Guttman)

5.5.3 To set a central point of escalation

The empirical findings show that one frequently brought up and acknowledged method is to establish a central team, function or unit within the organization. This central point owns the transformation journey, brings scattered voices into a unified objective, provides support and allocates resources to different units.

"Then it is to start creating a structure which in the organization, to start off with some sort of one-stop-shop like a centre of excellence or some area which owns the development and this journey, this transformation." (Christian Guttman)

"So instead of doing ad hoc and doing discoveries, we'd rather establish a project, so we have the core teams, the reference teams, the steering committee. We have committed resources and committed leadership across the board." (Kanda Kumar)

5.5.4 To enforce agile development methodology

"It is very much about new and immature technology and solutions. So it is very much about trying, failing, trying and failing…" (Nils Kristensen)

Emphasized in the empirical findings, the agile method is central to all AI adoption projects. Yet it is also pointed out that many organizations do not have adequate agile set ups to enable the development.

Also demonstrated in the empirics, there are three motivations behind choosing the agile method (in addition to it being a novel method in software development):

1. Early and predictable delivery. To start small and show quick wins as a method of proving and justifying moving forward with the project:

   "But what is important here is to try different smaller projects and see if there are fruits or if you should try something else. Rather than go enterprise already, at the first phase." (Fredrik Holmgren)

2. Stakeholder alignment. Working with minimum viable products (MVP) increases the transparency which in turn involves and keep business stakeholders updated throughout the process.

3. Predictable cost and efficiency. Organizations can drive multiple projects with minimized cost. Successful MVPs can be further developed, while failing ones can be discarded in an early stage.

   "...You are not putting all your eggs in one basket. In a certain area, you need to allow yourself to not be successful. And this is obviously both agile development and way of minimizing the whole big bang project going south and protecting your investments." (Peter Beronius)

Aligned with the agile approach, the empirics also emphasize the importance of having value realization structure and KPIs that are not too structured and target oriented, but rather show capability development and enable future actions.

"it is dangerous to be too structured early, because it maybe discounts certain opportunities and possibilities. If you don't quite know what the end result is, because you haven't done it in the past, because AI is providing so many different capabilities. It can be dangerous to be too structured..." (Peter Beronius)

"It would be KPIs which are not indicating a past performance but that give you an indication of how ready you are for the next step, I think. That would be a different type of thinking..." (Christian Guttman)

5.5.5 To engage business stakeholders

"So when I came in, I spoke to a lot of different people, I just tossed some open questions like what do you think about automation. How are you thinking we are doing? What do you think the approach is? Is it going well? What are the pain points or challenges? You know, just tell me. No specific questions, just give me your views I am coming in new; I would like to get your inputs on how we can move forward in this area…" (Kanda Kumar)

Suggested in the empirics, already in the initial stage of setting strategy, stakeholder management becomes one of the most important components for driving change. As mentioned previously, AI adoption is an organizational wide vision, and to arrive at the common ground, different stakeholders in the organization need to be aligned. Furthermore, to quite Milap Patel: "*nobody knows the business better than the business itself, so it is a lot about the collaboration*".

Meanwhile, as AI typically spans over many different business lines, the AI drivers will need to get buy-in from different business decision makers. To scale up, everyone needs to be involved and aligned.

5.5.6 To help people find the motivation

Demonstrated in the empirics, one critical aspect of driving AI is to make people in the organization understand the motivation behind, and act upon it actively. This is something where a lot of companies fall down.

"...because if people don't understand the motivation, they will be reluctant to change. I think knowledge about AI is one thing, but now I think it is about the motivation…" (Vik Li)

"I think Ericsson has gone through a few pretty tough years which means we understand that nobody will want to go through that again, nobody wants to run into a 20% headcount reduction in a few years, so we understand that in order to stay relevant, to stay competitive, to stay profitable, AI can actually support that…." (Milap Patel)

5.5.7 To prove the value in continuing

The empirics suggest that, for the change driver/project team, there is always a need to prove both their own and the technology's credibility, especially towards the beginning. It can be done through for example working on MVP, showcasing success, picking low hanging fruits, etc.

"When it comes to any innovation or when it comes to new tech and so on, you need to prove your value in a sense. Until I actually implemented something in production, show some kind of value realization, it's always going to be question." (Milap Patel)

"You need to be able to go in and showcase a few things right. Then you create more of trust and curiosity about what is happening, and that can lead into other things like creating a proactive approach and a buy in among the organization." (Kanda Kumar)

5.5.8 To communicate to and to involve the whole organization

"So Information, information information, and involvement, involvement, involvement. Especially in Sweden. Involvement, involvement, involvement." (Niclas Hansson)

Demonstrated strongly in the empirics, communication towards the whole organization when driving AI plays a very central role. Starting even before the projects are taken into running, people in the organization need to be communicated to, motivated and aligned. Along the process, they need to be updated with what's happening and where this is going. In general, people in the organization should be made part of the journey through communication, if not direct collaboration. Adequate levels of transparency and regular communication are key.

"AI is a revolution, I don't even call it transformation, it's another level. Then you create a revolution, how do you go and communicate it. It cannot happen just from the top, it cannot happen just in the middle, it has to go across. It's like a ripple effect, you are supposed to communicate." (Richa)

Another aspect suggested by the empirics is to show that the goal of AI is to augment, not to replace. Regardless, people in the organization will be taken care of, with for example a competence development plan. To get people's support, you need to make sure they are not scared.

