Master

Understanding the role of organizational culture on Artificial Intelligence capabilities and organizational performance

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“AI is whatever hasn't been done yet”

- Larry Tesler

Foreword

This master thesis is done by two students attending the master's degree in Information Systems at University of Agder. We have previously collaborated on most projects, starting from the first semester during our bachelor's degree.

Our interest for big data was caught early on in the course of our studies and we have had a desire to extend our knowledge on this ever since. Particularly the way organizations could use their data in relation to artificial intelligence was something we found interesting, as artificial intelligence has become more and more present in both the technology field and media.

When deciding on a topic for our thesis, we quickly came to an agreement on that we wanted to study data and how this affected organizational decisions and the culture. This was then narrowed down to artificial intelligence and organizational culture. Our ability to research this has been made possible by a well-constructed master's programme and supportive instructors. We especially want to thank our supervisor, full professor of Information Systems Ilias Pappas at UiA for great help and guidance through the process.

Abstract

Context:
The past few years Artificial Intelligence has become the top technological priority for many organizations. AI technologies have a huge potential to improve organizational performance, however many organizations face challenges when adopting AI technologies.
Firms achieve competitive advantage when they are able to build capabilities that are hard to imitate. Organizational culture is an important factor when building AI capabilities in order to achieve success when adopting AI technologies.

Purpose: The purpose of this thesis is to explain how organizations can develop and exploit AI capabilities by changing their organizational culture. To measure this, we looked at how; 1) organizational culture impacts AI capabilities. and 2) how AI capabilities impact social-, market- and competitive performance.

Methods: The methods in this research consist of a systematic literature review and a quantitative survey. The systematic literature review was conducted as a foundation for this research by looking at what research is done on organizational culture and AI adoption. We had to establish how to define and measure organizational culture, AI capabilities and organizational performance. With the help of previous literature, we created a survey that was distributed to mainly Norwegian organizations, but we also got some respondents from other countries. We got a total of 326 respondents, and 299 of them responded that they were using AI technologies or did see the potential of using AI technologies. We developed a model with four hypotheses to investigate the relationship between organizational culture, AI capabilities and organizational performance. The data was analysed using partial least squares structural equation modelling (PLS-SEM) in SmartPLS, and the survey was distributed using SurveyXact.

Results: Our analysis validates our four hypotheses. First, organizational culture has a positive effect on artificial intelligence capabilities. Second, artificial intelligence capabilities have a positive effect on social performance. Third, artificial intelligence capabilities have a positive effect on market performance. Fourth, artificial intelligence capabilities have a positive effect on competitive performance.

Conclusion: We can conclude that organizational culture is an important factor for developing AI capabilities, and that AI capabilities have a positive impact on an organizational performance. To utilize AI technologies organizations should look at the organizational culture to improve their AI capabilities.

Keywords: Organizational culture, artificial intelligence capabilities, social performance, market performance, competitive performance.

Table of content

List of tables

List of Figures

1.0 Introduction

Society has been experiencing technological leaps for decades throughout the industrial revolution, computer age, internet, social network. Advances in technology, the abundance of data has prompted many industries to reposition themself to take advantage of the potential Artificial Intelligence (AI) technologies can provide them. This progress and change in technology lead to a change in how societies are organized, and how we are interacting with each other (Pappas et al., 2018).

Organizations are considered to be responsible for multiple challenges the society is facing today, that can lead to social, environmental and economic consequences. Now that the society has become more aware of the impacts coming from their consumption of diverse services, organizations has been led to operate in more sustainable and transparent ways. The massive amounts of data have made organizations realize that the data they own, and the way they use them can give them a competitive edge (Pappas et al., 2018). Organizations are investing in technology that can take advantage of Big Data, such as AI technologies. Being able to use data from multiple sources, sharing them with various stakeholders, and analysing them in different ways allows the achievement of digital transformation and creation of sustainable societies (Pappas et al., 2018).

Moore’s law, the abundance of data, and the rise of machine learning have transformed AI computers to something more than just a tool. The increase in computing power, along with the data available, makes it possible to do things that only a few years ago were considered to be science fiction (Friedman & Shashua, 2021). According to Gartner’s 2019 CIO survey the number of enterprises implementing AI grew 270% in the past four years (Howard & Rowsell-Jones, 2019). And despite the impact of COVID-19, 47% of AI investments were unchanged since the start of the pandemic, and 30% planned to increase their investments in AI (Goasduff, 2020).

While there is much interest about what potential AI technologies can provide organizations, it is reported that the organizations adopting these technologies are facing challenges that prevent them from achieving the performance gains wanted. According to a report by MIT Sloan Management Review from 2019, seven out of ten companies report minimal to no impact by adopting AI technologies. The organizations that struggle to generate value from AI, show up as having organizational challenges rather than technological. The organizations that are able to capture value from their AI activities exhibit a distinct set of organizational behaviour. While many organizations look at AI as a technological aspect, the organizations that look at AI with an organizational perspective are more likely to derive value from their AI investments (Fehling et al., 2019).

In a survey conducted by Appian in 2019 the most important factors in gaining value from AI investments are changing the existing IT and business cultures. Earlier technology acceptance studies recognize organizational culture as an important influential factor for adopting new technologies (Duan et al., 2019). Organizational culture impacts many different aspects of an organization and is viewed as a critical factor for why new technological initiatives fail (Shamim et al., 2019). Organizations are embedding Big Data Analytics and AI technologies into their organizations to transform information into insight and use this insight to obtain a competitive advantage (LaValle et al., 2011; Mikalef et al., 2020). The most common challenges that organizations face is managerial and cultural rather than related to the technology and data aspect (LaValle et al., 2011).

Prior studies have been focusing on capabilities as a primary focus for adopting AI and Big Data Analytics, and less on the cultural perspective. A large proportion of empirical studies assume that there is a direct relationship between big data, organizational capabilities, and performance, however there is a lack of research that takes organizational culture as a primary factor (Mikalef & Gupta, 2021; Mikalef et al., 2018). With organizational culture having such a large impact on organizations, we saw the need to look at how organizational culture impacts AI initiatives.

The goal of this study is to understand the importance of organizational culture in the context of AI capabilities, and the ability of organizations to successfully adopt AI technologies by proposing the following research question:

"*To what extent does organizational culture affect an organization's ability to adopt and use AI*"

The research question was answered through an extensive study consisting of three phases. We conducted a systematic literature review to gain insight into the existing research about organizational culture within the field of AI. By the information we gathered from the literature review we developed a conceptual model and a survey. Lastly, we distributed the survey and analysed the data to answer our research question and our four hypotheses.

1.1 Key concepts

Artificial intelligence: As there is no definition of intelligence, there is no soul definition of artificial intelligence. But the term is often used to describe intelligent machines and computer programs (McCarthy, 2004). Today, this is categorized as machine learning with the functionality of finding patterns by using data. This allows for mathematically constructed data-based decision-making (Ergen, 2019).

Organizational culture: The term organizational culture describes the working environment and how this influences the employees' way of thinking, acting and experiencing work (Warrick et al., 2016). It can have a significant influence on performance, the way people engage, their efforts and the organization's attraction towards new talent (Warrick, 2017).

