Master's thesis

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Examining the Dimensions and Development of an Artificial Intelligence Capability With Effect on Competitive Performance

Master's thesis in Computer Science
Supervisor: Patrick Mikalef
July 2020

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Trondheim, 16.07.2020
Nikolai Helgheim Tellmann

Abstract

Artificial intelligence (AI) has become one of the key technologies to be considered by organizations worldwide, and many consider it the next source of business value. However, there is an evident gap between ambition and execution. Grounded in the resource-based theory of the firm and recent studies on AI in a business context, this study (i) examines the validity of a proposed theoretical framework for an AI capability, (ii) examines the claims that organizations struggle to realize business value from AI initiatives, and (iii) examines what conditions might foster the acquisition of resources that support and complement AI initiatives. Findings (i) empirically support the suggested theoretical framework for an AI capability, (ii) add to the pool of scientific evidence that organizations struggle to realize value from AI investments, and (iii) provide empirical evidence that an organizational emphasis on development and innovation fosters the acquisition of resources that support and complement AI initiatives.

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Abbreviations

AI	Artificial intelligence
RBT	Resource-based theory
IS	Information system
PLS-SEM	Partial least squares structural equation modeling
HTMT	Heterotrait-Monotrait Ratio
CA	Cronbach alpha
CR	Composite reliability
AVE	Average Variance Extracted

Chapter 1

Introduction

AI has become one of the key technologies to be considered by organizations worldwide (Gartner, 2019). This is largely due to the increasing availability of sufficient computational power, which enables AI technology (Mehta, 2018). The recent years have seen a surge of interest in AI, which is reflected in academic literature spanning multiple disciplinary domains. There is now a large number of articles on the potential business value that can be derived from AI initiatives (Ning et al., 2018; Ransbotham et al., 2017; Jones, 2018; Wilson and Daugherty, 2018; Vieira and Sehgal, 2018). However, reports and empirical studies from early adopters of AI indicate that organizations are struggling to realize business value from their AI investments (Davenport and Ronanki, 2018; Alsheibani et al., 2019; Wirtz et al., 2019; West et al., 2018; Schlögl et al., 2019; Quan and Sanderson, 2018; Brynjolfsson et al., 2017). As described by Ransbotham et al. (2017), there is an evident gap between ambition and execution when it comes to AI initiatives. Authors suggest that patterns of success and failure with AI initiatives are found to have evident correlations with a certain set of organizational resources - resources that are found to support and complement AI initiatives. There is emerging literature on what this set of complementary resources might comprise, and some refer to these resources as dimensions and indicators of an *AI capability* (Mikalef and Gupta, 2020).

Consistent within information system (IS) literature and resource-based theory (RBT), a competitive advantage is said to be gained by combining and deploying several complementary resources to create unique and hard to imitate capabilities (Bharadwaj, 2000; Kohli and Grover, 2008; Schryen, 2013; Gupta and George, 2016). In line with this, AI technology is unlikely to yield business value on its own - there is a need for a specific set of complementary resources to enable the AI technology, and thus gain a competitive advantage. Studies involving early adopters of AI technology suggest that these complementary resources comprise a unique blend of physical-, human-, and organizational resources (Davenport and Ronanki, 2018; Ransbotham et al., 2018; Chui and Malhotra, 2018). Thus, in line with recent research on what resources an AI capability might comprise (Mikalef and Gupta, 2020), and drawing on RBT (Grant, 1991) and past IT capability literature (Wang et al., 2012; Mikalef et al., 2019b; Kim et al., 2012; Gupta and George, 2016), this study defines *AI capability as the ability of a firm to select, orchestrate, and leverage its AI-specific resources*, and further defines AI capability as comprising a set of eight distinct AI-complementary resources categorized into tangible-, human-, and intangible resources. In light of this, what remains is to confirm the validity of this proposed AI capability construct as a means to gain a competitive advantage. Consequently, this study seeks to answer the following question:

- *(1) Does the proposed AI capability construct lead to competitive performance gains?*

Following this, there is an important distinction to be made between *'leading to competitive performance gains'* and *'leading to successful AI initiatives'*. The resources that are found to support and complement AI initiatives and thus constitute the proposed AI capability construct can be useful to any company whether they launch an AI initiative or not. To address this distinction, this study will explore the effects of the proposed AI capability construct on the outcomes of AI initiatives involving the three most common forms of AI (i.e., cognitive engagement, process automation, and cognitive insight), as identified by Davenport and Ronanki (2018). Consequently, this study seeks to answer the following question:

- *(2) Does the proposed AI capability construct lead to successful outcomes with* *cognitive engagement, process automation, and cognitive insight?*

In light of this, and to explore the many claims of reports and empirical studies that organizations are struggling to realize business value from their AI investments, I'd also like to explore whether successful outcomes with these three forms of AI affects competitive performance. Consequently, this study seeks to answer the following question:

- *(3) Does successful outcomes with cognitive engagement, process automation, and cognitive insight lead to competitive performance gains?*

Finally, while emerging theoretical frameworks for an AI capability are meant to capture the resources that support and complement AI initiatives, they will not necessarily address what might foster the acquisition of such resources. To begin addressing this gap in existing literature, this study proposes that an emphasis on development and innovation is key to developing an AI capability. To that end, this study proposes the concept of *developmental emphasis* as a catalyst for developing the resources that constitute an AI capability. Thus, this study defines *developmental emphasis as the organizational culture and conditions that foster dynamism, entrepreneurship, acquisition of new resources, and a craving for new challenges.* Consequently, this study seeks to answer the following question:

- *(4) Does developmental emphasis foster the acquisition of resources that are expected to constitute an AI capability?*

These questions were answered by means of an empirical study conducted with a questionnaire-based survey method aimed at data scientists and senior level IT managers of various backgrounds. I analysed the collected data using a combination of spreadsheets and structural equation modeling (SEM). To validate and analyse the SEM-models, I applied partial least squares-based structural equation modeling (PLS-SEM).

The paper is structured as follows: Chapter 2 provides an overview of the literature that this study builds on, including various definitions of AI, the RBT of the firm, and developmental culture. Chapter 3 presents the research model, along with relevant literature and hypotheses. Chapter 4 presents the empirical study, including the data collection process and constructs for measurements. Chapter 5 presents the process by which the structural model was validated and the hypotheses were tested, and the results. Finally, chapter 6 discusses theoretical and practical implications as well as some important limitations of the research.

Chapter 2

Background

2.1 Defining AI in the business context

The surge of interest in AI is reflected in academic literature spanning multiple disciplinary domains. Given that many of these domains have diverging notions of the key concepts related to AI, is it imperative to identify and clearly define these concepts, and to account for the diverging notions. This section discusses the various definitions of AI and concepts related to AI that are found in previous studies.

2.1.1 Artificial intelligence

As a starting point, I will provide an overview of how AI has been has been defined in past studies. Table 2.1 shows the definitions of AI that were extracted from previous studies dated between 2006-2019 listed chronologically.

The studies demonstrate two approaches to the definition of AI. The first approach is to define AI as the *field of study* related to systems exhibiting intelligence, as in the definition from Amazon (Jones, 2018). The second approach is to define AI as *the systems* exhibiting intelligence, as in the definition from Brookings Institute (Jones, 2018). The core aspect of AI seems to be largely agreed upon: *AI concerns systems* *exhibiting intelligence*. The studies demonstrate that there are four different ways in which a system can exhibit *intelligence*, and this splits the definition of AI into four different categories (Russell and Norvig, 2010): Systems that think rationally, systems that act rationally, systems that think like humans, and systems that act like humans.

There is also an evident change in the perception of AI throughout the years. Some of the more recent definitions express an optimism about the potential of AI - such as mentioning the possibility to exceed human capabilities (Adams et al., 2012) - whereas earlier definitions generally do not; one of the definitions even explicitly define AI as attempting to make computers do something that, at the moment, *people do better* (McCarthy et al., 2006). This change of perception over time - and transition into definitions expressing optimism and opportunity - reflects the timeliness and importance of discussing the readiness of organizations to adopt AI.

Table 2.1: Definitions of AI

Author(s)	**Definition**
McCarthy et al. (2006)	"The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it".
Rich et al. (2009)	[. . .] "the study of how to make computers do things which, at the moment, people do better".
Russell and Norvig (2010)	"AI may be organized into four categories: Systems that think like humans. Systems that act like humans. Systems that think rationally. Systems that act rationally".
Adams et al. (2012)	[. . .] "a system that could learn, replicate, and possibly exceed human-level performance in the full breadth of cognitive and intellectual abilities".

Continued on next page

Table 2.1 – continued from previous page

Author(s)	Definition
Rosa et al. (2016)	[. . .] "programs that are able to learn, adapt, be creative and solve problems".
Thierer et al. (2017)	"The exhibition of intelligence by a machine. An AI system is capable of undertaking high-level operations; AI can perform near, at, or beyond the abilities of a human. This concept is further divided into weak and strong AI".
Ransbotham et al. (2017)	Oxford Dictionary: "AI is the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages."
Jones (2018)	Brookings Institute: "Machines that respond to stimulation consistent with traditional responses from humans, given the human capacity for contemplation, judgment, and intention".
Jones (2018)	Amazon: "The field of computer science dedicated to solving cognitive problems commonly associated with human intelligence, such as learning, problem solving, and pattern recognition".
Vieira and Sehgal (2018)	"In its simplest form, Artificial Intelligence (AI), consists of a set of algorithms that can perform complex cognitive tasks, some deem – up to now – being exclusive to humans, and makes them amenable to machines".
Garbuio and Lin (2019)	"The fundamental principle of AI is machine learning, or the ability of a computer to improve upon its own capabilities by continuously analyzing its interactions with the real world".
Lee et al. (2019)	"Mimicking human cognitive function, particularly learning and problemsolving".

2.1.2 Artificial Intelligence in a Business Context

Some of the studies refer to business oriented definitions of AI (Table 2.2), which demonstrates that AI is already being defined in a business context.

In *Artificial Intelligence for the Real World* (Davenport and Ronanki, 2018), Davenport and Ronanki state that there are three different types of AI: Process Automation, which is the automation of digital and physical tasks using robotic process automation (RPA) technologies; Cognitive Insight, which is using algorithms to detect patterns in vast volumes of data and interpreting their meaning; and Cognitive Engagement, which is the engagement of employees and customers using natural language processing chatbots, intelligent agents, and machine learning. Note that all of these types are angled at different ways in which an organization can adopt AI to create value. These are also cited by some of the other studies, which demonstrates their relevance.

In *Artificial Intelligence as a Growth Engine for Health Care Startups: Emerging Business Models* (Garbuio and Lin, 2019), Garbuio and Lin state that the three different types of AI are the following: Assisted Intelligence, which is AI that *improves what people and organizations are already doing*; Augmented Intelligence, which is AI that *enables organizations and people to do things they couldn't otherwise do*; and Autonomous Intelligence, which is AI that *creates and deploys machines that act on their own.* Note that these are also all angled at different ways in which an organization can adopt AI to create value.