"And the thing is, we are going to use robots so you can spend three times more time talking with the woman, because the robot will do all the bureaucracy that you do. So we will unleash time for you to interview her more! To spend more time with the customer!" (Niclas Hansson)

5.6 Synthesis of Empirical Findings

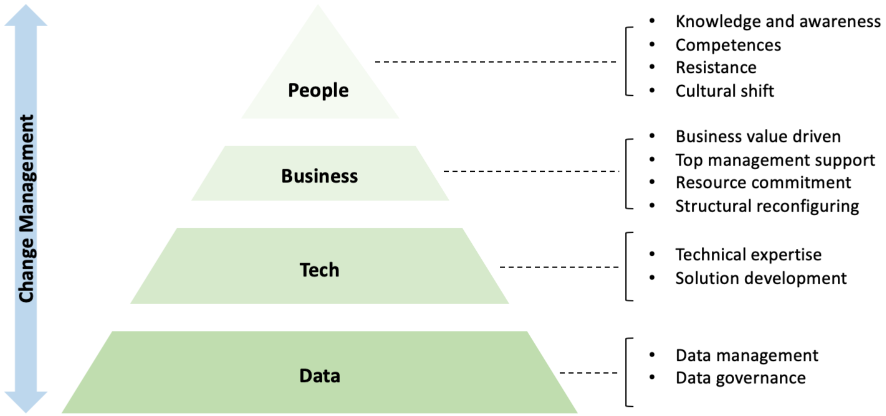

Figure 7: Synthesis of empirical findings

To sum up the presented five themes in relation to each other, a pyramid framework is constructed (see figure 7). Although having quality data and means of technology development sit on the bottom two floors and are the foundation for organizational AI adoption, the empirical findings show clearly the criticality of aligning the business side and engaging people into part of the transformation. Besides identifying these four elements on the pyramid, it is also demonstrated in the empirics that organizational adoption of AI should not be treated as a technology initiative, but as a change management project (the fifth element). To potentially succeed in organizational adoption, as supported in the empirical findings, all five elements need to be managed under a unified AI strategy.

Chapter 6. Analysis

This study aims to explore, describe and analyse ***"How do organizations manage successful AI adoption from a change management perspective?"*** To fulfil the purpose, the authors analyse the empirical findings through the theoretical framework, which combines two interrelated theories, as presented in chapter 3. Structured in accordance to the research questions, this chapter is divided into three parts:

(1) Organizational AI adoption & dynamic capabilities
(2) Organizational AI adoption & three-step model of change
(3) Synthesis of analysis

6.1 Organizational AI Adoption & Dynamic Capabilities

In the following section, the empirical findings are analysed through the lens of dynamic capabilities theory. The purpose is to identify characteristics that help generate sensing, seizing, and reconfiguring capabilities, to answer sub-question 1: ***"What organizational micro foundations undergird the dynamic capabilities for AI adoption?"***

6.1.1 Sensing

Sensing capabilities in this area are taken to describe the organization's ability to sense and identify opportunities for AI adoption.

6.1.1.1 Involvement of the entire organization

As described in the theoretical framework, dynamic capabilities literature can place a lot of responsibility for these on the organization's leadership. While the empirical findings do support the top leadership being important for sensing capabilities relating to AI adoption, they also seem connected to lower levels in the organization. Identifying pain points in the organization's activities or offerings where AI can be used to generate a lot of business value is stressed in the findings as being both important and difficult, and respondents described the benefit of having extensive domain knowledge in order to identify such application areas.

This business expertise was described as often being missing from the technology experts developing the solutions, and while it may instead come from top managers or external advisors, respondents also described how business practitioners further down in the organization could identify application areas for AI in their own domains. Hence, sensing capabilities for AI adoption appear to benefit from the involvement of the entire organization.

6.1.1.2 Knowledge of data and AI

The main roadblock to overcome for the organization to be able to sense and identify AI opportunities appears related to insufficient knowledge. Partially regarding an understanding of what AI is and what it can be used for, but in many organizations the lack of knowledge appears to extend significantly further than that. Lack of data literacy appears widespread, and as AI is essentially an advanced use of digital data, one should know about the former to understand the latter. As a result, a company should be characterised by a relatively high knowledge of AI and data extending throughout the organization.

As making the organization aware of AI and data to a greater extent than is common today appears important, concerted educating efforts of its members seems to be a recurring characteristic. The findings support that organizations interested in adopting AI often bring in outside expertise with more knowledge about the technology. Either by recruitment or as temporary consultants. These experts do not appear to just take over and head the related projects themselves, but a lot of what they do seem related to teaching the rest of the organization about AI and related technologies. Either in the form of meetings or similar face to face settings, to formal training programs for larger parts of the organization. While some of this is connected to building support in the organization for the AI initiatives, it also seems to serve the purpose of getting people with domain expertise (i.e. non-AI experts in the company) up to a sufficient degree of understanding of the technology that they can start identifying usage areas for themselves. As a result, sensing opportunities for these technologies appears to be connected to knowledge of data and AI, and processes for improving this inside the organization.

6.1.1.3 Tech oriented perspective

A further element of sensing opportunities appears related to the general technology orientation of the organization. Respondents bring up how tech companies currently tend to be quicker at AI adoption. While one reason for this may be their access to skilled data scientists that let them develop the actual systems, respondents also describe how these organizations tend to be interested in and used to keeping up with outside technological developments to a greater extent than many other organizations. This is given as a reason for why they seem to have been willing to explore and try out AI opportunities at a relatively early stage. As a result, a technology-oriented mindset within an organization may be beneficial to its sensing capabilities.

6.1.2 Seizing

Seizing capabilities are here interpreted to mean the capacity of the organization to decide, invest in, and execute on opportunities for AI implementation that it has identified via its sensing capabilities.

6.1.2.1 Committed top leadership

In order to seize on AI opportunities, commitment from the top appears crucial. The reasons being that adopting AI is described as often constituting major changes. It may have significant effects on how the organization is organized, and hence risks upsetting its stakeholders. The development itself may also require the involvement and cooperation of several different units within the organizations, such as for sharing data, competences, or similar. A top leadership that is committed to adopting AI is by respondents described as an important characteristic for making the initiatives happen, both by providing them with sufficient resources and managing resisting stakeholders.

6.1.2.2 Tolerance for risk and learning

AI initiatives appear relatively uncertain in comparison to many other investments. Respondents give the impression of it being difficult to know what you are going to get before you start in terms of results. This would make AI initiatives comparatively risky, and the findings hence support risk tolerance as a beneficial characteristic for its adoption. As the time to full value may be long as the systems gradually learn and the organization itself builds up competencies for using them, the organization should be characterised by decision making abilities that favour longer investment horizons.