1.2 Motivation

Organizations are aware of the business value gain AI can provide. Still, there are many organizations struggling to realise the potential of AI and attain the value benefits from it. The majority of organizations that have invested in AI, report minimal to no performance gains from implementing AI (Fehling et al., 2019). As the business world of today is rapidly changing, we see AI as a big potential for organizations seeking to increase their business performance and competitive advantage. This brings radical changes to the business- and organizational culture in the firms for them to achieve accurate decision-making to improve innovation and performance (Chatterjee et al., 2021). Although AI can improve innovation and performance, theoretical grounded knowledge about how to build AI capabilities is minimal (Mikalef & Gupta, 2021). We take great satisfaction in knowing that we contribute to AI research and especially that this paper can contribute to the practical usage of AI in organizations. As this is still a relatively unexplored area, where research is both needed and wanted.

During our academic degree, both of us have developed an interest in data analytics and AI. We have always looked at AI as an expression, but also how it can be a useful technology for organizations. We wanted to look deeper into the aspects of AI. Since the technology is relatively new in a business perspective and a very much talked about subject, it sparked an interest in us and we decided to write about AI.

1.3 Content and structure

The report is structured as followed; chapter two addresses the theoretical foundation. Chapter three describes our conceptual model and hypotheses. Chapter four explains the methodology, and chapter five shows the findings after the described methods are applied. Chapter six and seven contains the discussion and conclusion. Lastly, the references and appendix are presented.

2.0 Theoretical foundation

The theoretical foundation of this thesis is based on an extended systematic literature review. In addition to gather all our research from the field of AI, we researched outside the field to gain a clear theoretical foundation for organizational culture. The amount of data on organizational culture was too limited to conceptualize and measure the constructs. Most dimensions used to develop the organizational culture have been gathered from (Hogan & Coote, 2014). Their dimensions were developed based on Schein's model of organizational culture.

2.1 Organizational culture

Organizational culture is a well-researched area, but still there is no consensus on a single definition of what organizational culture is. Organizational culture is complex, even though there is no single agreement on a definition of organizational culture, it is often defined as "*a collection of shared assumptions, values, and beliefs that is reflected in its practices and goals and further helps its members understand the organizational functions.*" (Dubey et al., 2019) Some would say that organizational culture is the glue that keeps an organization together (Gupta & George, 2016). According to Edgar Schein, organizational culture refers to the values and beliefs that provide norms of expected behaviours that employees might follow. He also considers organizational culture to be a social force that is invisible, but yet very powerful (Hogan & Coote, 2014). Organizational culture is a system of shared beliefs held by the members of an organization, those shared meanings distinguish the organization from other organizations. Organizations do have common behaviour patterns that are used by employees to achieve an objective, these are taught to new members and represent the tacit and intangible level of an organization (Soltani et al., 2016).
Prior research suggests that organizational culture significantly influences financial performance and pride a greater effectiveness than organizational strategy and structure (Hogan & Coote, 2014).

Organizational Culture by (Hogan & Coote, 2014)	Organizational Culture by (Chatman & Jehn, 1994; O'Reilly et al., 1991)	Organizational Culture by (Martins & Terblanche, 2003)
Success	Orientation towards outcome and results / Emphasis on growth and rewards	Means to achieve objectives
Openness & flexibility	Innovation	Strategic vision and mission
Competence & professionalism	Detail orientation	Customer focus (external environment)
Responsibility	Stability	Employee needs and objectives
Appreciation of employees	Respect for people	Interpersonal relationships
Risk-taking	Aggressiveness and competitiveness	Management processes
Internal communication	A collaborative and team orientation	Leadership
Inter-functional cooperation	Decisiveness	

Table 1. Dimensions of measuring organizational culture

In table 1 have we gathered different dimensions of measuring organizational culture. We can draw lines between the different dimensions presented by Hogan & Coote, O'Reilly, Chatman & Caldwell and Chatman & Jehn. These dimensions can be tied to the three dimensions described by Schein in his model; Schein divides organizational culture into three different dimensions, Artifacts, espoused beliefs and values, and basic underlying assumptions (Schein, 2017). These dimensions have been widely accepted among researchers.

2.1.1 Artifacts

Artifacts are what you see, hear, and feel when you are present in an organization. This is the easiest dimension to observe when you go into an organization (Schein, 2009). Artifacts provide a context for employees to understand what is expected within the organization. This can be language, behaviour, and material symbols such as statements, meetings, inspection reports, dress codes, personal protective equipment, posters, bulletins (Guldenmund, 2000). Artifacts are divided into three different dimensions:

Dimension	**Definition**	**Source**
Artifacts	Visible organizational structures and processes.	
Success	Values success and strives for highest standards of performance.	(Chatman & Jehn, 1994; Hogan & Coote, 2014)
Inter-functional cooperation	Coordination and teamwork within the organization	(Caldwell & O'Reilly, 2003; Hogan & Coote, 2014)
Appreciation of employees	Value, recognize and reward employees for their accomplishments	(Hogan & Coote, 2014)

Table 2. Artifacts references

Success

The *success* layer is concerned to which degree an organization values success and strives for the highest standards of performance, while also encouraging employees to excel and reach for challenging goals. When an organization values success it raises the performance expectations of the organization's employees. This could lead to employees getting a psychological ownership of organizational goals. The psychological ownership ensures that members' objectives correspond to organizational objectives. This has the potential to increase employees' motivations to find new and creative solutions to organizational problems, which will improve the innovative performance of the organization.

Organizations use organizational culture, or social control, to instil pride in membership, intensity, and feelings of loyalty among organization members. Social control ensures that the members' objectives correspond to the organizational objectives.

Inter-functional cooperation
This layer is about coordination and teamwork within the organization. Expectations and encouragement of teamwork where coordinating and sharing information is valued can promote creativity or new ways of doing things in the organization. A high degree of cooperation, complex coordination, strong communication and conflict resolution influences innovation success within the organization.

Appreciation of employees
Appreciation of employees refers to how an organization values, recognizes employees and rewards them for their accomplishments. Output expectations are more successful when the employees are given rewards and feedback. Showing the employees respect and recognizing the contribution the employees make towards the organizational goals is crucial for the organization's success. Rewarding employees for their work can positively influence commitment to the work, and influence innovation.

2.1.2 Espoused beliefs and values

The *espoused beliefs and values* are ideals, goals, values and aspirations, ideologies and rationalities. These are shared by most members within the organization (Guldenmund, 2000; Wittrock et al., 2021). These are the values that are supposed to create an image of the organization (Schein, 2009). Values develop through the influences of cultural and social contexts. Values espoused within an organizational environment are standards for what individuals conduct as right or wrong. Values serve as an important function guiding the norms or expected behaviour within an organization. Espoused beliefs and valuers are divided into two dimensions:

Dimension	Definition	Source
Espoused beliefs and values	Strategies, goals, philosophies.	
Competence and professionalism	Organizations value knowledge and skills among their employees.	(Hogan & Coote, 2014)
Risk-taking	Valuing experimenting with new ideas.	(Hogan & Coote, 2014; Tellis et al., 2009)

Table 3. Espoused beliefs and values references

Competence and professionalism
Competence and professionalism are how organizations value knowledge and skills among their employees. It is also about how they work towards upholding the ideals and beliefs associated with a profession. Increased professional knowledge and expertise within an organization leads to better problem analysis and solution provision. This increased knowledge can increase initiation and adoption of technical innovations. When the competence of the employees is at a high degree, the innovation capability will radically increase.