There are some similarities worth noting among these definitions. The concept of Assisted Intelligence incorporates Process Automation, the concept of Augmented Intelligence incorporates Cognitive Insight, and the concept of Cognitive Engagement requires a degree of Autonomous Intelligence. These similarities imply that there is a common notion about the possible applications of AI in a business context.

To define AI in a business context and aiming to be more specific regarding the way in which AI achieves specific goals, Kaplan and Haenlein (2019) defined *AI as a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation.* This is the definition that was presented to participants of the empirical study.

Table 2.2: Definitions of AI in a Business Context

Author(s)	Definition
Davenport and Ronanki (2018)	**Process automation:** Automation of digital and physical tasks using robotic process automation (RPA) technologies.
Davenport and Ronanki (2018)	**Cognitive insight:** Using algorithms to detect patterns in vast volumes of data and interpreting their meaning.
Davenport and Ronanki (2018)	**Cognitive engagement:** Engagement of employees and customers using natural language processing chatbots, intelligent agents, and machine learning.
Garbuio and Lin (2019)	**Assisted Intelligence:** AI that "improves what people and organizations are already doing" by automation based on clearly defined, rule-based, repetitive tasks to remove redundancies from business operations, improve efficiency, and boost the value of existing activity.
Garbuio and Lin (2019)	**Augmented Intelligence:** AI that "enables organizations and people to do things they couldn't otherwise do" through sophisticated algorithms built for natural language processing and sifting through massive accumulations data and records.
Garbuio and Lin (2019)	**Autonomous Intelligence:** AI that "creates and deploys machines that act on their own," making decisions based on their best interests using machine learning algorithms that operate independently of human instruction or oversight.

2.2 The RBT of the firm

The resource-based theory (RBT) of the firm is one of the most widely applied theoretical perspectives for explaining how the resources that an organization owns or has under its control can lead to differences in performance in the same industry (Barney, 2001). Grounded in literature on strategic management, the RBT argues that a firm's competitive advantage ultimately stems from the characteristics of its resources. Based on a framework proposed by Wernerfelt (1984), resources that are *valuable, rare, difficult to imitate, and non-substitutable (VRIN)* can generate performance gains (Bharadwaj, 2000). Literature proposes a distinction between resource-picking and capability building as two central facets of theory. Amit and Schoemaker (2012) define *resources as tradable and non-specific firm assets* and *capabilities as non-tradable firm-specific abilities to integrade, deploy, and utilize resources within a firm.* This perspective implies an inherent assumption that firms' capabilities are dependent and developed based on the available set of organizational resources (Sirmon et al., 2007). Thus, the strength of a firm's capabilities are determined by the resources on which they are developed (Makadok, 2001).

The RBT has been a central perspective in understanding how IT investments produce value and enable firms to attain performance gains (Wade and Hulland, 2004). In the case of AI, knowing which AI resources to develop is crucial to generating rents from investments (Duan et al., 2019). In that regard, the RBT is highly relevant to this study. The value of RBT for explaining organizational-level phenomena is made evident by it's use across multiple business disciplines, including those of operations management (Bromiley and Rau, 2016), supply chain management (Barney, 2012), and marketing (Srivastava et al., 2001). More than three decades of empirical testing have established RBT as a prevailing paradigm for developing theoretical arguments and empirically examining the effect that organizational resources have on firm performance (Barney et al., 2011). Given that a resource-based AI capability is central to this study, and that the aims of this study include confirming the validity of a set of organizational resources as a means to develop AI capabilities leading to competitive gains, I deem the RBT an appropriate underlying theoretical framework.

There are several studies on the types of resources resources required for developing organizational capabilities that drive performance (Barney, 1991). One of the most widely accepted classifications is that proposed by grant (Grant, 1991), who makes a distinction between tangible (e.g., physical and financial), human skills (e.g., knowledge and skills), and intangible (e.g., strategic orientation). This classification is used extensively in IS literature (Bharadwaj, 2000; Gupta and George, 2016). In light of this, the same classification has been used to categorize the resources that constitute the AI capability proposed in this study.

2.3 Developmental culture

The notion of a developmental culture as a strategic resource for competitive performance gains has been explored by several previous studies. A study exploring the relationship between multidimensional organizational culture and performance found that developmental culture is shown to be the strongest predictor of performance(Prajogo and McDermott, 2011). These results are consistent with the work of Dellana and Hauser (1999), which found that developmental culture is the best predictor for the six *Malcolm Baldrige National Quality Award* criteria, which are considered as the framework for best practice among US high-performing firms. Furthermore, a study drawing on the resource-based view proposed that an organizational culture with the characteristics of being valuable, rare, inimitable and non-substitutable (VRIN) would lead to a competitive advantage (Genç, 2013). This study seeks to expand upon this notion, and introduces *developmental emphasis* as a possible catalyst for developing AI capability resources.

Chapter 3

Research model

This study proposes the research model shown in Fig. 3.1. The following sections describe the different constructs in the model, and present each hypothesis in its relevant context.

3.1 Competitive performance

Competitive performance refers to the degree to which a firm attains its objectives in relation to its main competitors (Rai and Tang, 2010).

3.2 AI capability

Several academic publications and business reports highlight the diversity of resources that organizations need to foster in order to derive business value form their AI investments. However, there is a lack of theoretically grounded research about how organizations can create an AI capability. Drawing on the RBT, and line with recent research conducted by Mikalef and Gupta (2020), this study defines AI capability as the ability of a firm to select, orchestrate, and leverage its AI specific resources, and proposes that firms need a combination of tangible-, human-, and intangible resources

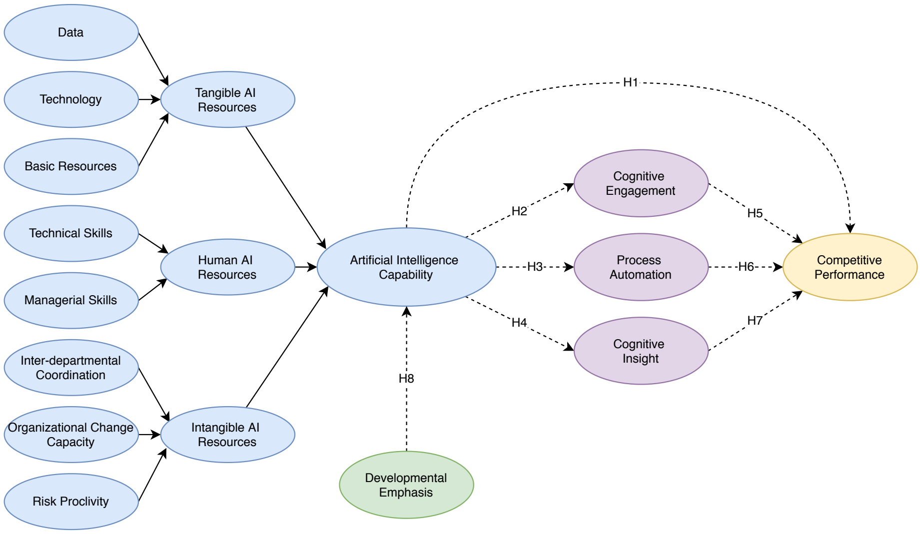

Figure 3.1: Research model.

to build an AI capability. In line with Mikalef and Gupta (2020) building on the theoretical underpinnings of RBT (Barney, 2001; Grant, 1991; Wernerfelt, 1984), on empirical work adopting the RBT in the IS domain (Bharadwaj, 2000; Ravichandran et al., 2005; Wade and Hulland, 2004), as well as on recent studies that outline the challenges related to AI adoption and value generation (Chui, 2017; Chui and Malhotra, 2018; Davenport and Ronanki, 2018; Fountaine et al., 2019; Mikalef et al., 2019a; Ransbotham et al., 2018, 2017), this study proposes eight resources that jointly constitute an AI capability. Based on the framework of Grant (1991), these are grouped into tangible-, human-, and intangible resources, a classification which is a well accepted practice within IT literature, and has been used in several other studies (Gupta and George, 2016; Bharadwaj, 2000; Chae et al., 2014; Santhanam and Hartono, 2003). Tangible resources comprise data, technology, and basic resources, human resources comprise technical- and managerial skills, and intangible resources comprise inter-departmental coordination, organizational change capacity, and risk proclivity.

Consistent within IS literature and RBT, a competitive advantage is said to be gained by combining and deploying several complementary resources to create unique and hard to imitate capabilities (Bharadwaj, 2000; Kohli and Grover, 2008; Schryen, 2013; Gupta and George, 2016). In line with this, I believe that the proposed AI capability will yield competitive performance gains. Thus, I hypothesize the following:

- **H1.** The proposed AI capability has a positive effect on competitive performance.

3.2.1 Tangible resources

Following the literature on RBT, tangible resources are considered those that can be sold or bought in a market (Barney, 1991). Tangible resources can be physical assets such as equipment and facilities, or financial assets such as dept and equity. Given that these resources to a large extent are available for all firms, they are not likely to provide a competitive advantage by themselves. In this study, I am interested in the tangible resources that - based on previous literature - have proven important to successful adoption of AI technology, and hence should be part of an AI capability.

3.2.1.1 Data

A sizeable difference between companies that already understand and have adopted AI, and 'laggards', is their approach to data (Ransbotham et al., 2017). The availability of high-quality data is considered critical to AI adoption, as it is used to train the AI algorithms. Thanks to the big data revolution and advanced computational capabilities, companies have a deeper access to customer data than ever before (Vieira and Sehgal, 2018). Yet, a paper on the AI business ecosystem, Quan and Sanderson (2018) identified data acquisition as one of the three major challenges to managing an AI ecosystem. The research conducted by Wirtz et al. (2019) on 17 studies addressing AI challenges in a public sector found that system/data quality and integration are among the main challenges to AI adoption. According to a study on how banks can better serve their customers through AI (Vieira and Sehgal, 2018), one of the primary challenges to adopting AI is to store, organize and create views over unstructured data in a cost-effective way. This is an important of successfully leveraging data for AI adoption, as today's organizations capture a large diversity of data stemming from multiple sources and in different formats (Kersting and Meyer, 2018). Organizations are limited by their data quality and quantity (West et al., 2018) in terms of volume, granularity, integration, access, inter-organizational sharing, and processing.