6.1.2.3 Identification of business cases

The findings imply that adopting AI should follow a business first approach, where its potential implementation is strongly connected to solving important business problems. As opposed to looking for excuses to use the technology. This means that an organization should have the capacity for evaluating business applications of AI, in order to be able to identify and design proper use cases. Many respondents present this as being quite difficult and demanding.

6.1.2.4 Extensive collaboration across the organization

In order for maintaining a strong business connection when adopting AI, cooperation between technology experts and business experts seems desirable. Initiatives may also span across the organization’s traditional units and functions in terms of the competences or resources that are needed to realize particular applications. The findings also support multidisciplinary teams as the organizational form for projects in this area. In order to facilitate the existence of such teams and ensuring that they have the mandate to access the resources that they may need from across the company, it seems that the organization should be characterised by extensive collaboration.

6.1.3 Reconfiguring

Reconfiguring is here understood as the ability of the organization to change its own internal structures, culture and practices in order to facilitate effective adoption of AI.

6.1.3.1 Decentralized structures and simplified processes

Several respondents bring up bureaucracy and hierarchies as characteristics that their own companies are trying to reduce as they start adopting AI and advanced analytics. Aside from getting in the way of collaboration, such structures can also impede communication and decision making, and thus slow down change initiatives in general. As AI adoption often seems to generate many changes throughout the organization, such slowing down is undesirable. Respondents hence support more decentralized organizations, where decision layers are fewer and changes can be quick.

6.1.3.2 Extensive investments in competence development

Another finding is the organization's capacity to reskill its members. This refers particularly to training that supplies the organization with required competencies after it changes. As AI serves to mimic human intelligence, adoption of such technologies can significantly change the tasks done by the organization's personnel. While the respondents did tend to stress that the main purpose of AI was to augment rather than replace humans, they pointed out that wholesale replacement did happen too. Furthermore, even AI that augments human work can change the competencies needed for it.

It hence appears that effective AI adoption is connected to the organization having effective competence development structures. Either to upskill its members to work with the new tools, or to be able to move them to new functions in the organization. Otherwise it may be difficult for organizations to effectively reconfigure themselves to handle continuous AI adoption, as they might find difficulties in acquiring the necessary skills and competences such changes may result in the demand for.

6.1.3.3 A culture of change

AI can bring significant changes to an organization, as its application areas can end up affecting all the parts of a business. This process may also be continuous, as gradual learning may mean that the organization can keep identifying opportunities for using AI. The organization's culture should hence be tolerant of repeated change. This change attitude appears to extend beyond the structure of the organization itself, in that its members may also need to be ready to change their own characteristics over time. Gradual adoption of AI may mean that work practices and required skills change, which means that the organization's members may need to be comfortable with being required to learn continuously throughout their careers.

6.1.4 Concluding Remarks

Dynamic Capabilities
Micro foundations
Sensing
Involvement of the entire organization
Knowledge of data and AI
Tech oriented perspective
Seizing
Committed top leadership
Tolerance for risk and learning
Identification of business cases
Extensive collaboration across the organization
Reconfiguring
Decentralized structured and simplified processes
Extensive investments in competence development
A culture of change

Figure 8: Analysis - dynamic capabilities

Applying a dynamic capabilities view, a number of AI specific micro-foundations for sensing, seizing and reconfiguring are identified (See figure 8). For the organization to sense and recognize areas where AI solutions could create value within the business, knowledge, involvement and technology orientation stand out as beneficial. For then seizing on these AI opportunities, a committed leadership, an organization that tolerates risk and longer-term investments, has sufficient competence with AI to properly make business cases, and extensively collaborates, appears important. For reconfiguring the organization according to the changes that these AI adoptions are likely to bring to it, a culture used to change, decentralized structures and simplified processes, and extensive competence development initiatives act as facilitating elements.

6.2 Organizational AI Adoption & Three-step Model of Change

To answer the sub-question 2: "***How do change agents support driving forces and decrease restraining forces to enable organizational AI adoption?***", the authors first conducted force field analysis on the first two stages of change. "Driving forces" describes actions that support move beyond equilibrium while "restraining forces" describe factors in favour of the status quo. While restraining forces are scattered and reactive, actions supporting driving forces are structure and proactive to combat one or a set of restraining forces. Then, stabilizing actions in stage three to sustain the change at the third stage were also identified.

6.2.1 Stage One: Unfreeze

This is the initiation stage of organizational AI transformation. Here, the talk starts, concepts are introduced, and people start to see the need and urgency for change. The goal of this stage is to break the status quo and provide a safe and supported environment for change to emerge.

6.2.1.1 Restraining Forces

1. Inadequate digital infrastructure and data foundation

   As pointed out in the empirics, companies may have become interested in or seen the need for AI, but only later to find out that there is a lot of groundwork to be done; or the process of sorting out the data gets so lengthy that the organization loses patience and focus before any value comes back.

2. Lack of commitment from top management

   To initiate the change, the leadership team needs to first understand the critical relevance of AI in future strategic landscape, then set out the vision and strategy, but most importantly, give full commitment and support to put the whole organization into a position that enables actions. Without the real commitment and support from top management, AI transformation dies when it encounters any stronger resistance and setbacks. As a consequence, there will be a lot of talk, but no actual progression.

3. Business case missing

   Effective AI deployment has to be connected to the organization's very core business and understanding of the mechanisms and pain points. In another word, if it does not make business sense, or one has not found the business sense, there is no point doing it. People will question the change as the change brings nothing beneficial, but extra work.

4. Competing priorities and resource constraints

   Pointed out in the empirics, AI initiatives have to compete with not only other technology initiatives, but also other strategic and operational issues spread out everywhere with pressing deadlines. And as organizations do not have unlimited resources, it is likely AI projects that are resource demanding are deprioritized or killed (due to failures from resource constraints).

5. Organizational structural and cultural heritage

   An organizational structure that is characterized with being old, overcomplicated, disjoint between different departments and bureaucratic. A culture that sits on past achievements and resists changes. Together they pose major restraining forces to organizations' AI initiatives.

6. People's negative reactions

   Fear, lack of trust, not seeing the need, along with general resistance to change, these negative reactions towards AI adoption are a major restraining force in both the unfreeze and change stages and need to be dealt with constantly.