Risk-taking
Organizational theory refers to *Risk-taking* as how an organization values experimenting with new ideas and challenging the current status in the organization. Organizations should encourage employees to take calculated risks and challenge the current status of the organization. This is important because it gives the employees freedom and the sense of being able to do things without the fear of negative consequences. Providing employees with the resources to explore, research, and build on future technologies is essential for an innovative culture.

2.1.3 Underlying assumptions

The *underlying assumptions* refers to the beliefs about the organizational environment that are taken for granted. They are the source of values in a culture and what causes actions within the organization. The assumptions are unconscious thoughts, beliefs, perceptions and feelings (Schein, 2017). Employees share beliefs and values as they work together. The employees observe successful problem resolution and achievements based on their beliefs and values, discarding those that do not work in the context of the organization. Those beliefs and values become ingrained over time and become a part of the subconscious and become non-negotiable (Cotter-Lockard, 2016). *"If we are willing to argue about something, then it has not become taken for granted. Therefore, definitions of culture that deal with values must specify that culture consists of non-negotiable values—which I am calling assumptions"* (Schein, 2017). The moment those values are taken for granted, they become assumptions (Cotter-Lockard, 2016). Assumptions are divided into three dimensions:

Dimension	Description	Source
Underlying assumptions	Unconscious, taken for granted beliefs, perceptions, thoughts, and feelings.	
Openness and flexibility	Value openness and responsiveness to new ideas, and flexible approaches to solving problems.	(Hogan & Coote, 2014)
Responsibility	Employees taking initiative and responsibility for achieving the overall goals of their work.	
Internal communication	Open communication that facilitates information flows within an organization.	

Table 4. Underlying assumptions references

Openness and flexibility
Openness and flexibility are how an organization values openness and responsiveness to new ideas, and flexible approaches to solving problems. Openness and flexibility facilitate creativity, empowerment and change in organizations. It promotes variety seeking among employees and drives the organizations towards new ideas. An organization that is open and flexible supports the production of new and creative ideas.

Responsibility
Responsibility regards how an organization's values employees' proactiveness, initiative, autonomy, and responsibility for their work. The employees should take initiative and responsibility for achieving the overall goals of their work. This will give them a sense of ownership over their work and ideas. This would lead to employees wanting to overcome potential problems with persistence and determination, they will become more creative and come to more innovative problem solving.

Internal communication
Internal communication is about having open communication that facilitates information flows within an organization. Having social interaction and communication of information provides access to diverse knowledge, this can improve the quality of decision-making.

2.2 Artificial Intelligence Capabilities

In order to fully benefit from AI, organizations need to develop a data-driven culture and the business analytics needs to become a part of the organizational culture across the whole organization and shared between all employees (Carillo et al., 2019). *AI capabilities* is the ability of a firm to select, orchestrate, and leverage its AI-specific resources. AI capabilities constructs can be conceptualized through three dimensions: tangible resources, human resources, and intangible resources. Of these dimensions there is no single dimension that can sufficiently explain the concept of an AI capability. The three main dimensions cover facts of the overall capability, as the AI capability constructs are quite broad. There is a minimal degree of overlap between them (Mikalef & Gupta, 2021). Earlier research shows that firms achieve a competitive advantage and performance gain by building unique capabilities (Gupta & George, 2016). Mikalef and Gupta define AI capabilities as *"the ability of a firm to select, orchestrate and leverage its AI-specific resources"*. This definition is rooted in that equally to the technological aspect of AI, the organizational factors are as important to utilize AI. The three dimensions are identified by surveying earlier literature and interviewing practitioners (Mikalef & Gupta, 2021).

After reviewing previous research, we decided to follow the framework provided by Mikalef & Gupta (2021) to determine the variable concerning AI capabilities. The framework includes tangible resources which are data, technology, and basic resources. Human resources consist of human and business skills. Intangible resources which are divided into inter-departmental coordination, organizational change capacity and risk proclivity. The resources will be defined in the following section.

2.2.1 Tangible resources

Tangible resources are considered resources that can be sold or bought in a market. For instance, physical assets (e.g. equipment, facilities) and financial assets (e.g. dept, equity). These resources are mostly available for all firms in the market and are not considered to provide a competitive advantage. Still, they are necessary even though they are not sufficient by themselves to create capabilities (Mikalef & Gupta, 2021). Tangible resources are divided into three dimensions:

Dimension	Description	Source
Tangible resources	Physical and financial assets	
Data	Access and use of internal and external data	(Mikalef & Gupta, 2021; Ransbotham et al., 2018)
Technology	Exploration and/or adoption of tools for; visualising, analysing, and storing data,	(Chui & Malhotra, 2018; Mikalef & Gupta, 2021)
Basic resources	Time and financial resources	(Mikalef & Gupta, 2021; Schryen, 2013)

Table 5. Tangible resources references

Data
A study published in 2018 by MIT Sloan Management Review shows that data is considered one of the key enablers in leveraging the potential of AI by manager. Traditionally, organizations have focused on structured data to assist business decisions. The businesses today focus on capturing a large diversity of data origin from multiple sources. As data is used to train AI algorithms, availability of high-quality data is considered critical. The merging of big data with AI has raised as one of the most important developments and is shaping the way firms drives business value from their data-resources.

Looking at the data that are accessible for organizations, it can roughly be divided into two types; internal and external data. Internal data refers to all data created by the organization's internal operations (e.g. accounting, sales, manufacturing). A large part of the overall data organizations utilized to base their decisions on, was traditionally internal data. This is unlikely to result in a competitive edge. External data includes data that is not directly related to the organization's operations but can provide a deeper insight towards the competitive market where modern organizations operate. For contemporary organizations, the large volumes of external and internal data provide remarkable opportunities, but also presents great challenges. Organizations must handle filtering out noisy data and reduce the size of data so that it is manageable and meaningful. However, to achieve a right degree of granularity toward the desired objective, there is a need to be an equilibrium when cleansing data. Summarized data could obscure key insights, relationships, and patterns. Integration of internal and external data is a must toward leveraging data to enable AI. At the same time organizations need to manage cleansing, processing, and distribution of data.

Technology
To bring AI applications to life, it is required that the underlying technological infrastructure is in place. Such underlying infrastructure is one of the main challenges when leveraging data sources to build AI applications. These modern forms of data require radically new technologies to store, process, transfer, and secure data through all stages of acquiring AI applications. The new technologies requires organizations to invest in scalable data storage infrastructures that support a large volume and different formats of data. AI also pressures organizations to invest in technologies that can quickly process data and run complex algorithms. Many organizations also adopt cloud-based solutions to deal with the cost of an AI infrastructure. A report published in 2018 by McKinsey highlights that one of the main

barriers in AI adoption is the lack of technological infrastructure. The AI requirement of infrastructure investments on multiple levels proves to be a major obstacle for many organizations. Furthermore, organizations can end up investing in several different supporting technologies, as the technological infrastructure depends on the type of techniques being used.

Basic resources

Apart from data and technological infrastructure investments to support AI, organizations need to provide time and financial resources to allow such initiatives to deliver an expected result. Before releasing value of AI, the vast majority of initiatives will need time to mature. It is essential to allocate financial resources for AI projects. Both technical and non-technical employees need to utilize some working hours in developing AI applications, as well as having the technological infrastructure to do so. In a paper review by Schryen, 2013 on IS business value, time and financial investments are considered required resources to realize value.