3.2.1.2 Technology

According to a recent report published by McKinsey, technological infrastructure is one of the main barriers to adopting AI technology (Chui and Malhotra, 2018). Having the proper technological infrastructure is vital when it comes to leveraging large, unstructured, fast-moving, and complex data sources to build AI applications. With these novel forms of data, we require novel forms of technology to store, process, transfer, and secure data through all the steps from data acquisition to data application for AI training. Data requirements depend on the scale and type of the AI initiative, meaning that the required storage infrastructure would differ for different AI initiatives in terms of volume, support of formats, and scalability (Bayless et al., 2020). Different AI initiatives also require different technological infrastructure for generating and processing data, such as computer vision, which requires devices with build in cameras able to capture images at a high frame-rate, high-bandwidth networks, and hardware designed specifically for handling the processing complexity of image segmentation, object detection, pattern detection, and feature matching (Nixon and Aguado, 2019). Firms will also need to invest in sufficient computational power based on the scale and type of their AI initiative. Sufficient computational power is key to AI technology, as AI algorithms need to run complex algorithms on vast volumes of data. A common approach to acquiring sufficient computational power is to utilize GPU-intensive clusters and parallel computing (Nurvitadhi et al., 2017). Another common approach is to outsource the problem by adopting external cloud-based solutions (Kumar, 2016), which is often more cost effective than acquiring the technological infrastructure. This approach is gaining traction, and the recent years have seen an increased prevalence of integrated cloud services that allow complex AI methods through simple API calls (Del Sole, 2018).

3.2.1.3 Basic resources

This study refers to *basic resources* as financial resources and time. According to the survey by Davenport and Ronanki (2018) asking 250 executives about challenges related to the adoption of AI, the second most common challenge to be mentioned was that technologies and expertise is too expensive. The research conducted by Wirtz et al. (2019) on 17 studies addressing AI challenges in a public sector found that financial feasibility was among the major challenges to adopting AI. Brynjolfsson et al. (2017) predicts that - among other factors - the most successful adopters of AI will be those with the lowest adjustment costs. Jones (2018) states that one of the primary challenges of AI adoption is the initial costs. It is clear that one of the key requirements for AI initiatives is financial resources. Furthermore, AI initiatives will require time to prove their value and deliver their expected outcomes, and time requires financial resources. Given that most organizations are just now experimenting with AI, the vast majority of initiatives will need some time to mature before being released and yielding any value (Ransbotham et al., 2018). In order to have success with AI initiatives, adequate financial resources must be planned for and allocated. Yet, in a 2017 study by McKinsey, the majority of respondents reported that less than 10% of their digital technology spending was on AI initiatives (Chui and Malhotra, 2018). Given the apparent importance of financial resources and time as requirements for successful AI initiatives, and in accordance with prior studies on IS business value (Gupta and George, 2016; Schryen, 2013; Wixom and Watson, 2001), I argue that these resources must be dimensions of an AI capability construct. Furthermore, to distinguish these resources from the other resources introduced in this study, I will refer to them as *basic resources.*

3.2.2 Human resources

The human resources of an organization is often measured by assessing the knowledge, skills, experience, leadership qualities, vision, communication and collaboration competencies, and problem-solving abilities of its employees. Prior studies on digital capabilities has identified technical- and managerial skills as critical pillars of human resources (Bharadwaj, 2000; Ravichandran et al., 2005). In accordance with this, this study proposes AI-specific technical- and managerial skills as dimensions of human AI resources, and hence dimensions of an AI capability.

3.2.2.1 Technical skills

This study refers to technical skills as the skills and knowledge - or expertise - necessary to deal with implementation and realization of AI algorithms, manage the infrastructure required for AI initiatives, and ensure that AI applications adhere to goals.

Lack of expertise is one of the most frequently mentioned challenges to adoption of AI technology. Through an online questionnaire involving 207 small, medium and large-sized organizations, Alsheibani et al. (2019) found that a lack of skills to evaluate, build and deploy AI solutions was the most common barrier to adopting AI. In a survey by Davenport and Ronanki (2018), 35% of 250 executives said that getting enough people with AI expertise was one of the primary challenges to adoption. The research conducted by Wirtz et al. (2019) on 17 studies addressing AI challenges in a public sector also found that acquiring specialization and expertise are among the main challenges.

Skilled algorithm developers are necessary to utilize the latest AI research and transform it into repeatable processes through mathematical formulas that can be implemented through hardware and software (Spector and Ma, 2019). AI initiatives will require individuals with a strong background in statistics, probability, predictions, calculus, algebra, Bayesian algorithms and logic. Furthermore, a solid background in programming, logic, data structures, language processing, and cognitive learning theory have been highlighted as essential technical AI skills (Lesgold, 2019). A recent article in the MIT Sloan Management Review presents three key roles that will emerge as technical profiles in the age of AI: trainers, explainers, and sustainers (Wilson et al., 2017). In short, trainers train AI systems, explainers explain the inner workings of AI to non-technical audiences, and sustainers ensure that AI systems run as expected and address any unanticipated consequences. Although these skills are currently scarce, they are expected to become more common as higher-education and online training courses are emerging, making this resource a commodity across firms over time (Danyluk and Buck, 2019).

3.2.2.2 Managerial skills

This study refers to managerial skills as the ability among managers to understand and anticipate business problems, and effectively direct AI initiatives, utilize resources, coordinate AI related activities, and in general provide strong leadership to support AI initiatives.

A study conducted by Ransbotham et al. (2017) - involving a global survey of more than 3000 executives, managers and analysts across various industries, as well as in-depth interviews with more than 30 technology experts and executives - found that many leaders aren't sure what to expect from AI, or how it fits into their business model. The research surfaced several misunderstandings about the resources needed to train AI, and a lack of expertise. The study found that firms with successful AI initiatives usually have leaders with a much deeper appreciation for what's required to produce AI than laggards. Furthermore, the successful firms are also more likely to have senior leadership support and a rigorously developed business case for AI initiatives. The lack of managerial support is a common challenge related to adoption of AI. Through an online questionnaire involving 207 small, medium and large-sized organizations, Alsheibani et al. (2019) found that lack of leadership support was the third most common barrier to AI adoption.

Organizations are limited by their knowledge of AI applications (West et al., 2018), and it seems that many companies struggle in finding the right tools and use cases for their distinct fields of application (Schlögl et al., 2019). A study by Davenport and Ronanki (2018) involving 250 executives found that the third most common challenge to AI adoption was that managers don't understand cognitive technologies or how they work. In another study involving semi-structured interviews of 19 employees from various different industry sectors, Schlögl et al. (2019) found that many companies - although stating that they had collected sufficient data - didn't know what to do with their data, or which aspects of AI that could be applied.

Successful AI initiatives require true understanding and commitment from leaders to carry out large-scale change. However, a study by Davenport and Ronanki (2018) found that one in three managers do not understand how AI technologies work. For managers to successfully direct AI initiatives, it is imperative that they equip themselves with sufficient knowledge about the different AI technologies and their potential uses.

3.2.3 Intangible resources

Among the three main types of organizational resources that have been identified in the RBT (Grant, 1991), intangible resources are the non-physical resources that are more difficult to replicate for other firms and are of heightened importance in uncertain and volatile markets (Morgan et al., 2006). Unlike the other two categories of resources, intangibles are much more elusive and difficult to identify within organizations (Grant, 1996). Intangible resources meet the VRIN status of the RBT (Seddon, 2014), meaning that they are *valuable, rare, inimitable and non-substitutable*, thus providing a sustained competitive advantage. Intangible resources are the result of the unique mixture that makes up the characteristics of an organization, such as organizational history, culture, people and processes. Early reports on the drivers of AI success (Chui and Malhotra, 2018; Davenport and Ronanki, 2018; Ransbotham et al., 2018), as well as a long history of empirical IS research (Bharadwaj, 2000; Melville et al., 2007; Schryen, 2013) highlight the importance of intangible resources in reaping business benefits from adopted technologies. In the context of AI, the intangible resources that were identified are inter-departmental coordination, organizational change capacity, and risk proclivity.

3.2.3.1 Inter-departmental coordination

The ability to coordinate tasks and share a mutual vision among different departments of an organization is regarded as a cornerstone of success in cross-disciplinary projects (Kahn, 2001). Inter-departmental coordination has been defined as *a state of high degrees of shared values, mutual goal commitments, and collaborative behaviors* (Souder, 1977). There is value in maintaining a continuous relationships between departments, rather than simple transactions (Kahn, 1996), and the role of inter-departmental coordination has long been noted as a key enabler of innovation and creativity in organizations (Evanschitzky et al., 2012). Recent studies on AI and business value argue that in order to unleash the value of AI technologies, organizations must foster a culture of teamwork, collective goals, and shared resources (Ransbotham et al., 2018).

In an article on *Building the AI-Powered Organization*, Fountaine et al. (2019) note that AI has the biggest impact when it's developed by cross-functional teams with a mix of skills and perspectives. Doing this will ensure that AI initiatives address broad organizational priorities rather than just isolated business issues. By fostering inter-disciplinary teams, they suggest that organizations are more capable of thinking through the operational challenges of new applications, thus improving the overall performance of deployed AI solutions. Furthermore, enhancing inter-departmental coordination is likely to make organizations more agile and adaptable when deploying AI applications, as a shared language and a mutual understanding among employees between different departments will lead to reduced times in deploying new AI applications or adapting existing ones when the need arises (Appian, 2019). The importance of inter-departmental coordination is also noted in a recent study which highlights that functional silos are one of the most impactful barriers to deriving value from AI initiatives, as they constrain end-to-end solution being developed (Chui and Malhotra, 2018).

3.2.3.2 Organizational change capacity

We are in the midst of a wide-spread digital transformation, and being successful in today's ever-shifting competitive landscape requires the ability to initiate and execute change - in short, we need to think about organizational change capacity. Business models need to be redesigned to take advantage of AI (Quan and Sanderson, 2018). There will be a change in business value generation (Ransbotham et al., 2017), and one of the main challenges will be to transform existing business processes and translate insights into competitive advantages (Vieira and Sehgal, 2018). Realizing the benefits of AI requires an effort and entrepreneurship to develop the needed complements, and adaptability at the individual, organizational, and societal levels to undertake the associated restructuring (Brynjolfsson et al., 2017).

Organizational change capacity requires the ability to integrate AI technology with existing processes and systems. A survey by Davenport and Ronanki (2018) revealed that, among 250 executives, 47% named 'integration of cognitive projects with existing processes and systems' as the most common challenge to AI initiatives. Research conducted by Wirtz et al. (2019) on 17 studies addressing AI challenges also revealed integration as one of the primary challenges. The process of integration can prove difficult in many ways. For one, integration might require difficult changes to several dependent processes and systems depending on the organizational structure and modularity. Furthermore, these changes must be executed concurrently with ongoing business, which means that integration could interfere with existing processes and systems that are vital to ongoing business. Integration might also require an integration of data from multiple systems, which is a difficult process if the data is poorly organized and structured.

Another aspect of organizational change capacity is the ability to communicate change and handle human resistance. The heightened momentum of AI technology has raised and continues to raise many questions (Fagerli, 2018), and there is currently a mix of human attitudes towards AI. Employees' willingness to work with AI is an important aspect to consider. Although companies claim to have no intention of reducing the workforce in favor of AI technology, employees fear job loss and thus often reject adoption (Schlögl et al., 2019). When Schlögl et al. (2019) asked interviewees from both large and small companies about organizational challenges related to adopting AI, interviewees focused more on struggles originating in human resistance of AI than technical difficulties. This human resistance is believed to stem from employees' lack of trust in AI, fear of change (Alsheibani et al., 2019), fear of incompetence, and fear of losing importance and eventually their job.