6.2.1.2. Driving Forces

1. Top down vision and initiation

   In accordance with top management's central position in organizational AI transformation, formal strategy and vision come from them and are then announced. In the first unfreezing stage, top management initiating the "change" and bring it to the whole organization can be seen both as a strong drive force and the foundation enabling actions that give rise to other driving forces.

2. Central change team and multidisciplinary expertise

   A praised practice in the early stage is to establish a central team, function or unit within the organization. This central point owns the transformation journey, brings scattered voices into a unified objective, provides support and allocates resources to different units. This together with brought in/ together tech and business expertise in each target area serves as the premises for initiative to start spreading out. In comparison with "top down vision and initiation" that occurs at the top, this driving force starts in the middle and works across the organization.

3. Awareness and knowledge building

   Similar to all change projects, but especially in this context, due to the fact that AI has high complexity and people's general knowledge of AI is limited and scattered, particularly because the information from mass media is often misleading. So in order for the change to move forward, awareness and knowledge about AI among people needs to be built.

4. Provide motivation

   To make change happen, one needs to first make people see and understand the need for change. This happens through multiple communication channels and the end goal is not only to make people recognize the need, but also to help them internalize the motivation and associate it with personal goals.

5. Stakeholder engagement

Besides having support and commitment from the top management, aligning stakeholders from different line of business or units is another strong driving force that must be attained. It is both to get buy-in from different lines, and to use them as a middle ground to reach and engage wider circle of audiences.

To sum up, at the unfreeze stage of change, top management announcing a vision and initiating an AI strategy works as the foundation for other driving forces to arise. Change agents, as part of the central change team, become the critical point of escalation in the middle, linking top management, business stakeholders and broader group of audiences (See figure 9 below). Through engaging, motivating and providing means of learning, the whole organization, glued together around the central change team, is set into a position ready to implement changes.

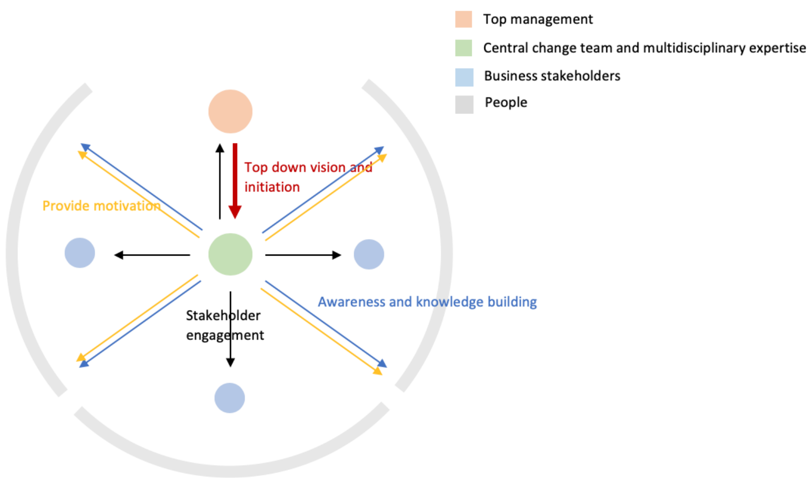

Figure 9: Stage 1 – actions support driving forces

6.2.2 Stage Two: Change

In the context of organizational wide AI adoption, this stage of change usually consists of multiple sub projects targeting different areas, working under a unified strategy. Here, change implementation is driven by rapid exploration and experimentation. For change to take place, driving forces must outweigh any restraining forces.

6.2.2.1 Restraining Forces

1. Lack of continuous commitment from top management

   Similar to the restraining force “Top management not fully committed” at the unfreeze stage, problems arise from top management withdrawing their commitment and support at any point.

2. Competing priorities, resource constraints and distractions

   In addition to the restraining force “Competing priorities and resource constraints” at unfreeze stage, the longer into the change process, the more likely distractions will occur. It can be either path deviation due to inadequate governance structure, or emergence of other technologies and opportunities.

3. Organizational structural and cultural heritage

   Similar to the previous stage, a structure and culture that favours old routines and is risk aversion continue to hinder change. However, assuming the organization has successfully moved from “unfreeze” to “change” stage, its structure and culture should have moved a step further to the desired state and therefore become less powerful a restraining force here than in the previous stage.

4. People’s negative reactions

   As mentioned in previous section, people’s negative reactions towards AI adoption are a major restraining force in both unfreeze and change stages and need to be dealt with constantly.

6.2.2.2 Driving Forces

1. Ongoing communication

   Emphasized in the empirical findings, people across the whole organization should be made part of the journey through ongoing communication or collaboration. Depending on stages of change and audience category, messages conveyed vary from status update, knowledge and story sharing, vision and future direction to inviting contribution and commitment. This is done through multiple channels like workshops, forums, roadshows and meetings. Successful communication can move people from being reactive recipients to acting proactively.

2. Celebrate quick wins

   Working with agile development, together with value realization structure and KPIs that focus on progression and future actions, it is made possible to have early and predictable deliveries. There can also be an element of picking low hanging fruits. Celebrating and making the quick wins visible across the organization keeps people excited and engaged to implement more of the changes. It also works in the direction of proving to business stakeholders that AI is value adding and worth the investments.

3. Competence development

   Another important driving force addressing people in the organization is to show them that the desired state does not involve automating them out of jobs. Thus a competence development platform and career progression plan is essential for people to support and to internalize AI into part of their daily work.

4. Organizational restructuring

   A flatter organizational structure that enable collaboration is brought up in the empirical findings as necessary. Instead of always looking up at the managers or taking orders, people work in the direction of satisfying customer needs by bring together expertise from different units.

Moving from unfreeze into the change stage, change agents actions go from convincing and preparing the organization to change, to keeping them onboard continuously while changes are undergoing. New challenges, compared to the previous stage, are for one, that more resistance will likely occur when people actually start to see that changes are decomposing their comfort in old routines; and secondly, due to AI's uncertain and resource demanding nature, unexpected failures and long time to value realization may disrupt people's earlier beliefs and determination.