2.2.2 Human Resources

Human resources are considered resources that address the human capital of an organization. This is often measured by assessing the knowledge, skills, experience, leadership qualities, vision, communication and collaborations competencies, and problem-solving capabilities of the employees in an organization. Technical and business skills are considered critical elements of human resources (Mikalef & Gupta, 2021). With this as a basis, this study suggests that AI-specific skills are important components of an organization's human AI resources. Human resources are divided into two dimensions:

Dimension	Description	Source
Human resources	Human assets; skills, experience, communication, etc.	
Technical skills	Skills for dealing with implementation and realization	(Mikalef & Gupta, 2021; Wilson et al., 2017)
Business skills	Managing organizational change along with capturing technology	(Mikalef & Gupta, 2021; Ransbotham et al., 2018)

Table 6. Human resources references

Technical skills

Technical AI skills are the skills necessary to deal with implementation and realization of AI algorithms. Further, it involves the management of infrastructure to support AI initiatives and it is necessary with algorithm developers. It has been suggested that employees within the technical aspect of AI need to have a strong background in both analytical (e.g. logic, statistics) and technical AI skills (e.g. programming, data structures). An article published in 2017 by MIT Sloan Management Review, present three key roles that will emerge as technical profiles in the age of AI; trainers, explainers and sustainers. Trainers are the ones who teach AI systems how to perform. Explainers are concerned with bridging the gap between technologists and business managers. They provide clarity to the non-technicals regarding the inner workings of AI systems. Sustainers ensures that AI systems are operating as expected. Each of these roles will most likely become more and more sought, as the skills required in these roles are currently scarce in the market and are job functions that already are becoming crucial in modern businesses.

Business skills
Managers' lack of knowledge regarding how and where to apply AI technologies is one of the most common cited barriers in adopting and leveraging such technologies. For AI investments to realize business value it is required a real understanding and commitment from the leaders, to drive a large-scale change. In a study from 2018 by MIT Sloan Management Review, lack of leadership was ranked one of the top hindrances in adopting AI. It is important that leaders get familiar with AI technologies and their potential use in different functions of an organization. The ability of initiating and planning AI deployments is also an important ability of managers. As there are existing strong forces against change within organizations since AI is a threat to replacement of jobs currently held by employees, managers ability to initiate and planning the deployments is especially important. To avoid delay in AI adoption and hinder business value, it is important that managers develop a good relationship between technical and non-technical employees. The ability to manage organizational change along with capturing AI technology opportunities will likely be difficult to imitate by other organizations.

2.2.3 Intangible resources

Intangible resources are resources that are regarded as those which are difficult to replicate by other organizations and are of high importance in an uncertain and volatile market. Unlike the other two resources, intangibles are much more elusive and difficult to identify within organizations. In addition to the three intangible resources that Mikalef & Gupta suggests, we decided to two additional resources. These are data-driven culture and intensity of organizational learning, which is suggested by Gupta & George as resources that are likely to benefit organizations trying to reap benefits from big data. We have chosen to include these two resources as it aligns with our research that is culture based. Intangible resources are divided into three dimensions:

Dimension	Description	Source
Intangible resources	Reputation, skills, and experience	
Inter-departmental coordination	Coordination of tasks and visions between departments	(Fountaine et al., 2019; Mikalef & Gupta, 2021)
Organizational change capacity	Ability to execute plans	(Appian, 2019; Fountaine et al., 2019; Mikalef & Gupta, 2021)
Risk Proclivity	A risk oriented and ambitious approach	(Mikalef & Gupta, 2021; Ransbotham et al., 2018)
Data-driven culture	The extent of data-based decisions by all member of an organization	(Gupta & George, 2016; McAfee & Brynjolfsson, 2012)

Intensity of organizational learning	Organizations willingness to explore, store, share and apply knowledge	(Grant, 1996; Gupta & George, 2016; Teece et al., 1997)

Table 7. Intangible resources references

Inter-departmental coordination

In cross-disciplinary projects, the ability to coordinate tasks and share vision among the different departments of an organization is regarded as a cornerstone for success. It is important for organizations that the departments have a continuous relationship between them. Organizations must foster a culture of teamwork, collective goals, and shared resources to free the value of AI technologies. A recent study from Harvard Business review argues that AI has the biggest impact when it is developed by cross-functional teams with a mixed skillset. This ensures that AI initiatives address broad organizational priorities. An organization focusing on inter-departmental coordination is likely to be more agile when deploying AI applications. This is because a shared understanding between the different departments can reduce time in deploying AI applications.

Organizational change capacity

Organizational change capacity focuses on potential problems that can occur due to failure in a transition from an old to a new process. A key factor for success in digital transformation is the organization's ability to follow through on the execution of plans. Minimizing friction during change is seen as an important capacity in digital transformation capacity and overall business value. To realize value from AI investments, it is suggested that the ability of being able to manage change in multiple levels of the organization is an important component. Fountaine et al. note that the ability to overcome unique barriers to change is one of the main factors on how to make AI deliver business value. In a recently published survey in Appian’s future of Work, 500 senior level IT managers responded that changing an existing IT and business culture is one of the most important barriers in utilizing AI investments. Even though an organization has access to vast amounts of data, technical personnel, and a state-of-the-art AI infrastructure. The organization will not be able to realize performance gains if they do not change their existing way of doing business when incorporating AI.

Risk Proclivity

Risk proclivity is a strategic orientation toward risk-taking where organizations can harvest the benefits of AI before their competitors by adopting a more risk-oriented approach. This orientation is associated with proactive and aggressive initiatives to alter the competitive scene. Ransbotham et al. argues that organizations can make it harder for others to catch up and establish their position by embracing a risk proclivity to AI adoption. The main idea is that a company gains strong AI capabilities by moving out of standard practices and adopting new and more ambitious targets. By having a high-risk proclivity approach towards projects, an organization is more likely to be the first to adopt AI and gain an advantage on their competitors. By doing so, they can be in a group of pioneers that holds a competitive advantage from AI.

Data-driven culture

Data-driven culture is defined as to which extent all members of an organization make data-based decisions This includes top-level executives, middle managers, and lower-level employees. Many organizations in all industries collect a large amount of data, but few actually benefits from their technological investments. A reason for this is that many organizations are relying on their past experience of their top executives to make decisions.

In order to realize full potential, it is critical that the firms develop a data-driven culture. A firm solely relying on a few individuals making and influencing the decisions, are unlikely to gain return on their technological investments. Having employees in all levels of the organization required to make some decisions, will likely spread the culture of data-driven decision-making to all levels of the organization. This will likely cause that organizational members, regardless of their position in the firm, will be able to make good decisions that are grounded in some tangible evidence suggested from data.

Intensity of organizational learning
Organizational learning refers to the process to what extent organizations explore, store, share and apply their knowledge. An organization with the ability to change their resources according to the changes in the external market will likely gain a competitive advantage. This will likely be affected by the intensity of organizational learning. Firms need to continuously make efforts to exploit their existing knowledge and explore new knowledge to cope with an uncertain market. It is safe to suggest that organizations who have a high intensity of organizational learning are likely to have lots of organizational knowledge that can be used to create analytic capabilities. Further, they will likely have an advantage of applying their knowledge to further validate the initial insights gathered from data.