3.2.3.3 Risk proclivity

A recent study by Ransbotham et al. (2018) involving top level executives in 29 industries and 126 countries found that organizations with a more risk-oriented approach to new ventures such as AI reap the benefits long before their competitors or new entrants do. The strategic orientation towards risk-taking has been highlighted in management under many different terms (e.g., risk proclivity, entrepreneurial orientation, proactive stance) (Avlonitis and Salavou, 2007; Sambamurthy et al., 2003), and is associated with typologies that reflect proactive and aggressive initiatives to alter the competitive scene (e.g., prospectors) (Miles et al., 1978). The research emphasize the impact of adopting such a risk-taking and proactive stance, which is commonly associated with higher levels of innovation output and market leadership (Salavou et al., 2004). In the context of AI adoption, Ransbotham et al. (2018) note that organizations that embrace risk proclivity and commit resolutely to AI initiatives tend to gain a head start on their competitors who refrain from such commitments. Fountaine et al. (2019) argue that organizations must depart from risk-averse strategies and rather become agile, experimental, and adaptable. Overall, existing literature indicate that organizations with a high risk proclivity are likely to be the first to embrace AI and hence gain a head start in the competitive landscape.

3.3 Three types of AI

Davenport and Ronanki (2018) studied 152 cognitive technology projects, and found that they fell into three distinct categories: 71 of the projects were related to robotics & cognitive automation, 57 were related to cognitive insight, and the remaining 24 were related to cognitive engagement.

As introduced, I'd like to explore the effects of the proposed AI capability construct on the deployment and outcomes of AI initiatives. To that end, and given that the proposed AI capability construct is designed specifically to enable AI initiatives, I immediately hypothesize the following:

- **H2.** AI capability has a positive effect on outcomes with cognitive engagement.
- **H3.** AI capability has a positive effect on outcomes with process automation.
- **H4.** AI capability has a positive effect on outcomes with cognitive insight.

As for whether outcomes with these technologies lead to competitive performance gains, there is conflicting literature. A large number of articles swear to the potential business value that can be derived from AI initiatives (Ning et al., 2018; Ransbotham et al., 2017; Jones, 2018; Wilson and Daugherty, 2018; Vieira and Sehgal, 2018), but in contrast, a large number of reports and empirical studies from early adopters of AI indicate that organizations are struggling to realize business value from AI investments (Davenport and Ronanki, 2018; Alsheibani et al., 2019; Wirtz et al., 2019; West et al., 2018; Schlögl et al., 2019; Quan and Sanderson, 2018; Brynjolfsson et al., 2017). Furthermore, it is likely that factors such as the cost and difficulty of implementation will affect the effect of the various forms of AI on competitive performance. However, for the sake of this study, I hypothesize the following:

- **H5.** Successful outcomes with cognitive engagement have a positive effect on competitive performance.
- **H6.** Successful outcomes with process automation have a positive effect on competitive performance.

- **H7.** Successful outcomes with cognitive insight have a positive effect on competitive performance.

3.3.1 Cognitive Engagement

Cognitive engagement was the least common among the three types of AI discovered in the study conducted by Davenport and Ronanki (2018). Cognitive engagement is defined as 'engagement of employees and customers using natural language processing chatbots, intelligent agents, and machine learning (Davenport and Ronanki, 2018).

There are several cases of successful cognitive engagement projects. Vanguard, for example, is piloting an intelligent agent that helps its customer service staff answer frequently asked questions (Davenport and Ronanki, 2018). SEBank, in Sweden, and the medical technology giant Becton, Dickinson, in the United States, are using the lifelike intelligent-agent avatar Amelia to serve as an internal employee help desk for IT support (Davenport and Ronanki, 2018). Tech giants have invested in chatbots that interact with customers through their products; Google has Google Assistant, Microsoft has Cortana, Apple has Siri, and Amazon has Alexa. All of these grew very popular after their release, and have provided a lot of value to the companies. These chatbots both made their products more attractive, provided the companies with a lot more valuable data for insights, and laid the ground for future products and services - like Amazon's Echo products, all incorporating Alexa as their core feature. One of the core values of cognitive engagement is that it allows users to communicate their intents to a system as if it were human. This provides a more intuitive human-system interaction, which is one of the key attributes of a well-designed user interface. In light of this, I hypothesize the following:

3.3.2 Process Automation

Process automation was the most common among the three types of AI discovered in the study conducted by (Davenport and Ronanki, 2018). It is the automation of digital and physical tasks - typically back-office administrative and financial activities - using Robotic Process Automation (RPA) technologies (Davenport and Ronanki, 2018). RPA is more advanced than earlier business-process automation tools, because the 'robots' (that is, code on a server) act like a human inputting and consuming information from multiple IT systems (Davenport and Ronanki, 2018).

RPA is the least expensive and easiest to implement of the three AI technologies discussed here, and it typically brings a quick and high return on investment (Davenport and Ronanki, 2018). Previous cases of adoption has proven its value. One example is an adoption by NASA, which proved to be highly effective. As a result, 86% of all transactions in their HR application were completed without any human intervention (Davenport and Ronanki, 2018). NASA has also launched several other successful RPA projects with high returns on the investment. Given that RPA is said to be the least expensive and easiest to implement of the three AI technologies, I hypothesize the following:

Assisted intelligence - a type of AI proposed by Garbuio and Lin (2019) - is defined as 'AI that improves what people and organizations are already doing' by automation based on clearly defined, rule-based, repetitive tasks to remove redundancies from business operations, improve efficiency, and boost the value of existing activity. Note that this concept is fairly similar to the concept of process automation, as proposed by (Davenport and Ronanki, 2018). Assisted intelligence helps improve what the business is already doing by amplifying the value of current activities (Garbuio and Lin, 2019).

3.3.3 Cognitive Insight

Cognitive insight was the second most common among the three types of AI discovered in the study conducted by (Davenport and Ronanki, 2018). Cognitive insight applications apply algorithms on vast volumes of data to detect patterns, and interpret their meaning (Davenport and Ronanki, 2018). Cognitive insight applications take analytics to a whole new level. They differ from traditional analytics in three ways: They are usually much more data-intensive and detailed, the models are typically trained on some part of the data set, and their ability to make predictions and categorize things based on new data improves over time (Davenport and Ronanki, 2018). Cognitive insight is typically used to improve performance on jobs that demand data crunching and automation on a level beyond human capabilities, such as predicting customer behavior, identifying fraud in real time, and personalizing ads (Davenport and Ronanki, 2018). Skilled technology professionals at innovative firms such as Google, Tesla and Uber, have leveraged the power of data analytics to break into new markets, build stronger relationships with consumers, and streamline processes such as supply chain and marketing management (Phillips, 2019).

Augmented intelligence - a type of AI proposed by Garbuio and Lin (2019) - is defined as AI that 'enables organizations and people to do things they couldn't otherwise do' through sophisticated algorithms built for natural language processing and sifting through massive accumulations data and records (Garbuio and Lin, 2019). Note that this concept is fairly similar to the concept of cognitive insight, as proposed by Davenport and Ronanki (2018). Augmented intelligence is an emerging technology in AI, and provides provides organizations with new capabilities and differs from assisted intelligence in that it alters the nature of an activity, which as a consequence requires changes in the business model (Garbuio and Lin, 2019).

3.4 Developmental emphasis

While *organizational change capacity* refer to the capacity for change, *developmental emphasis* refer to the commitment to innovation and development. This commitment requires an organizational culture that fosters dynamism, entrepreneurship, acquisition of new resources, and a craving for new challenges. For the same reasons that organizations should start thinking about organizational change capacity, they should also start thinking about developmental emphasis.

A study conducted by Ransbotham et al. (2017) - involving a global survey of more than 3000 executives, managers and analysts across various industries, as well as in-depth interviews with more than 30 technology experts and executives - found that the gap between ambition and execution is large at most companies. Three-quarters of executives believe AI will enable their companies to move into new businesses. Almost 85% believe AI will allow their companies to obtain or sustain a competitive advantage. But only about one in five companies has incorporated AI in some offerings or processes. Only one in 20 companies has extensively incorporated AI in offerings or processes. Less than 39% of all companies have an AI strategy in place, and the largest companies — those with at least 100,000 employees — are the most likely to have an AI strategy, but only half have one.

In a study exploring the relationship between multidimensional organizational culture and performance, Prajogo and McDermott (2011) found that developmental culture is shown to be the strongest predictor of performance. These results are consistent with the work of Dellana and Hauser (1999), which shows that developmental culture is the best predictor for the six *Malcolm Baldrige National Quality Award* criteria, which are considered as the framework for best practice among US high-performing firms. Prajogo and McDermott (2011) notes that these findings call for attention to the importance of developmental culture in enhancing organizational performance.

In the case of AI, change is about preparing for the future. Industries are changing in a rapid pace to keep up with The Big Data age, and continuous change is a necessity to stay ahead of the game. We live in The Big Data age (Wikipedia, 2019), and AI is a tool to revolutionize the way we deal with data. The technology is available, and the value is evident. Yet, the extensive study by Ransbotham et al. (2017) demonstrate that many companies are still not following through with their ambitions. I believe that this is due to a lack of developmental emphasis. Furthermore, I believe that developmental emphasis is key to developing the AI resources that are required to execute change. Thus, I hypothesize the following:

- **H8.** Developmental emphasis has a positive effect on AI capability.

Chapter 4

Empirical study

4.1 Survey, administration, and data

The study was conducted with a questionnaire-based survey method, as it enables generalization of outcomes, allows for easy replication, and facilitates the simultaneous investigation of a large number of factors (Pinsonneault and Kraemer, 1993). It is a well-documented way of accurately capturing the general tendency and identifying associations between variables in a sample. Straub et al. (2004) emphasize the importance of survey-based research in exploratory settings and predictive theory to enable generalization. The constructs and corresponding survey items used in the questionnaire are based on previously published latent variables with psychometric properties that support their validity. The survey comprised 80 items which operationalized all constructs and respective items with a 7-point Likert scale. The Likert scale is a well-accepted practice in large-scale empirical research where no standard measures exist for quantifying measured notions (such as resources and capabilities) (Kumar et al., 1993). As part of developing the questionnaire, a pre-test was conducted to assess the face- and content validity of the items and confirm the statistical properties of the measures.

The questionnaire was distributed to a mailing list of approximately 500 data scientists and senior level IT managers located in USA. These positions are likely to have a clear grasp on their firm's AI resources, investments and outcomes. To ensure that all the items of the questionnaire were answered accurately, the respondents were instructed to consult with their coworkers if they felt unequipped to answer an item. Data was collected over a period of approximately three months (November 2019 - February 2020). The average completion time of the questionnaire was 14 min. A total of 112 firms completed the survey, with 107 providing complete responses that were retained for further analysis.