Consequently, to keep the change going, change agents communicate regularly to top management, business stakeholders and broader audiences in the organization to update them with what is undergoing, and celebrate small successes with them. Beyond this, competence development in the form of for example, education courses and lectures, need to be provided to help people internalize AI and new changes into their daily work life. Last but not the least, the most challenging step at this stage is to get top management onboard that structures and processes hindering the change must be altered or removed (See figure 10).

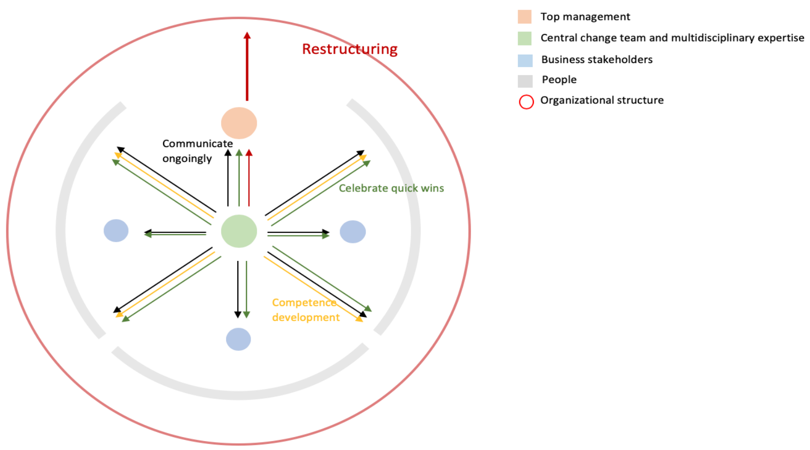

Figure 10: Stage 2 – actions support driving forces

6.2.3 Stage Three: Refreeze

The goal of refreezing is not only to make AI part of the organizational life and people's daily work environment, but also to alter the organizational structure and processes to stabilize the change. However, for most organizations, their AI journey is still at either a primitive or ongoing stage, with smaller sub projects done but organizational wide transformation far ahead. Therefore, identified stabilizing actions to sustain the change at the refreeze stage come from interviewed change agents' experiences from earlier digital transformation projects and speculation, instead of description of actual occurrence in AI initiatives.

1. End to end communicate

   Key to change management at any stage is communication conveying varying messages. Here, the goal of communication is to make sure the success is visible to everyone and the entire change journey becomes a compelling story of why and how change is of the organization's and everyone's interest.

2. Continuous knowledge and competence development

   To help people get more used to the new way of working in the presence of AI, knowledge and competence development at this stage is as crucial as in previous stages. It can even now provide richer content and reach broader audiences in the organization. Besides educating people about AI related technologies, strategies and ways of working, knowledge and competence development at this stage also opens the door for employees to rapidly changing technological and business landscape and inspires and motivates them to be excited and ready for future change.

3. Implementation of new structure and process

As the ways of working have changed as a result of organizational wide AI adoption and to accommodate new values, structures and processes that support, and control operating procedures need also be revisited to solidify the change. While a complete list of practices to achieve that is missing, some commonly mentioned ones by the interviewed experts are for example having a matrix organizational structure, and performance evaluations based on group achievement rather than individual success.

6.2.4 Concluding Remarks

To conclude, change agents, as part of the central change team, sit in the centre on both organization's formal and informal network, connecting top management, business stakeholders and broader audiences (See figure 11). At the same time, they also exert indirect influence on organizational restructuring associated with the change implementation. Further, top management is found to have the deciding role in all stages of change. Its continuous commitment can be seen as the foundation of organizational AI adoption.

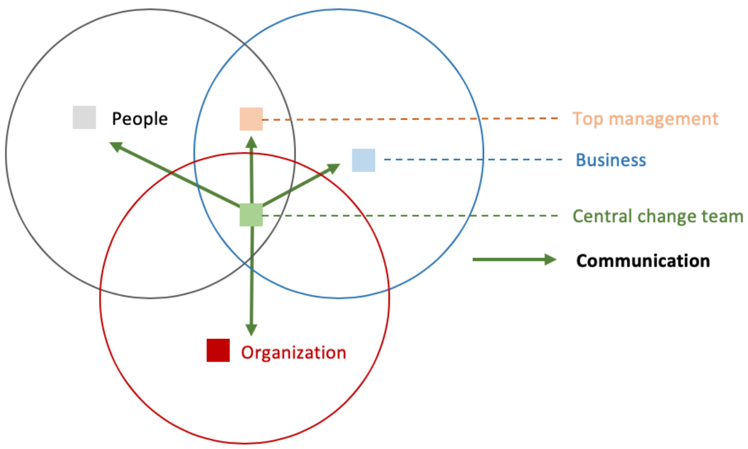

Figure 11: 3-stage of change concluding remarks

Moreover, to support driving forces that move the organization beyond equilibrium and achieve AI adoption, change agents communicate continuously to all presented essential parties, in slightly different priorities at different stages in response to where the strongest restraining forces occur. Targeted towards different audiences, messages conveyed vary from one stage to another, but with the same goal to active role specific actions from top management to operational level employees. For example, top management announces the vision and give continuous support; business stakeholders give buy-in and permission; operational employees help define business cases, etc.

Overall, from the perspective of change agents, to successfully manage organizational AI adoption requires aligning, balancing and enabling actions from all above presented parties on the network.

Chapter 7. Discussion

In this study, the authors draw on the dynamic capabilities view and three-stage of change model to research organizational AI adoption from change management perspective. Built on the authors' prior belief that dynamic capabilities support driving forces to move beyond equilibrium at different stages of change, findings from two parts of the analysis are compared to confirm the assumed relationship.

The following table (See figure 12) illustrates the supporting relationship from dynamic capabilities to driving forces at three stages of change. For example, having committed top leadership in dynamic capabilities supports getting top down vision and initiation, stakeholder management at the unfreeze stage, and organizational restructuring at the change stage.