2.3 Firm performance

AI has become a top technical priority for many organizations over the past few years. This is due to the availability of big data and the new arising technologies (Mikalef & Gupta, 2021). AI technology has led to astonishing breakthroughs in algorithmic machine learning and autonomous decision-making, creating opportunities for ongoing innovation and gaining a competitive advantage among the many organizations (Abbad et al., 2021). In order to gain value from AI technologies recent studies show that organizations need to foster a culture of teamwork, collective goals, and shared resources (Mikalef & Gupta, 2021). To measure firm performance, we have divided it into three dimensions: Social performance, market performance and competitive performance.

2.3.1 Social performance

Corporate social responsibility is a concept whereby organizations contribute to a better society and environment. The corporate social responsibility is represented by the contributions undertaken by organizations to society through its business activities and its social investment (Pothuraju & Alekhya, 2020). New technology gives many opportunities for increasing social performance, and previous research concludes that technology such as AI has a positive impact on social performance (Bag et al., 2020; Hong et al., 2021).

2.3.2 Market performance

Market performance is a company's ability to satisfy clients, retain existing customers, attracting new customers and obtaining market growth (Ahmed et al., 2017; Hogan & Coote, 2014).

2.3.3 Competitive performance

Organizational *competitive performance* is the consequence of a firm's strategic position and the degree to which it executes those positions through an integrated system of activities. These activities generate a strategic advantage over its competitors that gives them a large market share (Sambamurthy et al., 2003). Early adopters of AI-driven technologies have shown an increase in profit margins in different sectors of the economy, which shows that they are more successful than their competitors (Kordon, 2020).

3.0 Conceptual model and hypotheses

The conceptual model was based on our research question and systematic literature review. The model is representing the relationships between key constructs within our research area. The hypotheses were formulated in order to explain the connection between the variables in the model. The model and theory in detail is described in the following section.

3.1 Conceptual research model

The conceptual research model is based and developed on elements from the research done in our systematic literature review. By taking elements from established principles, we ensure quality and make it more understandable and recognizable to the field. Further, we implemented our own empirical work to increase reliability and validity of the conceptual research model. The model has been continuously adapted through the research. The research conceptual model is shown in figure 1.

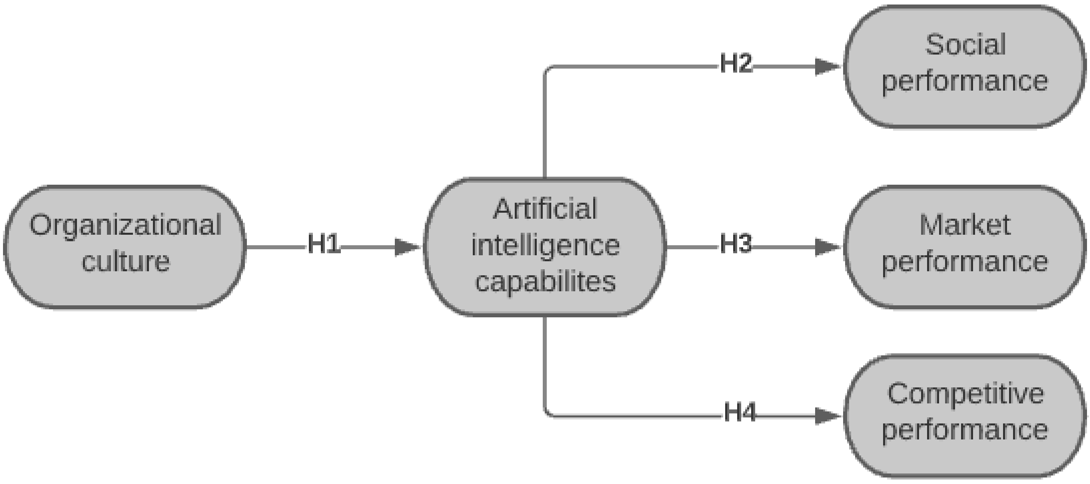

Figure 1. Conceptual model

3.2 Hypothesis

We formulated a total of four hypotheses, after we developed our model. These were developed to test if there was a positive effect between the elements described in the model. The following section presents the four hypotheses.

Hypothesis 1
In utilizing AI investments culture, is one of the most important barriers to overcome (Appian, 2019). To gain the most advantage from AI implementation, organizational culture should be carefully considered. Many earlier technology acceptance studies recognize culture as an important influential factor (Duan et al., 2019). AI brings radical changes to the organizational culture in businesses in order to achieve accurate decision-making and improve performance (Chatterjee et al., 2021). AI uses large-data sets in order to assist professionals with their tasks and is argued to facilitate better decision-making by providing a

wider range of insight (Mazzone & Elgammal, 2019), and is seen as a crucial strategy for gaining a competitive advantage (Shi et al., 2020). Organizational culture is the shared meanings and assumptions among the members of an organization. These are used by employees to achieve an objective (Soltani et al., 2016). When incorporating AI, an organization will not be able to realize performance gains unless they change their existing way of doing business, even though all the other factors are in place (Mikalef & Gupta, 2021).

Based on the foregoing argumentation, we can hypothesize the following:

H1: "Organizational culture has a positive effect on artificial intelligence capabilities"

Hypothesis 2, 3 and 4
Previous studies argue that AI technologies cannot provide a competitive advantage by themselves, as they are available for all firms in the market. An organization can achieve a competitive advantage by developing AI capabilities (Mikalef & Gupta, 2021). Leveraging IT in order to build dynamic capabilities is a key component for gaining a competitive advantage (Mikalef & Pateli, 2017). Building and seizing dynamic capabilities, enables organizations to form a strategy and business model, and organizational transformation that leads to a competitive advantage (Warner & Wäger, 2019). Earlier research has shown that developing big data analytic capabilities (BDAC) has a positive effect on operational performance. In their empirical study, (Gupta & George, 2016) found that there is a significant positive effect between BDAC and operational performance. They validated the relationship between BDAC and firm performance by using survey data collected from 108 executive-level technology leaders. Developing AI capabilities, a combination of tangible, human and intangible resources, can result in performance gains for organizations (Mishra & Pani, 2021). AI can improve innovation and performance within organizations, despite the promising improvements, there is a minimal knowledge about how to build AI capabilities (Mikalef & Gupta, 2021). New technology gives many opportunities and earlier research argues that AI has a positive impact on social performance (Bag et al., 2020; Hong et al., 2021). Further, those who are early adopters of AI-driven technologies show an increase in profits and are more successful than their competitors (Kordon, 2020).

Based on the foregoing argumentation, we can hypothesize the following:

H2: "Artificial intelligence capabilities has a positive effect on social performance"

H3: "Artificial intelligence capabilities has a positive effect on market performance"

H4: "Artificial intelligence capabilities has a positive effect on competitive performance"

4.0 Research method

This chapter explains the methods used for gathering and analysing the data from the survey. We will answer the research question based on this analysis.

4.1 Research approach

To best answer the research question, a quantitative approach was used. We decided to use an extensive research design, focusing on several respondents with relatively few variables. This study is deductive, and by completing the systematic literature review, we gained theoretical knowledge that was used to establish the hypotheses. The approach is suitable for collecting empirical data, which then can be used to answer our research questions and hypotheses.