The firms in our sample operated in a variety of industries 4.1, the most represented being technology (34.6%), followed by bank & financials (18.7%), ICT and telecommunications (11.2%), consulting services (10.3%), and a variety of other industries (25.2%). The vast majority (75.7%) were large firms (250+ employees), followed by small (12.1%) and medium (9.3%) firms, and a very small portion (2.8%) with less than ten employees. Respondents occupied a variety of positions relating to business and IT management, the most represented position being Data Scientist (26.2%), followed by Chief Information/Technology/Digital Officer (10.3%), Software Engineer (8.4%), and a variety of other roles related to business and IT management. A large portion (72.0%) had at least 2 years of experience with AI, and a large portion (70.0%) had worked in their firm for more than 3 years.

Table 4.1: Descriptive statistics for survey respondents.

Factors	**Sample (N)**	**Proportion (%)**
Firm size (Number of employees)		
1-9 employees	3	2.8%
10-49 employees	13	12.1%
50-249 employees	10	9.3%
250+ employees	81	75.7%

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Table 4.1 – continued from previous page

Factors	Sample (N)	Proportion (%)
Industry		
Bank & Financials	20	18.7%
Basic Materials (Chemicals, paper, industrial metals & mining)	2	1.9%
Consulting Services	11	10.3%
Consumer Goods	4	3.7%
Consumer Services	6	5.6%
Education	2	1.9%
Health Care	3	2.8%
ICT and Telecommunications	12	11.2%
Industrials (Construction & industrial goods)	3	2.8%
Media	3	2.8%
Oil & Gas	2	1.9%
Property	1	0.9%
Technology	37	34.6%
Transport	1	0.9%
Years using AI in organization		
0-1 years	9	8.4%
1-2 years	21	19.6%
2-3 years	20	18.7%
3-4 years	13	12.1%
4+ years	44	41.1%

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Table 4.1 – continued from previous page

Factors	Sample (N)	Proportion (%)
Years working in organization		
0-1 years	8	7.5%
1-3 years	24	22.4%
3-5 years	24	22.4%
5-7 years	22	20.6%
7-10 years	12	11.2%
10-15 years	10	9.3%
15-20 years	4	3.7%
20+ years	3	2.8%

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Table 4.1 – continued from previous page

Factors	Sample (N)	Proportion (%)
Role in organization		
Business Analyst	3	2.8%
Business Manager	6	5.6%
Chief Executive Officer	3	2.8%
Chief Information/Technology/Digital Officer	11	10.3%
Data Scientist	28	26.2%
Enterprise Architect	3	2.8%
Head of IT Department	5	4.7%
IT Director	5	4.7%
IT Project Manager	6	5.6%
Operations Manager	4	3.7%
Other	12	11.2%
Software Engineer	9	8.4%
Systems Analyst	5	4.7%
Technical Consultant	7	6.5%

4.2 Measurements

The scales for the various constructs were adopted from prior literature, and have therefore been previously tested in empirical studies. Appendix A provides a summary of the scales used, their descriptive statistics, and the supporting literature.

AI capability is conceptualized and developed as a third order formative construct that comprises three second order formative constructs: tangible-, human-, and intangible AI resources. Each of these in turn comprise a set of first order constructs.

Specifically, the tangible resource components of AI capability comprise data (e.g., quality and quantity), technology (e.g., software and hardware), and basic resources (e.g., financial), represented as formative first-order constructs. The human resource components of AI capability comprise technical skills (e.g., expertise and execution) and managerial skills (e.g., leadership support and directive), represented as reflective first-order constructs. The intangible resource components of AI capability comprise inter-departmental coordination (e.g., collective goals and shared resources), organizational change capacity (e.g., ability to manage and communicate change), and risk proclivity (e.g., proclivity for high risk projects), represented as reflective first-order constructs. The development of the AI capability construct and the dimensions and sub-dimensions that comprise it are depicted in 4.2.

Cognitive Engagement, *Process Automation*, and *Cognitive Insight* are conceptualized as reflective latent variables with indicators measuring typical signs of success with the respective AI technologies. Respondents were asked to assess the degree to which they agreed with statements indicating success with the technologies on a 7-point Likert scale.

Developmental emphasis is developed conceptually as the degree to which firms emphasize dynamism, entrepreneurship, commitment to innovation and development, acquisition of new resources, and meeting new challenges. It is conceptualized as a reflective latent variable. Respondents were asked to assess the degree to which they agreed with statements indicating a developmental emphasis on a 7-point Likert scale.

Competitive Performance is developed conceptually as the the degree to which a firm attains its objectives in relation to its main competitors (Rai and Tang, 2010). It is conceptualized as a formative latent variable comprising five dimensions: Success, market share, growth rate, profitability, and innovativeness (Rai and Tang, 2010; Li and Zhou, 2010; Liu et al., 2013). Respondents were asked to assess the degree to which they believed that their firm performed better than their main competitors in these aspects on a 7-point Likert scale.

Control Variables (Table 4.1) comprised firm size, industry, years using AI in organization, years working in organization, and role in organization.

Table 4.2: AI capability and sub-dimension development.

Order	Type	Construct
Third-order	Formative	AI Capability
Second-order	Formative	Tangible resources
		Human resources
		Intangible resources
First-order	Formative	Data
		Technology
		Basic resources
	Reflective	Technical skills
		Managerial skills
		Inter-departmental coordination
		Organizational change capacity
		Risk proclivity

Chapter 5

Analysis

To assess the hierarchical research model's validity and reliability, I applied partial least squares-based structural equation modeling (PLS-SEM) analysis. The software package SmartPLS 3 (Ringle and Becker, 2015) was used to conduct the analysis. I consider PLS-SEM an appropriate method for this study as it permits the simultaneous estimation of multiple relationships between one or more independent variables, and one or more dependent variables (Hair et al., 2011). PLS-SEM is a soft modeling technique and is variance-based, with the advantage of allowing (i) flexibility with respect to the assumptions on multivariate normality, (ii) usage of both reflective and formative constructs, (iii) the ability to analyze complex models using smaller samples, (iv) the more robust estimation of formative constructs, and (v) the potential use as a predictive tool for theory building (Nair et al., 2018). PLS-SEM is widely used in analyzing data for the estimation of complex relationships between constructs in many subject areas including in business and management research (Ahammad et al., 2017; West et al., 2016). In addition, PLS-SEM enables the analysis of indirect and total effects, making it possible to not only simultaneously assess the relationships between multi-item constructs but also to reduce the overall error associated with the model (Astrachan et al., 2014). As for sample size requirements, the 107 responses exceed the requirements to be (i) ten times the largest number of formative indicators used to measure one construct, and (ii) ten times the largest number of structural paths directed at a particular latent construct in the structural model (Hair et al., 2011). Finally, given that the proposed research model builds more on exploratory theory building than theory testing, PLS-SEM is a better alternative than covariance-based SEM.

5.1 Measurement model

Given that the model contains both reflective and formative constructs as well as higher-order constructs, I used different assessment criteria to evaluate each. For the first-order reflective latent constructs, I conducted reliability, convergent validity, and discriminant validity tests (Table 5.1).

Reliability was assessed at the construct and item level. At the construct level, I examined Composite Reliability (CR) and Cronbach Alpha (CA) values, and established that their values were above the threshold of 0.70 (Nunnally, 1967). Indicator reliability was assessed by examining if construct-to-item loadings were above the threshold of 0.70 (Appendix C). To assess convergent validity, I examined if average variance extracted (AVE) values were above the threshold of 0.50, with the smallest observed value being 0.69, which greatly exceeds this threshold.

Discriminant validity was established by three means. First, I looked at the AVE square root of each construct to verify that it was greater than its highest correlation with any other construct (Fornell-Larcker criterion). Second, I tested if the outer loading of each indicator was greater than its cross-loadings with the other constructs (Farrell, 2010). Recently, Henseler et al. (2015) argued that a new criterion called the Heterotrait-Monotrait ratio (HTMT) is a better assessment indicator of discriminant validity. The HTMT ratio is calculated based on the average of the correlations of indicators across constructs measuring different aspects of the model, relative to the average of the correlations of indicators within the same construct. Values below 0.85 indicate sufficient discriminant validity. Hence, the obtained results confirm discriminant validity (Appendix B).

The results presented in table 5.1 suggest that the first-order reflective measures are valid to work with and support the appropriateness of all items as good indicators for their respective constructs.

Table 5.1: Assessment of reliability and convergent- and discriminant validity of reflective constructs.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
1	Data	**n/a**												
2	Technology	0.697	**n/a**											
3	Basic resources	0.681	0.655	**n/a**										
4	Technical skills	0.62	0.637	0.671	**0.832**									
5	Managerial skills	0.569	0.51	0.541	0.507	**0.889**								
6	Inter-departmental coordination	0.482	0.417	0.456	0.428	0.679	**0.843**							
7	Organizational change capacity	0.446	0.484	0.413	0.473	0.558	0.69	**0.84**						
8	Risk proclivity	0.43	0.409	0.518	0.457	0.555	0.626	0.67	**0.943**					
9	Developmental emphasis	0.464	0.505	0.545	0.494	0.736	0.627	0.565	0.669	**0.897**				
10	Cognitive engagement	0.483	0.415	0.431	0.308	0.515	0.471	0.406	0.397	0.376	**0.93**			
11	Process automation	0.467	0.338	0.383	0.269	0.535	0.484	0.415	0.34	0.35	0.654	**0.907**		
12	Cognitive insight	0.529	0.368	0.435	0.369	0.461	0.427	0.312	0.338	0.355	0.633	0.632	**0.923**	
13	Competitive Performance	0.355	0.373	0.402	0.281	0.501	0.399	0.55	0.445	0.493	0.366	0.452	0.311	**n/a**
	Mean	5.53	5.326	4.654	5.452	4.778	4.976	4.859	4.589	4.96	5.09	4.803	5.007	5.191
	Standard Deviation	0.975	1.312	1.516	1.085	1.436	1.246	1.238	1.644	1.434	1.461	1.593	1.587	1.329
	Cronbach's Alpha	n/a	n/a	n/a	0.926	0.955	0.932	0.916	0.937	0.878	0.922	0.893	0.912	n/a
	Composite Reliability	n/a	n/a	n/a	0.94	0.963	0.945	0.935	0.96	0.925	0.951	0.933	0.945	n/a
	AVE	n/a	n/a	n/a	0.692	0.79	0.711	0.706	0.888	0.804	0.865	0.823	0.851	n/a

To assess the appropriateness of formative indicators (Table 5.2), I first examined the weights and significance of their association with their respective construct. The *data* construct had three indicators marked as insignificant (D2, D4, and D6), the *technology* construct had five indicators marked as insignificant (T1, T2, T3, T6 and T7), and the *basic resources* construct had one indicator marked as insignificant (BR2). However, Cenfetelli and Bassellier (2009) highlight that any formative construct with many indicators is likely to have several indicators with non-significant weights. They recommend that non-significant indicators should be kept in the model as long as there is a strong theoretical justification for the inclusion, which contrasts the way of approaching reflective indicators. Given that the proposed dimensions and their corresponding items capture unique, critical facets of the constructs, I believe that retaining these non-significant indicators in the model was a necessity. Furthermore, an expert panel as well as several reports and studies suggested their importance toward an AI capability. Thus, I did not remove any items on the grounds that each item is designed to have a distinct contribution to it's respective construct.