Dynamic Capabilities	3-stage of change		
Microfoundations	Driving Forces		
Sensing	Unfreezwe	Change	Refreeze
Involvement of the entire organization			
Knowledge of data and AI	Provide motivation		
	Stakeholder engagement		
Tech oriented perspective	Provide motivation		
	Stakeholder engagement		
Seizing			
Committed top leadership	Top down vision and initiation	Organizational restructuring	
	Stakeholder engagement		
Tolerance for risk and learning		Celebrate quick wins	
Identification of business cases	Stakeholder engagement		
Extensive collaboration across the organization	Central change team and multidisciplinary expertise		
Reconfiguring			
Decentralized structured and simplified processes		Organizational restructuring	Implement new structure and process
Extensive investments in competence development		Competence development	Continuous knowledge and competence development
A culture of change		Organizational restructuring	Implement new structure and process

Figure 12: Analysis dynamic capabilities to three-stage of change

On the other hand, it is also found that as the organization moves from one to another stage of change, actions supporting driving forces to adopt AI will in turn change the internal processes and characteristics of the organization. The following table (See figure 13) illustrates the contributing relationship from actions supporting driving forces in three-stage of change, to dynamic capabilities. For example, stakeholder engagement action taken at the unfreeze stage adds to organizations dynamic capabilities in seizing in terms of identification of business cases and extensive collaboration across the organization.

3-stage of change	Dynamic capabilities		
Driving Forces	Microfoundations		
Unfreeze	Sensing	Seizing	Reconfiguring
Top down vision and initiation			
Central change team and multidisciplinary expertise		Identification of business cases Extensive collaboration across the organization	
Awareness and knowledge building	Involvement of the entire organization Knowledge of data and AI	Identification of business cases	
Provide motivation	Involvement of the entire organization		
Stakeholder engagement		Identification of business cases Extensive collaboration across the organization	
Change			
Ongoing communication		Extensive collaboration across the organization	A culture of change
Celebrate quick wins		Committed top leadership	
Competence development			A culture of change
Organizational restructuring		Extensive collaboration across the organization	A culture of change Decentralized structure and simplified processes
Refreeze			
Communicate continuously	Involvement of the entire organization Tech oriented perspective		A culture of change
Continuous knowledge and competence development	Involvement of the entire organization Tech oriented perspective		A culture of change
Implement new structure and process			Decentralized structure and simplified processes A culture of change

Figure 13: Three-stage of change to dynamic capabilities

Consequently, supported by the findings, the authors propose that, dynamic capabilities, which depicts an organization's abilities to alter itself in light of changing external circumstances, and change management, the process of an organization's continual renewal to accommodate the ever-changing needs of external and internal customers, exist together in a two-way co-evolving relationship. To integrate the findings, an adapted theoretical framework is presented below (See figure 13).

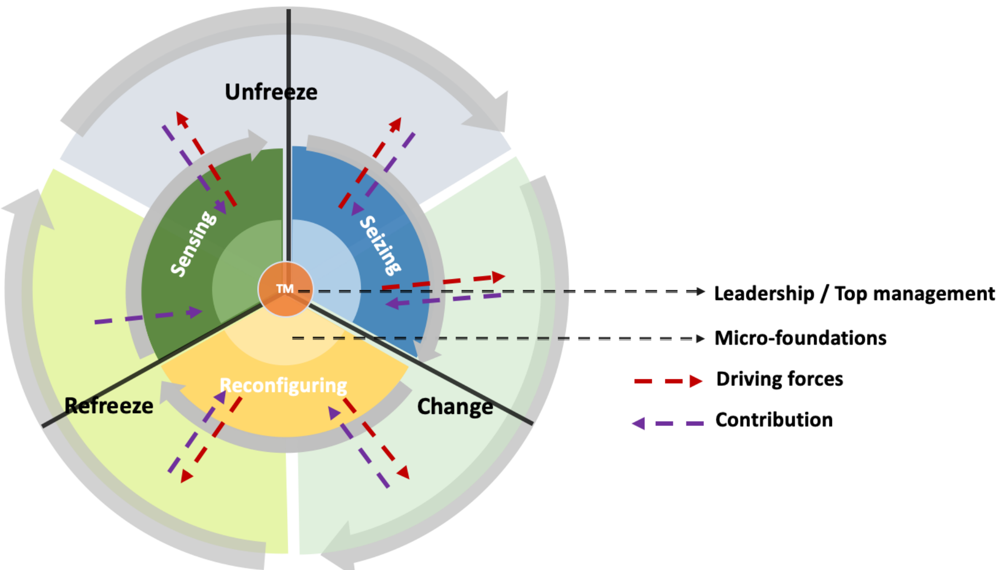

Figure 14: Revised theoretical framework

While dynamic capabilities are still in the centre of an organization's ability to possibly identify opportunities of and viability of change, and to integrate the change into part of the organizational life, change practices determine whether an organization can sense opportunities, seize the opportunities, and reconfigure itself to capture value from them. For organizations to successfully adopt AI on organizational level, the practices taken in change management need to be planned in accordance with organization’s dynamic capabilities; and the desired stage of any changes should in turn enhance and create new dynamic capabilities which provide stronger driving forces in the next round of change.

Further, the authors propose that the presented change model is continuous with new rounds of changes constantly being initiated in light of a changing external environment and emergence of new opportunities. Top management, pointed out to have the most critical role in the analysis of both theoretical concepts, sits in the centre of the presented model and is the mobilizing factor which decides if the organization is able to leverage dynamic capabilities and change management practices to adopt AI.

Moreover, as organizations are able to enhance or acquire new set of dynamic capabilities in the process of each change initiatives, the authors propose that it will increase the organization's ability to sense, seize opportunities and reconfigure itself to capture the value, and it will also increase the frequency and speed of change in the future. In a word, the more change organizations drive, the better organizations are likely to become at spotting and driving change.

Chapter 8. Conclusion

To investigate how AI adoption is being managed inside organizations from a change management perspective, the authors conducted a qualitative multiple-case study. Two interrelated theoretical concepts: dynamic capabilities and three-stage of change, were chosen and combined to guide the study. With data collected from 16 in depth interviews with organizational AI adoption practitioners, the study generated rich empirics on organizational characteristics and change management practices which enable AI adoption in a wide variety of organizations.