4.1.1 Survey

The main source for empirical data used to answer the research question has come from our survey. The survey was aimed at collecting data from our predefined group of respondents. For our questionnaire we have been using a 1 to 7 Likert scale for scaling responses from the respondents. In the Likert scare 1 is totally disagree, and 7 is totally agree. By doing this form of survey, we look at statistical patterns and aim towards generalizing the results within a population.

4.2 Research design

The research design shows the procedures that were followed to collect data to answer the research question. Our plan was divided into three phases. The first phase consisted of investigating the literature within the field. We completed a systematic literature review to make sure we gained good knowledge within the topic of interest before developing the conceptual model and collecting data. The second phase was developing the conceptual model and the survey, while defining the population and gathering different suitable companies' contact information. Phase two was ended by sending out the survey. The last phase consisted of sending out reminders to non-respondents and continuing with gathering contact information to collect a significant number of respondents. The data collection lasted three months. The report was gradually developed simultaneously with the different phases. The complete research design is illustrated in figure 2.

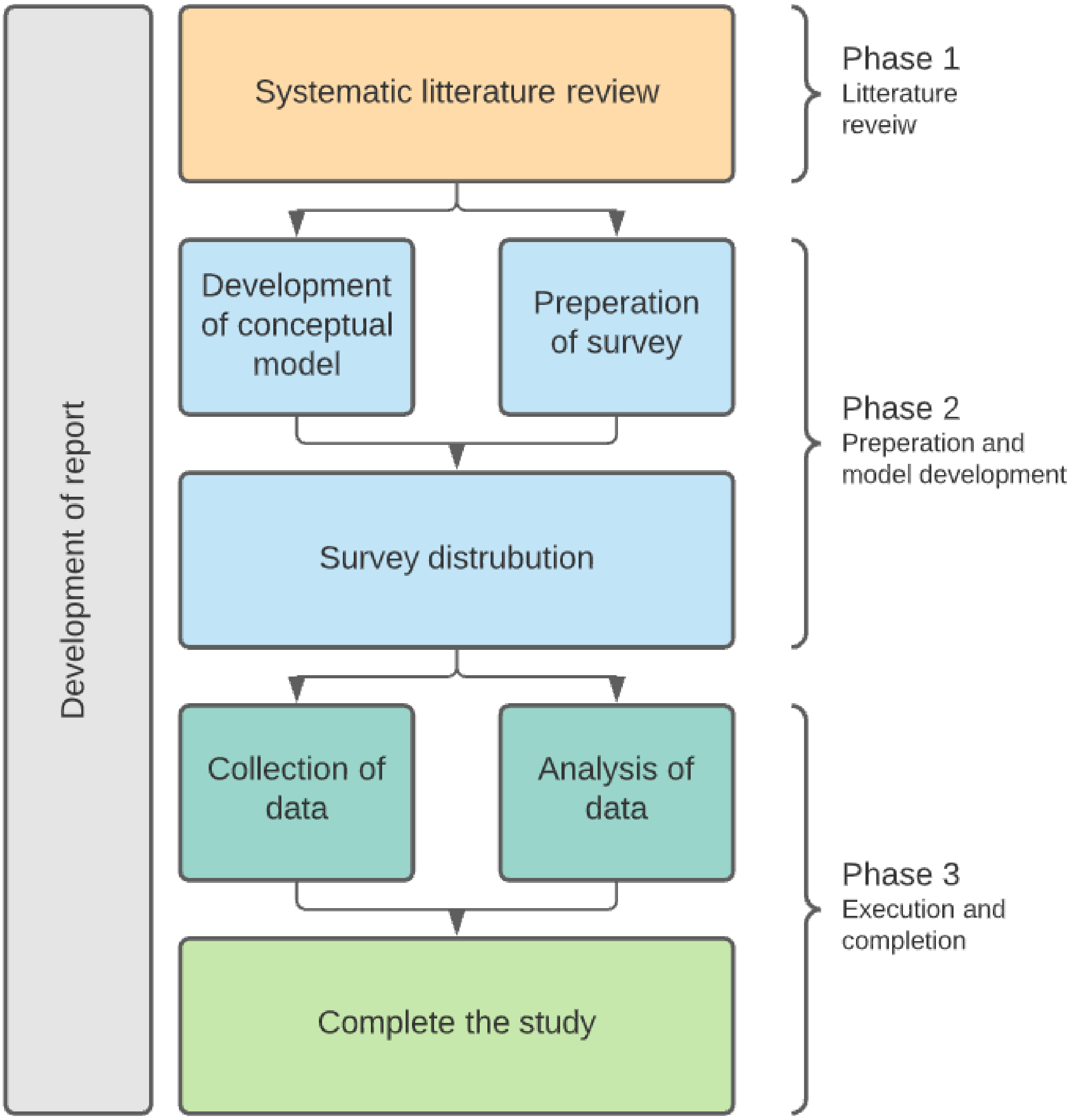

Figure 2. Research approach

4.3 Preparation and model construction

In order to develop the conceptual model, we conducted a systematic literature review. This section explains the process of developing the systematic literature review and the findings. Then we will proceed to describe how we operationalized the concepts and our procedure for ensuring the reliability and validity of the survey.

4.3.1 Systematic literature review process

In academic work, reviewing literature is a key element of the work. Performing a systematic literature review has the benefit of positioning new research activities by providing a framework/background of the topic. In every topic there is an overwhelming amount of literature. Reviewing all literature focusing on a specific topic is challenging. Therefore, using a systematic reviewing approach of the literature will increase the research quality, and a good-mannered reviewing process will be more achievable. A systematic approach also makes it less likely that the chosen literature is biased (Ba & Charters, 2007). Our reviewing process is documented in the next section of this article.

We have excluded research before 2016, since the topic of AI in businesses under constant development and recently adopted in the business world. Therefore, limiting our literature review to the last 5 years correlates with modern businesses usage of AI. Furthermore, we have excluded all articles not written in English and required the articles to have an author and be written in an academic setup to meet our quality criterias. Our research is within the scope of several other subject areas than just the information systems (IS) field, but we have chosen to exclude these, since we want to focus on the field of IS. The articles that met the requirements in the inclusion criteria were used in the primary studies. Articles that included the exclusion criteria, were not used in the study. The inclusion and exclusion criteria are shown in table 9.
To meet our excluding- and including criterias we used the database Scopus. The search string can be seen in table 8.