Next, to evaluate the validity of the items for the formative constructs, I followed the guidelines of MacKenzie et al. (2011) and Schmiedel et al. (2014) using Edwards' (Edwards, 2001) adequacy coefficient (R_a^2). I calculated R_a^2 values by summing the squared correlations between the construct and its dimensions (i.e., indicators) and dividing the number of dimensions (i.e., indicators). All R_a^2 values exceeded the threshold of 0.50 except for the data construct with a R_a^2 value of 0.44, which is acceptably close to the threshold. Values above the suggested threshold suggest that the majority of variance in the indicators is shared with the overarching construct, and that the indicators are valid representations of the construct. I repeated the calculations for the higher order constructs, and all values were greater than the threshold of 0.50.

Next, I examined the extent to which the indicators of the formative constructs presented multicollinearity. Although multicollinearity is desirable among reflective indicators, it is problematic in the case of formative measurements. The thresholds for multicollinearity are typically set at below values of 10 (MacKenzie et al., 2011). All values were below the threshold of 5 as recommended by Hair et al. (2011) and Ringle et al. (2012), with most values being below the even more strict threshold of 3.3 as recommended by Petter et al. (2007), indicating an acceptable degree of multicollinearity.

Table 5.2: Formative construct validation.

Construct	Measure	Weight	Significance	VIF	R_a^2
Data	D1	0.369	$p < 0.05$	1.182	0.44
	D2	-0.181	ns	1.368	
	D3	0.278	$p < 0.05$	1.771	
	D4	0.169	ns	1.413	
	D5	0.471	$p < 0.001$	1.98	
	D6	0.189	ns	1.822	

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Table 5.2 – continued from previous page

Construct	Measure	Weight	Significance	VIF	R_a^2
Technology	T1	-0.06	ns	1.896	0.62
	T2	0.137	ns	2.392	
	T3	0.217	ns	2.002	
	T4	0.415	$p < 0.05$	3.195	
	T5	0.523	$p < 0.01$	2.286	
	T6	-0.048	ns	2.789	
	T7	-0.002	ns	4.346	
Basic Resources	BR1	0.334	$p < 0.01$	2.147	0.82
	BR2	0.202	ns	4.426	
	BR3	0.562	$p < 0.01$	3.539	
Tangibles	Data	0.374	$p < 0.01$	2.355	0.78
	Technology	0.373	$p < 0.001$	2.211	
	Basic resources	0.375	$p < 0.001$	2.118	
Human	Technical Skills	0.517	$p < 0.001$	1.346	0.75
	Managerial Skills	0.633	$p < 0.001$	1.346	
Intangibles	Inter-departmental Coordination	0.488	$p < 0.001$	2.103	0.77
	Organizational Change Capacity	0.406	$p < 0.001$	2.321	
	Risk Proclivity	0.234	$p < 0.001$	2.002	
AI Capability	Tangibles	0.337	$p < 0.001$	2.468	0.79

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Table 5.2 – continued from previous page

Construct	Measure	Weight	Significance	VIF	R_a^2
	Human	0.368	p < 0.001	3.055	
	Intangibles	0.416	p < 0.001	1.999	

5.2 Structural models

Several structural models were used during the PLS-SEM analysis to examine the hypothesized relationships. The models in Fig. 5.3 and 5.1 show the estimated relationships between developmental emphasis, AI capability, and competitive performance, and the model in Fig. 5.2 shows the estimated relationships between AI capability, success with three common types of AI (i.e., cognitive engagement, process automation, and cognitive insight), and competitive performance. The structural models present the explained variance of endogenous variables (R^2) and the standardized path coefficients (β). The structural model was verified by examining coefficients of determination (R^2) values, effect size of predictor variables (f^2), predictive relevance (Stone-Geisser Q^2), and the effect size of path coefficients. To obtain the significance of estimates (t-values), I performed a bootstrap analysis with 5000 samples, as per the recommendation for minimum number of samples by Hair et al. (2011). A summary of the hypotheses and results is shown in table 5.3.

Table 5.3: Summary of hypotheses and results.

Structural path	Effect	t-value[a]	Bias corrected 97.5% confidence interval	Conclusion
AIC -> CP	0.676	13.309***	[0.533 - 0.748]	H1 supported
AIC -> CE	0.56	8.596***	[0.405 - 0.666]	H2 supported
AIC -> PA	0.536	8.551***	[0.387 - 0.636]	H3 supported
AIC -> CI	0.526	6.988***	[0.351 - 0.652]	H4 supported
CE -> CP	0.123	0.756	[-0.230 - 0.410]	H5 not supported

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Table 5.3 – continued from previous page

Structural path	Effect	t-value[a]	Bias corrected 97.5% confidence interval	Conclusion
PA -> CP	0.373	1.821	[-0.213 - 0.662]	H6 not supported
CI -> CP	-0.002	0.008	[-0.553 - 0.538]	H7 not supported
DE -> AIC	0.762	19.828***	[0.651 - 0.819]	H8 supported
Developmental emphasis (DE), AI capability (AIC), competitive performance (CP) cognitive engagement (CE), process automation (PA), cognitive insight (CI)				

[a] * significant at p < 0.05; ** significant at p < 0.01; *** significant at p < 0.001 (two-tailed test)

As for H1 (Fig. 5.1), I found a significant positive effect of AI capability on competitive performance (β=0.676, t=13.309, p<0.001), accounting for 45.7% of the variance, supporting the hypothesis.

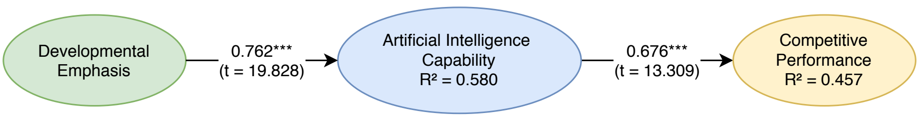

Figure 5.1: Estimated relationships between developmental emphasis, AI capability, and competitive performance.

As for H2, H3, and H4 (Fig. 5.2), I found significant positive effects of AI capability on successful adoption of cognitive engagement (β=0.560, t=8.596, p<0.001), process automation (β=0.536, t=8.551, p<0.001), and cognitive insight (β=0.526, t=6.988, p<0.001), accounting for 31.3%, 28.7%, and 27.7% of the variance, respectively. Thus, these hypotheses were supported.

However, as for H5, H6, and H7 (Fig. 5.2), the effects of having success with these respective AI technologies on competitive performance were not significant, meaning that these hypotheses were not supported.

As for H8 (Fig. 5.3), I found a significant positive effect of developmental emphasis on possessing the resources that build an AI capability. This is further reflected in the significant positive effect of developmental emphasis on AI capability (β=0.762,

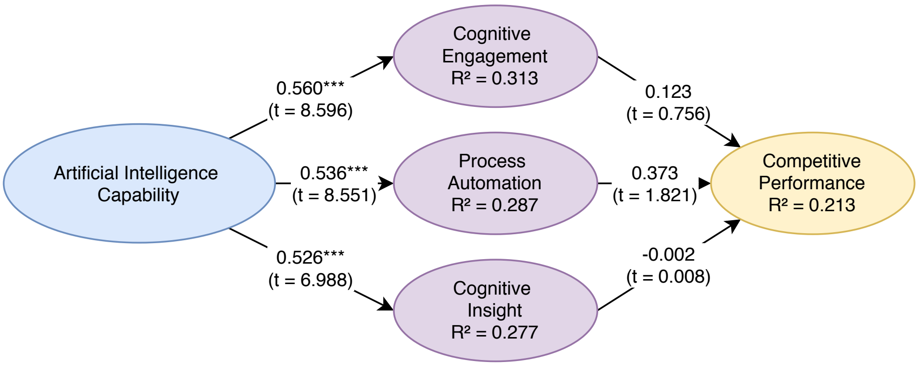

Figure 5.2: Estimated relationships between an AI capability and successful adoption of three common types of AI: cognitive engagement, process automation and cognitive insight.

t=19.828, p<0.001) (Fig. 5.1), accounting for 58.0% of the variance, supporting the hypothesis.

In addition to examining the R^2, the structural model was evaluated by assessing the effect size f^2. The effect size f^2 allows us to assess the contribution of an exogenous construct to an endogenous latent variable R^2. Based on the thresholds for effect size (i.e., small: 0.02, medium: 0.15, large: 0.35), the direct values for the three types of AI technologies to competitive performance (i.e., H5, H6, and H7) demonstrated small effect sizes (i.e., cognitive engagement: 0.009, process automation: 0.087, cognitive insight: 0.000). The direct values for the rest of the hypotheses were greater than the thresholds of 0.15 and 0.35, indicating medium to large effect sizes.

At last, consistent with other IS studies, I examined the influence of control variables on the constructs (Table 5.4). For competitive performance, none of the control variables had a significant effect. However, for AI capability, industry (β=0.404, t=7.137, p<0.001) and years of experience with AI (β=0.469, t=8.648, p<0.001) had a significant effect. Same with developmental emphasis, industry (β=0.246, t=2.974, p<0.01) and years of experience with AI (β=0.222, t=2.544, p<0.05) had a significant effect. For the three types of AI (i.e., cognitive engagement, process automation, and cognitive insight), only

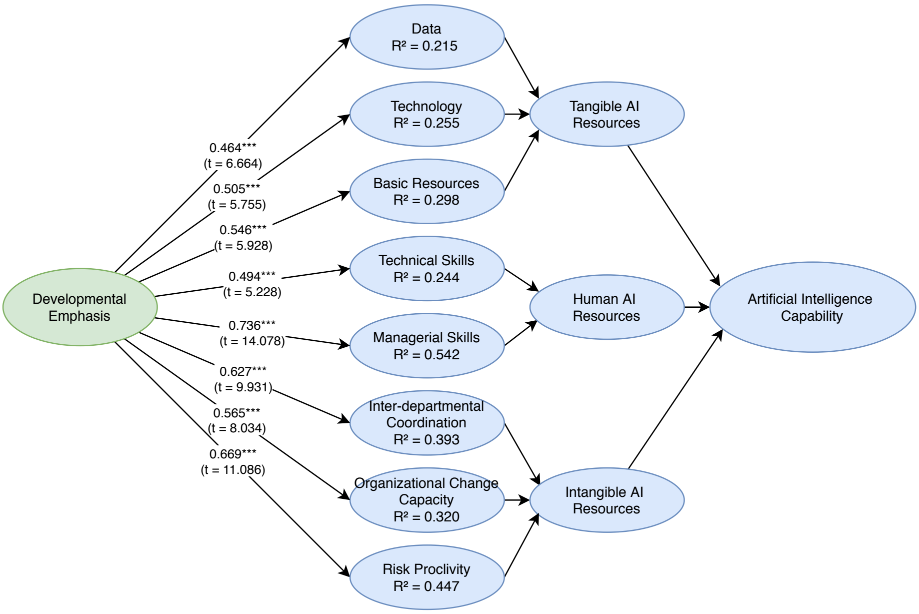

Figure 5.3: Estimated relationship between developmental emphasis and the resources that build an AI capability.

cognitive engagement was affected, with industry (β=0.256, t=3.594, p<0.001), years of experience with AI (β=0.235, t=2.313, p<0.05), and years working in the organization (β=0.291, t=3.000, p<0.01) having a significant effect.