In addition, the study confirmed the critical role of both dynamic capabilities, which depicts the organization's' ability to alter itself proactively, and change management practices that support driving forces to move the organization away from the equilibrium. On the one hand, having a set of AI specific dynamic capabilities increases the likelihood of organizations sensing, seizing and reconfiguring themselves to capture AI opportunities; On the other hand, applying stage specific change management practices in response to the embedded organizational environment determines if AI can actually be adopted.

In contrast to the prior assumption that only dynamic capabilities support change management practices, the study suggests that dynamic capabilities and change management practices, exist in an interrelated co-evolving relationship, where change management practices driving AI adoption will also add to organization's dynamic capabilities by exerting positive influence on micro-foundations.

Moreover, consistent with prior research (Kane et al., 2017, Ransbotham et al, 2017, Hillmer, 2009), top management and change agents are found to play central roles in organizational AI adoption. While top management works at the foundation and are the initiators of change, change agents are the point of escalation that connect all relevant parties in organizational adoption of AI.

Chapter 9. Contribution and future research

9.1 Theoretical Contribution

Taking a qualitative approach to study organizational AI adoption from a change management perspective, this paper has made the following theoretical contributions:

1. Built on prior research that took a static perspective of a firm's resources and capabilities needed for AI adoption (Höglund, 2017), the study presents a dynamic view on AI adoption capabilities.
2. The study explored the AI adoption in a wide range of organizations by combining the dynamic capabilities view with 3-stage of change model to investigate the organizational characteristics and change management practices that facilitate successful AI adoption. It expanded literature on dynamic capabilities and change management theories into a nascent research area - organizational AI adoption, and suggested the existence of their interrelated co-evolving relationship.
3. Results of the study confirm the relevance of digitalization and organizational technology adoption literature in the field of AI. However, the authors also do not exclude the possible explanation that AI change practitioners tap into their prior knowledge about digitalization and other technology adoption when working with AI, due to the lack of theoretical and empirical guidance on AI adoption in specific.

9.2 Managerial Implications

The findings of the study are of relevance to a wide range of actors in the field of AI analytics adoption in organizations: IT & management consultants, leadership teams, middle management, operational level employees etc.:

1. A human perspective of AI adoption is suggested. Instead of focusing only on the technology, organizations should treat AI adoption as a change project and focus on managing its possible implications on people.
2. To successfully adopt AI, the organization should focus on developing a set of organizational characteristics to transform the way it responds to changes and does innovation.
3. Change agents role should be given more attention, especially in relation to the rest of the organization, as they sit in the middle and exert huge influence on the whole network in AI adoption.

9.3 Limitations

The methods and perspectives used in the study create certain limitations. Firstly, the study is mostly based on outside-in views of external consultants, with only two interviewees having been part of the organization for longer period. Similarly, as the interview sample only consists of AI change practitioners, the study does not take in other individuals' perspectives in the organization. Further, as most interviewees work with clients from a wide variety of industries, the representation for any particular one is also limited in the sample. Lastly, generalizability of the results to outside this geographical area could potentially be reduced, as data collection is limited to only the Nordic region.

9.4 Future Research

Several potentially interesting areas for further research have been identified throughout the study. The first one concerns studies on AI analytics adoption that are more industry specific. This study focused on AI analytics adoption in general, but it is possible that there are differences between how the changes are or should be managed in different industries. Further, it could be fruitful to study other organizational aspects of AI adoption in organizations. Particularly the political environment and how this may affect be affected by the technology adoption, as some findings suggest that internal politics may constitute an important part of change management (Burnes, 2017). Moreover, Studies could also be conducted on the experiences of individuals that are not directly involved in the AI initiatives, and how they perceive these changes. Lastly, the specific roles and characteristics of the change agents driving the adoption might be worth further study. For instance, change agents' background, position and particular skills.

Chapter 10. References

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Chapter 11. List of Appendices

Appendix 1. List of interviewees

No.	Name	Position	Organization	Type of organization	Interview type	Date
1.	IT Consultant 1	IT Consultant	Large IT-services firm	IT & Professional services	Skype	2019.03.06
2.	Nils Kristensen	Director, Head of AI & analytics	Knowit	IT & Management consulting	Skype	2019.03.07
3.	Fredrik Holmgren	Managing Director	Pedab Sweden	IT infrastructure and software	Skype	2019.03.11
4.	Tech consultant 1	Technology Consultant	Large professional services firm	IT & Professional services	Skype	2019.03.12
5.	Niclas Hansson	Vice President, Consulting	EVRY	IT Consulting & Business solutions	Skype	2019.03.20
6.	Adrien Vetterli	Data Scientist	BDS Bynfo	Software consulting	Skype	2019.03.27
7.	Peter Beronius	Sales Manager, AI and analytics	DXC	IT Services and solutions	In person	2019.03.27
8.	Sami Rouhe	Data Engineer	BDS Bynfo	Software consulting	Skype	2019.03.27
9	Reinhard Seifert	Data Scientist	Solita	IT & Management consulting	In person	2019.03.29
10.	Vince Guidotti	Business Development	Birst	BI & Analytics platform provider	In person	2019.03.29
11.	Christian Guttman	Vice President, Global head of AI	Tieto	IT Consulting & Services	In person	2019.03.09
12.	Nils Kristensen	Director, Head of AI & analytics	Knowit	IT & Management consulting	In person	2019.04.10
13.	Richa Khurana	Automation & AI Consultant	Tata Consultancy Services	IT Consulting	In person	2019.04.10
14.	Kanda Kumar	Engagement lead, AI & Transformation	Ericsson	Telecommunications & networking	In person	2019.04.16
15.	Vik Li	Innovation lead, AI & Transformation	Ericsson	Telecommunications & networking	In person	2019.04.17
16.	Milap Patel	Director, cognitive agent , AI & Transformation	Ericsson	Telecommunications & networking	In person	2019.04.23

Appendix 2. Interview guides

Interview Guide. Earlier Version.

This is a sample interview guide in its earlier version. As the interviews were semi-structured, the questions occasionally diverged from it.

Introduction

- We introduce ourselves, the purpose of our study, and inform the person that the conversation will be recorded and transcribed.
- Can you tell us about your background and what you work with?
- Can you tell us about your company, what does it do?