Number	Search string
1	TITLE-ABS-KEY("AI" OR "Artificial Intelligence" AND "Organizational Culture" OR "Culture") AND (LIMIT-TO (PUBYEAR,2021) OR LIMIT-TO (PUBYEAR,2020) OR LIMIT-TO (PUBYEAR,2019) OR LIMIT-TO (PUBYEAR,2018) OR LIMIT-TO (PUBYEAR,2017) OR LIMIT-TO (PUBYEAR,2016)) AND (LIMIT-TO (LANGUAGE,"English"))
2	TITLE-ABS-KEY("AI" OR "Artificial Intelligence" AND "Organizational Culture") AND (LIMIT-TO (PUBYEAR,2021) OR LIMIT-TO (PUBYEAR,2020) OR LIMIT-TO (PUBYEAR,2019) OR LIMIT-TO (PUBYEAR,2018) OR LIMIT-TO (PUBYEAR,2017) OR LIMIT-TO (PUBYEAR,2016)) AND (LIMIT-TO (LANGUAGE,"English"))

Table 8. Search string

Inclusion criteria	Exclusion criteria
Conference proceedings	Outside the field of IS
Focus on AI and relates to the RQ	Not written in English
Academic quality	Books

Table 9. Inclusion and exclusion criterias

4.3.2 Findings

The findings are presented in two parts in this literature review. The first part is in the form of a qualitative presentation. The second part contains analysing and interpreting the data from the selected studies in order to answer the research question. The main concepts discussed in the articles are AI and organizational culture. The literature discusses dimensions of both concepts, however each paper varies in the in its focus area. Most of the papers mentioned organizational culture as an important factor of AI adoption, but not many of them discuss organizational culture as a main focus. The remaining articles, even though it is in the context of AI, are primarily focusing on and contributing to the cultural part. During the analysis of the literature, several challenges have been discovered, and some articles also present solutions. We have decided to divide this into challenges and then strategies for overcoming these, to make this a useful contribution.

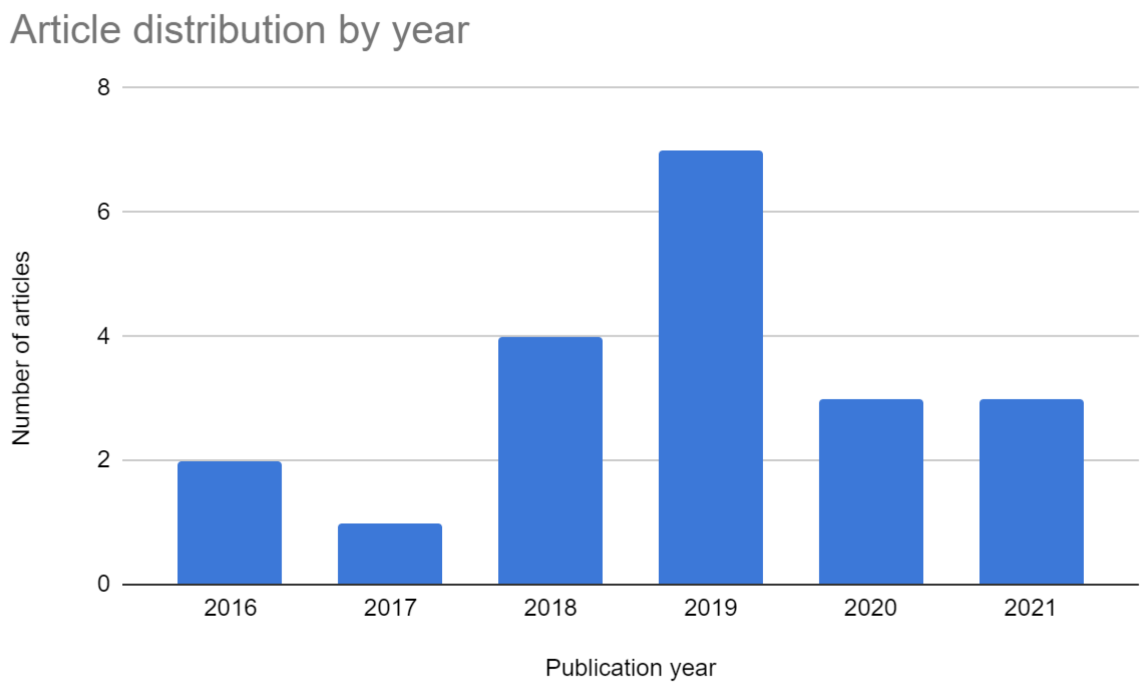

Figure 3. Articles distribution year

4.3.3 Concept matrix

The concept matrix illustrates what dimensions are discussed in the respective concepts in the literature. The concept matrix is shown in table 10.

	Organizational culture			Artificial Intelligence		
Articles / Concepts	Artifacts	Values	Assumptions	AI Capabilities	AI Adoption	Performance
Mikalef et al 2021	x	x	x	x	x	x
Duan et al 2019	x	x	x	x	x	x
Dubey et al 2019	x		x	x	x	x
Carillo et al 2018	x	x	x	x		x
Trenerry et al 2021	x	x	x	x	x	x
Shi et al 2020	x			x		
Lopes et al 2019		x	x	x		
Spano et al 2016		x	x	x		
Koohang & Nord 2021		x				x
Božič & Dimovski 2019		x	x			x
Ransbotham et al 2018	x	x	x	x	x	x
McKinsey, 2018				x	x	
Fountaine et al, 2019	x	x	x	x	x	
Gupta et al, 2016	x	x	x	x		
Wilson et al, 2017	x			x		
Warner & Wäger, 2019	x	x	x			x
Soni et al, 2020	x					x
Chatterjee et al, 2021	x	x	x			x
Davenport et al, 2018		x		x	x	x
IDG, 2019	x			x		

Table 10. Concept matrix

4.3.4 Organizational culture's impact on artificial intelligence adoption

Organizational culture can be defined as *"the set of beliefs, values and assumptions that are shared by members of an organization and thought to newcomers as the proper way to think and feel"* (Carillo et al., 2019). To keep up with the rapid changes in technology and the need for new skills and competencies in the workplace, demands a shift in mindset among individuals, teams, and organizations (Trenerry et al., 2021). We can see that organizational culture can be related to the challenges that organizations are facing when adopting AI to their organization. Studies show that organizational culture has a strong impact on the challenges the organizations are facing while adopting new technologies into the organization. Use of AI brings radical changes to the business- and organizational culture within the firms in order for them to achieve accurate decision-making to improve innovation and performance (Chatterjee et al., 2021). To gain value from AI technologies organizations must create a work culture that values collaboration, working towards collective goals, and shared resources (Mikalef & Gupta, 2021). This means that organizational culture will have a significant impact on the adoption of AI usage in an organization and can be critical for organizations that want to adopt AI into their organization.

4.3.5 Challenges of organizational culture in artificial intelligence adoption

AI is seen as strategic technology that is leading the future. In the majority of developed countries, AI is seen as a crucial strategy for enhancing competitiveness and gaining a competitive advantage (Shi et al., 2020). AI promises a significant impact on the workforce and is therefore a grand challenge that companies must face (Carillo et al., 2019; Davenport & Ronanki, 2018).

The advantages and changes that come with AI look promising, however among top executives there is already an awareness of the challenges that will arise in line with AI implementation. First of all, AI will replace several jobs and force layoffs, but also force companies to change their business vision, this leads to a change of workplace and organizational culture (Lopes et al., 2019; Ransbotham et al., 2018).
When implementing AI applications, it requires lengthy training procedures, calibrating and refining, and taking new sources of data into account (Mikalef & Gupta, 2021).
Without this training organizations risk wasting their time and money pursuing the wrong technology for the task. With a better understanding, the organizations are in a better position to determine what technology is needed for the specific needs (Davenport & Ronanki, 2018).