Kim et al. (2010) highlights the potential impact of interpretational confounding in structural models. To test for this, I followed the recommendation of Kim et al. and tested the AI capability construct with singular dependent variables in different models. The weights of the formative measures that comprise the AI capability construct remained consistent and statistically significant across the models, indicating that interpretational confounding was not an issue. Several studies including those of Wu et al. (2015) and Gupta and George (2016) have used this method to empirically validate formative constructs in their study.

Table 5.4: Mean values for the 7-point Likert scale responses across AI capability resources for the respective control values. Can be interpreted as most to least likely to have an AI capability (top to bottom). NB: potential bias in sample size.

N	Size	Score	N	Industry	Score	N	Yrs w/AI	Score	N	Yrs in org	Score	N	Role	Score
1	Property	5.74	13	10-49	5.23	44	4+	5.34	22	5-7	5.5	7	Technical Consultant	5.53
37	Technology	5.48	81	250+	5.08	20	2-3	5.26	10	10-15	5.38	5	Systems Analyst	5.49
12	ICT & Telecom.	5.31	3	1-9	4.55	13	3-4	4.67	12	7-10	5.19	9	Software Engineer	5.47
3	Media	5.15	10	50-249	4.54	21	1-2	4.64	8	0-1	5.14	3	CEO	5.27
11	Consulting Services	5.09				9	0-1	4.45	24	3-5	5.04	28	Data Scientist	5.26
3	Health Care	5.08							4	15-20	4.79	11	CIO/CTO/CDO	5.14
6	Consumer Services	5.06							24	1-3	4.52	4	Operations Manager	4.98
2	Oil & Gas	4.92							3	20+	3.81	3	Enterprise Architect	4.94
2	Basic Materials	4.88										5	Head of IT Department	4.92
4	Consumer Goods	4.55										12	Other	4.74
1	Transport	4.54										6	Business Manager	4.55
20	Bank & Financials	4.48										6	IT Project Manager	4.41
3	Industrials	3.73										5	IT Director	4.31
2	Education	2.97										3	Business Analyst	3.94

5.3 Predictive validity

In addition to examining the R^2, the model is assessed by examining the Q^2 predictive relevance of exogenous variables (Woodside, 2013). This indicator measures how well observed values are reproduced by the model and its parameter estimates, thus verifying the model's predictive validity through sample re-use (Chin et al., 1998). The technique is a synthesis of cross-validation and function fitting, and examines each construct's predictive relevance by omitting selected inner model relationships and computing changes in the criterion estimates (q^2) (Hair et al., 2012). Values of the Q^2 predictive relevance that are greater than 0 imply that the structural model has predictive relevance, whereas values below 0 are an indication of insufficient predictive relevance (Hair Jr et al., 2016). The outcomes of the analysis indicate that all constructs have a satisfactory predictive relevance, including AI capability (q^2 = 0.408), competitive performance (q^2 = 0.167), cognitive engagement (q^2 = 0.244), process automation (q^2 = 0.221), and cognitive insight (q^2 = 0.220). Developmental emphasis is an exogenous construct, and thus does not have a q^2 predictive relevance value.

To examine the model fit, a test of composite-based standardized root mean square (SRMR) was performed. The SRMR value is the difference between the observed correlation and the model implied correlation matrix. The current SRMR yields a value of 0.055, which is below the threshold of 0.08, thus confirming the overall fit of the PLS path model (Henseler et al., 2016).

Chapter 6

Discussion

While the hype around AI is surging and spanning multiple disciplinary domains, reports and empirical studies from early adopters indicate that organizations struggle to realize the business value from their AI initiatives (Davenport and Ronanki, 2018; Alsheibani et al., 2019; Wirtz et al., 2019; West et al., 2018; Schlögl et al., 2019; Quan and Sanderson, 2018; Brynjolfsson et al., 2017). This is surprising given the vast number of articles proposing its potential business value (Ning et al., 2018; Ransbotham et al., 2017; Jones, 2018; Wilson and Daugherty, 2018; Vieira and Sehgal, 2018). Drawing on RBT, studies indicate that this evident gap between ambition and execution for AI initiatives (Ransbotham et al., 2017) can largely be attributed to a lack of relevant organizational resources that are required to enable AI technology.

6.1 Implications for research

This study aims to expand our understanding of AI in a business context. More specifically, it aims to understand the conditions that cultivate a successful AI initiative. While there is much literature on the potential business value of AI, there is little about what conditions might cultivate the realization of this value. Furthermore, existing literature often disregard the challenges associated with both deploying AI solutions and aligning them with business objectives. Consequently, recent studies and commentaries emphasize the importance of identifying the resources that enable successful deployment of AI technologies (Duan et al., 2019; Dwivedi et al., 2019).

This study makes an important contribution to literature on *the business value of AI* in four main ways. First, it draws on the theoretical lens of RBT and IS literature as means for exploring what organizational resources might effectively leverage AI technologies, and thus lead to competitive performance gains. To that end, it explores a proposed theoretical framework for an AI capability (Mikalef and Gupta, 2020) to confirm its validity as a means to achieve competitive performance gains. By means of an empirical study and PLS-SEM analysis, the study confirmed the validity of this theoretical framework for an AI capability as a means for achieving competitive performance gains. In doing so, this study contributed to IS literature by adding to our understanding of what exact resources might lead to competitive performance gains. However, this does not necessarily imply that this gain in competitive performance was realized through enabling AI technology.

Second, to address whether the proposed AI capability effectively leverages AI technologies and hence leads to successful AI initiatives, the empirical study investigated it's effect on three common forms of AI (i.e., cognitive engagement, process automation, and cognitive insight), as identified by Davenport and Ronanki (2018). The study confirmed that the proposed AI capability construct indeed had a positive effect on success with deployment of AI technologies. In that regard, this study contributes to literature on *AI in a business context* by expanding our understanding of what resources might lead to successful deployment of AI initiatives, as proposed for future research by some studies (Duan et al., 2019; Dwivedi et al., 2019).

Third, to address the many claims of reports and empirical studies that organizations are struggling to realize business value from their AI investments, the empirical study investigated whether successful outcomes with three common forms of AI (i.e., cognitive engagement, process automation, and cognitive insight) led to competitive performance gains. In favor of the many claims, having success with any of these three forms of AI had no significant effect on competitive performance. This contributes to literature on *AI in a business context* by adding to the pool of scientific evidence that organizations are struggling to realize business value from their AI investments. Strikingly, in light of the way these measures were conceptualized, these results indicate that even successful deployments of AI (i.e., AI initiatives functioned as intended) does not necessarily lead to competitive performance gains. This might imply that the deployed AI technology (i) was not impactful enough to produce competitive performance gains, or (ii) did not address objectives that were important enough to produce competitive performance gains.

Fourth, while there is emerging literature on what resources an AI capability might comprise, there is little about what might foster the acquisition of such resources. To address this gap in existing literature, this study introduces the concept of *developmental emphasis as the organizational culture and conditions that foster dynamism, entrepreneurship, acquisition of new resources, and a craving for new challenges.* Furthermore, it proposes developmental emphasis as a catalyst for developing the resources that might constitute an AI capability. The empirical study confirmed that developmental emphasis indeed had a significant positive effect on developing each of the resources that collectively constitute the proposed AI capability. Thus, this study contributed to literature on *AI in a business context* and more specifically the emerging literature on developing an AI capability (Mikalef and Gupta, 2020) by suggesting that the intangible concept of *developmental emphasis* successfully acts as a catalyst for developing resources that support and complement AI initiatives.

6.2 Implications for practice

The results of this study present some interesting implications for practice. First, a large portion of existing literature focuses on the technical aspects of AI, and the infrastructure and techniques required to enable the technology. By confirming the validity of a theoretical framework for an AI capability that comprises a blend of tangible-, human-, and intangible resources, this study highlights the importance of developing the more elusive but equally important human skills and intangible resources that are required to build an AI capability.

Furthermore, the study highlights the importance of considering the conditions that foster the acquisition of these resources. The results imply that in order to develop the resources that constitute an AI capability, organizations should strive towards an organizational culture and conditions that foster dynamism, entrepreneurship, acquisition of new resources, and a craving for new challenges.

As for successfully deploying AI technologies, the results testify to the effectiveness of possessing the proposed AI capability comprising a carefully selected blend of tangible-, human-, and intangible resources. However, the results also imply that organizations might not be addressing objectives that are important enough to produce competitive performance gains. It is important to acknowledge that in order to derive value from AI initiatives, an effort must go into aligning the correct AI technologies with sufficiently important business objectives.

6.3 Limitations and future research

Despite the contributions of the this study, it is constrained by a number of limitations that future research should seek to address.

First, although considerable efforts have been made to mitigate potential biases in the data, there is bound to be some bias. The study was conducted with a questionnaire as a means of data collection, which means that it relies on self-reported data. Although efforts were made to ensure that the items of the survey instrument (Appendix A) were easy to understand, there could be potential bias in subjective interpretation. To mitigate this specific bias, the respondents were instructed to consult with their coworkers if they felt unequipped to answer an item. Adding to the bias of subjective interpretation, the questionnaire was sent to a single respondent of each firm, meaning that this respondent was assumed to accurately represent and describe their firm as a whole. To mitigate this potential bias, the respondents were carefully selected based on their role and hence expected expertise.

Second, as for the validity of the theoretical framework for an AI capability, the resources that support and complement AI initiatives are not the same for all firms. Thus, the theoretical framework can not be considered a universal model. In order to further develop the concept of an AI capability, future research should explore the effects of context by including other demographics than the ones in this study. On that note, this study was aimed at companies located in the United States. It is likely that the geographical location of a firm affects a variety of factors related to AI adoption. In that regard, future studies should attempt to include more regions to explore the underlying effects that this might have on the dimensions of an AI capability and the dynamics of AI initiatives.

Chapter 7

Conclusion

This study was motivated by the surge of interest in AI over the past few years, which is reflected in academic literature spanning multiple disciplinary domains. While there has been a lot of hype around the proposed business value of AI, recent reports and empirical studies from early adopters suggest that organizations are struggling to realize business value from their AI investments. Some studies suggest that this gap between ambition and execution can be attributed to a lack of resources that support and complement AI technology. Drawing on RBT and empirical study, this study (i) confirms the validity of a proposed theoretical framework for an AI capability comprising a blend of tangible-, human-, and intangible resources as a means to successfully deploy AI initiatives and achieve competitive performance gains, (ii) adds to the pool of scientific evidence that organizations are struggling to realize business value from their AI investments, and (iii) provides empirical evidence that developmental emphasis - defined as *the organizational culture and conditions that foster dynamism, entrepreneurship, acquisition of new resources, and a craving for new challenges* - foster the acquisition of resources that support and complement AI technology. Consequently, it highlights the importance of (i) developing the elusive but equally important human skills and intangible resources that complement AI initiatives, (ii) developing the conditions that foster the acquisition of such resources, and (iii) aligning the appropriate AI technologies with sufficiently important business objectives.