Questions about the current state of the technology

- What is your take on current AI & advanced analytics technology?
- How advanced is it? What can it do?
- What kind of decisions can be made by AI?

Questions about client organizations

- What is the demand and client interest for these technologies?
- How long does it take from talking to possible implementation?
- How do you go about convincing their managers?

Questions about personal experiences

- Can you tell us about a project you have worked with in implementing AI & A?
- What was the background? Why and how was the project initiated?
- What methods did you use? (Follow up if they don't describe this themselves)
- How long did the project take?
- How did people within the organization perceive it?

Questions about challenges and suggestions

- How do people in the organization react when the system doesn't work as it should?
- What would you say the main challenges of adopting AI are?
- What would you suggest to improve the process?
- What do you think about the future of organizations regarding these technologies?

Interview Guide. Later Version.

This is a sample interview guide in its later version. As the interviews were semi-structured, the questions occasionally diverged from it.

Introduction

- We introduce ourselves, the purpose of our study, and inform the person that the conversation will be recorded and transcribed.
- Can you tell us about your background, what you work with and the company you work for?

Questions about the current state of the technology

- What is your take on current AI & advanced analytics technology?
- What is your take on AI & advanced analytics in organizations?
- What is the state of companies' adoption?
- What changes does it bring to the organization? Structure, culture, operation?

Questions about personal experiences

- Can you tell us about a project you have worked with in implementing AI & A?
- What was the background? Why and how was the project initiated?

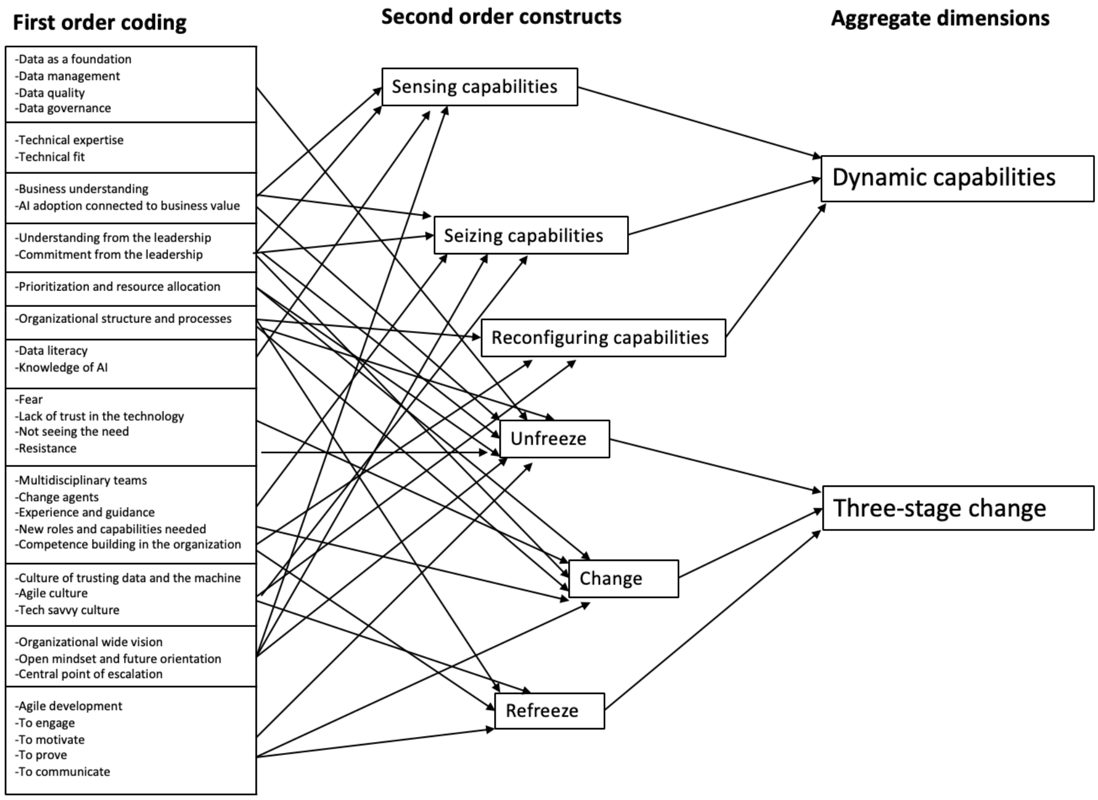
Questions about methods

- Who are working on this project? How do you build a team? Who are important to align?
- What happens next? How do you create a vision and strategy?
- What happens next? How do you communicate the vision and strategy?
- What happens next? …
- How do you track the progresses and value realization?
- What happens when you hit a wall?
- How do other people in the organization perceive the change?
- How do you scale up and consolidate the wins?
- Has it had an impact on organizational performance?
- How did it change the organization?

Questions about challenges and suggestions

- What would you say the main challenges are?
- What would you suggest to improve the process?
- What do you think about the future of organizations regarding these technologies?

Appendix 3. Coding table



Appendix 4. Sample Email to potential interviewees.

Hello ...,

Our names are Linus Olin and Iris Jiang, final year Master’s students in the Business and Management program at the Stockholm School of Economics. We are currently writing our Master’s thesis on Artificial Intelligence in organizations, and as part of the study we are going to conduct a series of interviews with experts in the field. We believe that you would be a very interesting interview participant, and it would be really valuable for us to talk with you!

The research area of our master thesis is the implementation of AI analytics in organizations. Or more precisely the factors and challenges within organizations that may prevent or enable the successful implementations of such systems. At this early stage we do not yet have a precise question, but the goal of our study is to develop a deeper understanding of the given area and contribute to discussions surrounding future implementation of such systems and organizational/managerial implications along with it.

So, if you are interested in participating in our study, we’d like to invite you to an approximately 1 hr interview with us, sharing your knowledge and experiences. If you wish, all the data regarding your identity and company can be anonymized (*a third person in the study, our supervisor from SSE will however have full access to the transcripts.)

Thank you in advance and we look forward to hearing from you soon!

Best wishes,

Linus Olin & Iris Jiang