Appendix A

Survey instrument

Table A.1: Survey instrument

Measure	Item
Data	
	D1. We have access to very large, unstructured, or fast-moving data for analysis.
	D2. We integrate data from multiple internal sources into a data warehouse or mart for easy access.
	D3. We integrate external data with internal to facilitate high-value analysis of our business environment.
	D4. We have the capacity to share our data across business units and organizational boundaries.
	D5. We are able to prepare and cleanse AI data efficiently and assess data for errors.
	D6. We are able to obtain data at the right level of granularity to produce meaningful insights.

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Table A.1 – continued from previous page

Measure	Item
Technology	
	T1. We have explored or adopted cloud-based services for processing data and performing AI and machine learning.
	T2. We have the necessary processing power to support AI applications (e.g. CPUs, GPUs).
	T3. We have invested in networking infrastructure (e.g. enterprise networks) that supports efficiency and scale of applications (scalability, high bandwidth, and low-latency).
	T4. We have explored or adopted parallel computing approaches for AI data processing.
	T5. We have invested in advanced cloud services to allow complex AI abilities on simple API calls (e.g. Microsoft Cognitive Services, Google Cloud Vision).
	T6. We have invested in scalable data storage infrastructures.
	T7. We have explored AI infrastructure to ensure that data is secured from to end to end with state-of-the-art technology.
Basic Resources	
	BR1. The AI initiatives are adequately funded.
	BR2. The AI project has enough team members to get the work done.
	BR3. The AI project is given enough time for completion.
Technical Skills	
	TS1. The organization has access to internal and external talent with the right technical skills to support AI work.

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Table A.1 – continued from previous page

Measure	Item
	TS2. Our data scientists are very capable of using AI technologies (e.g. machine learning, natural language processing, deep learning).
	TS3. Our data scientists have the right skills to accomplish their jobs successfully.
	TS4. Our data scientists are effective in data analysis, processing, and security.
	TS5. Our data scientists are provided with the required training to deal with AI applications.
	TS6. We hire data scientists that have the AI skills we are looking for.
	TS7. Our data scientists have suitable work experience to fulfill their jobs.
Managerial Skills	
	MS1. Our managers are able to understand business problems and to direct AI initiatives to solve them.
	MS2. Our managers are able to work with data scientists, other employees and customers to determine opportunities that AI might bring to our organization.
	MS3. Our managers have a good sense of where to apply AI.
	MS4. The executive manager of our AI function has strong leadership skills.
	MS5. Our managers are able to anticipate future business needs of functional managers, suppliers and customers and proactively design AI solutions to support these needs.

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Table A.1 – continued from previous page

Measure	Item
	MS6. Our managers are capable of coordinating AI-related activities in ways that support the organization, suppliers and customers.
	MS7. We have strong leadership to support AI initiatives and managers demonstrate ownership of and commitment to AI projects.
Inter-departmental Coordination	
	IC1. Collaboration
	IC2. Collective goals
	IC3. Teamwork
	IC4. Same vision
	IC5. Mutual understanding
	IC6. Shared information
	IC7. Shared resources
Organizational Change Capacity	
	OCC1. We are able to anticipate and plan for the organizational resistance to change.
	OCC2. We consider politics of the business reengineering efforts.
	OCC3. We recognize the need for managing change.
	OCC4. We are capable of communicating the reasons for change to the members of our organization.

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Table A.1 – continued from previous page

Measure	Item
	OCC5. We are able to make the necessary changes in human resource policies for process re-engineering.
	OCC6. Senior management commits to new values.
Risk Proclivity	
	RP1. In our organization we have a strong proclivity for high risk projects (with chances of very high returns).
	RP2. In our organization we take bold and wide-ranging acts to achieve firm objectives.
	RP3. We typically adopt a bold aggressive posture in order to maximize the probability of exploiting potential opportunities.
Cognitive Engagement	
	CE1. The use of AI has enhanced our responsiveness to customer service requests.
	CE2. The use of AI has helped us satisfy customer needs.
	CE3. The use of AI has enabled us to increase engagement with customers.
Process Automation	
	PA1. The use of AI has enabled us to automate back office administrative tasks.
	PA2. The use of AI has allowed us to automate financial activities and control expense claims.
	PA3. The use of AI has helped us automatize repetitive tasks (e.g. transferring of data, updating records).

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Table A.1 – continued from previous page

Measure	Item
Cognitive Insight	
	CI1. The use of AI has allowed us to gain insight about what our customers are likely to buy.
	CI2. The use of AI has enabled us to develop personalized targeting of marketing campaigns and products.
	CI3. The use of AI has allowed us to generate insight in key business activities that we previously did not have access to.
Competitive Performance	
	CP1. Compared to our key competitors our organization is more successful.
	CP2. Compared to our key competitors our organization has a greater market share.
	CP3. Compared to our key competitors our organization is growing faster.
	CP4. Compared to our key competitors our organization is more profitable.
	CP5. Compared to our key competitors our organization is more innovative.
Developmental Emphasis	
	DE1. The organization I work in is a very dynamic and entrepreneurial place.
	DE2. The glue that holds the organization I work in together is commitment to innovation and development.

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Table A.1 – continued from previous page

Measure	Item
	DE3. The organization I work emphasizes acquiring new resources and meeting new challenges.

Appendix B

Heterotrait-Monotrait Ratio (HTMT)

Table B.1: Heterotrait-Monotrait Ratio (HTMT) to assess discriminant validity. All values are below the threshold of 0.85, indicating sufficient discriminant validity.

		(4)	(5)	(6)	(7)	(8)
4	Technical Skills					
5	Managerial Skills	0.531				
6	Inter-departmental Coordination	0.456	0.713			
7	Organizational Change Capacity	0.503	0.58	0.73		
8	Risk Proclivity	0.483	0.584	0.667	0.715	

Appendix C

Cross-Loadings

	D	T	BR	TS	MS	IC	OCC	RP
D1	**0.621**	0.496	0.482	0.447	0.271	0.196	0.189	0.243
D2	**0.399**	0.29	0.261	0.14	0.203	0.189	0.219	0.165
D3	**0.711**	0.525	0.436	0.337	0.396	0.395	0.392	0.418
D4	**0.52**	0.285	0.267	0.231	0.42	0.442	0.391	0.304
D5	**0.865**	0.608	0.612	0.539	0.546	0.399	0.363	0.323
D6	**0.746**	0.544	0.515	0.495	0.351	0.363	0.36	0.266
T1	0.437	**0.634**	0.438	0.526	0.28	0.242	0.259	0.146
T2	0.549	**0.756**	0.506	0.517	0.367	0.244	0.331	0.274
T3	0.557	**0.758**	0.444	0.383	0.405	0.421	0.408	0.333
T4	0.662	**0.891**	0.619	0.608	0.421	0.27	0.406	0.335
T5	0.546	**0.817**	0.545	0.543	0.439	0.394	0.408	0.35
T6	0.592	**0.752**	0.462	0.45	0.328	0.262	0.348	0.298
T7	0.678	**0.875**	0.519	0.558	0.381	0.38	0.449	0.385
BR1	0.579	0.589	**0.86**	0.537	0.443	0.395	0.327	0.451

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Table C.1 – continued from previous page

	D	T	BR	TS	MS	IC	OCC	RP
BR2	0.665	0.613	**0.928**	0.655	0.475	0.386	0.348	0.429
BR3	0.642	0.588	**0.934**	0.635	0.528	0.434	0.411	0.5
TS1	0.549	0.606	0.689	**0.781**	0.5	0.32	0.433	0.388
TS2	0.467	0.383	0.496	**0.815**	0.355	0.186	0.215	0.235
TS3	0.487	0.506	0.503	**0.862**	0.41	0.324	0.358	0.336
TS4	0.499	0.513	0.474	**0.812**	0.316	0.423	0.356	0.348
TS5	0.548	0.607	0.544	**0.863**	0.445	0.428	0.5	0.443
TS6	0.471	0.476	0.542	**0.824**	0.386	0.324	0.387	0.383
TS7	0.569	0.597	0.626	**0.864**	0.502	0.46	0.465	0.494
MS1	0.5	0.387	0.415	0.351	**0.886**	0.557	0.417	0.392
MS2	0.456	0.367	0.426	0.379	**0.924**	0.609	0.486	0.488
MS3	0.444	0.391	0.427	0.393	**0.896**	0.58	0.462	0.418
MS4	0.409	0.414	0.429	0.481	**0.746**	0.458	0.392	0.46
MS5	0.558	0.464	0.533	0.48	**0.927**	0.687	0.51	0.54
MS6	0.542	0.507	0.524	0.483	**0.943**	0.698	0.571	0.576
MS7	0.558	0.561	0.569	0.559	**0.886**	0.606	0.58	0.555
IC1	0.5	0.365	0.49	0.376	0.577	**0.82**	0.589	0.569
IC2	0.351	0.369	0.383	0.321	0.557	**0.867**	0.606	0.506
IC3	0.472	0.432	0.477	0.453	0.622	**0.874**	0.623	0.602
IC4	0.444	0.381	0.341	0.306	0.597	**0.854**	0.626	0.507
IC5	0.403	0.36	0.385	0.366	0.627	**0.883**	0.625	0.564
IC6	0.337	0.272	0.283	0.34	0.571	**0.825**	0.517	0.48
IC7	0.3	0.256	0.285	0.352	0.432	**0.775**	0.443	0.45
OCC1	0.436	0.488	0.45	0.484	0.55	0.717	**0.856**	0.657

Continued on next page

Table C.1 – continued from previous page

	D	T	BR	TS	MS	IC	OCC	RP
OCC2	0.385	0.382	0.314	0.399	0.345	0.494	**0.792**	0.472
OCC3	0.293	0.341	0.264	0.344	0.286	0.424	**0.828**	0.488
OCC4	0.351	0.421	0.332	0.418	0.483	0.584	**0.892**	0.569
OCC5	0.41	0.451	0.291	0.372	0.504	0.621	**0.872**	0.561
OCC6	0.382	0.363	0.378	0.343	0.579	0.576	**0.796**	0.595
RP1	0.399	0.366	0.453	0.354	0.502	0.57	0.584	**0.92**
RP2	0.429	0.41	0.531	0.465	0.541	0.6	0.646	**0.966**
RP3	0.372	0.385	0.47	0.465	0.524	0.597	0.657	**0.941**

Data (D), Technology (T), Basic Resources (BR), Technical Skills (TS), Managerial Skills (MS), Inter-departmental Coordination (IC), Organizational Change Capacity (OCC), Risk Proclivity (RP)

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