Further, AI technology is limited to the minority of regions around the world. Causing a divide, similar to the digital divide that strengthens inequality in sectors (Soni et al., 2020). This would create a chasm that can have a negative effect on the organizational culture. Earlier research has shown that internal problems occur due to digital divide in the workplace, because of lack of motivation from employees to change work routines and acquire new competencies (Grundén, 2011).
Many companies will likely see the adoption of AI tools as a threat to their established work methods, job security and organizational culture and have a hard time adapting themselves (Lopes et al., 2019). This could lead to managers being concerned about losing their power (Warner & Wäger, 2019). A large-scale study conducted by MIT Sloan Management review indicated that more than 40% of respondents faced challenges of cultural resistance to AI approaches. As a result of this adoption and business value of AI investments was greatly hindered (Ransbotham et al., 2018). An organization that is unable to overcome these challenges are unlikely to utilize the value of AI investments. Even though an organization has all the technical aspects and required personnel in place, they will not be able to exploit the performance gains of AI if it does not change its way of doing business (Mikalef & Gupta, 2021).

When implementing AI, data-driven businesses need to redefine their overall strategy and business model. Because of this, data-driven decision making must be infused into all levels of management. Management must become skilled in analytic methods and learn how to explore big data to gain a competitive advantage. This means organizations implementing AI, will face challenges for management development (Carillo et al., 2019). Lack of leadership to support AI is one of the most important barriers in realizing value from AI (Chui & Malhotra, 2018). A survey done by (Davenport & Ronanki, 2018), shows that more than a third of managers do not understand AI technologies and how they work (Mikalef & Gupta, 2021).

4.3.6 Strategies for overcoming challenges of organizational culture in the context of artificial intelligence

In the literature there are several strategies, techniques, requirements, and suggestions to overcome the challenges of organizational culture in the context of AI. These are identified in this study and presented within the dimension of organizational culture.

To gain analytical skills a data-driven business must ensure that business-analytics becomes a part of the organizational culture that is shared between all employees and especially between those who are responsible for the decision making. Data-driven decision-making skills cannot simply be gained through recruitment of data scientists (Carillo et al., 2019). In order to utilize data-driven decision making, training of employees is vital. Lack of training leads to limited knowledge. Employees are likely to give up on using analytical systems if they do not understand how the systems work, or if it feels too time consuming (Spano & Bellò, 2016). A necessary precondition for successful AI deployments requires an AI orientation within the organization. This requires a culture of coordination, mutual understanding, and cooperation between the different departments within the organization (Mikalef & Gupta, 2021; Warner & Wäger, 2019). One of the most important barriers in utilizing AI investments is changing an existing IT and business culture (Appian, 2019).

Within an organization, technical, business, and relational skills should be top priority. 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). Trainers teach AI systems how to perform. Explainers are trying to bridge the gap between technologists and business managers. Sustainers are ensuring that AI systems are operating as expected. These skills are already becoming crucial in modern businesses and will likely become very sought of (Mikalef & Gupta, 2021). The training should include learning new technologies, interpreting business problems and developing appropriate data analytics solutions (Koohang & Nord, 2021). Employees equipped with the appropriate skills and knowledge get more confident and are better suited for using data analytics systems (Božič & Dimovski, 2019). It is assumed that analytics becomes a part of the organizational culture, as it is claimed that managers and employees should be trained to adopt an analytical mindset (Carillo et al., 2019). Focusing on reskilling of employees, change management and communication is important for overcoming the fear among the workforce for becoming redundant because of the adoption of AI. When the workers understand the basics of AI, they are able to identify opportunities for the organization (Ransbotham et al., 2018). Building a digital mindset and culture throughout the entire organization is essential for building sensing capabilities that will allow the workers to seize on the latest and unexpected trends (Warner & Wäger, 2019).

Recent studies in AI and business argue that to seize the value of AI technology, the organizational culture must foster teamwork, collective goals, and shared resources. To achieve an organizational culture on this line, it is important that organizations emphasize continuous relationships between departments. To coordinate tasks and share a mutual vision between departments is an ability that is regarded as a cornerstone of success in cross-disciplinary projects. A key enabler of innovation and creativity in organizations is inter-departmental coordination. Inter-departmental coordination has been defined as “a state of high degrees of shared values, mutual goal commitments, and collaborative behaviours”

(Mikalef & Gupta, 2021). AI has the biggest impact when it is developed by cross-functional teams with a mixed skillset (Fountaine et al., 2019).

Data-driven decision-making must be infused in all levels of management. Managers must become skilled in the methods and learn how to explore big data in order to gain a competitive advantage (Carillo et al., 2019). The management should be able to plan, coordinate and monitor the business performance in order to utilize analytical tools and systems. There should be a strategy behind the usage of the systems that is in accordance with the overall business strategy. Further, management should continuously examine innovative opportunities for planning their usage of analytical systems, since business requirements are dynamic (Koohang & Nord, 2021).

When the change in skills and competencies is determined by the change in advanced technologies, there is a need for a shift in the mindset among groups and individuals within an organization (Trenerry et al., 2021). Trenerry et al mentions that when employees perceive that the technology will be useful to their work and help them to perform, and is easy for them to learn and use, the odds of adoption increases. So, a change in the mindset and the culture of the organization will contribute to overcoming the challenges of adopting AI.

4.4 Construct definition and Measures

To answer our research question and test the hypotheses, we developed questions that measured the correct variables. In previous literature there is a lot of well-established operationalization of variables. Our systematic literature review contained these operationalizations. The questions used in our survey are found in previous surveys and research papers. The questions are based on previous literature, but in cooperation with our supervisor tweaked a bit in order to fit our research question. The questions chosen for this survey were sent to our supervisor for confirmation to make sure we were measuring the correct variables.

Operationalization of control questions
In order to collect demographic information on the respondents to support the study, we developed a few introductory questions. The first question we asked the respondents was if they are using AI in their organization. It was important to establish whether the respondent's organization used AI or not. If they did not use AI we followed up with a question asking if they thought their organization had potential for use of AI. Further, we asked a question about the number of employees to determine the company size. To address this, we measured it as an ordinal value in accordance with the European Commission's recommendations; micro (0-9 employees), small (10-49 employees), medium (50-249 employees) and large (>250 employees) (Mikalef et al., 2020). Determining the firm size provides a good background of information to extend our findings. Moreover, we asked a question regarding the type of the organization (e.g. public, private, profit, non-profit). More background information through the next two questions, where we asked about the country of residents and what type of industry the respondent worked in (e.g. IT, banking). These two questions were free text, where they could explain the type of industry they work in with their own words. These questions may also help extend the findings. The questions can be seen in table 11.

Indicator	Question
IN1	Does your organization use AI tools?
IN2	Is there a potential for AI use in your organization?
IN3	Are you personally using AI tools?
IN4	Is someone in your team or someone you professionally collaborate with using AI tools?
IN5	What kind of AI tools are being used in your organization?
IN6	Type of company are you working for
IN7	What is the size of the company you are working for
IN8	Country of residence
IN9	What type of industry do you work in?

Table 11. Operationalization of organizational culture

Operationalization of organizational culture

Schein presents three constructs to measure organizational culture, these are Artifacts, Values and Assumptions (Schein, 2009). We have adapted this construct and used Hogan & Coote's dimensions for measuring the organization's culture and attached these to Schein's constructs; artifacts, values and Assumptions. Artifacts consist of Appreciation of employees, Inter-functional cooperation, and Success. Values consist of Risk-taking and Competence and professionalism. Assumptions consist of Openness and flexibility, Internal communication, and Responsibility. The whole construct is shown in figure 4.

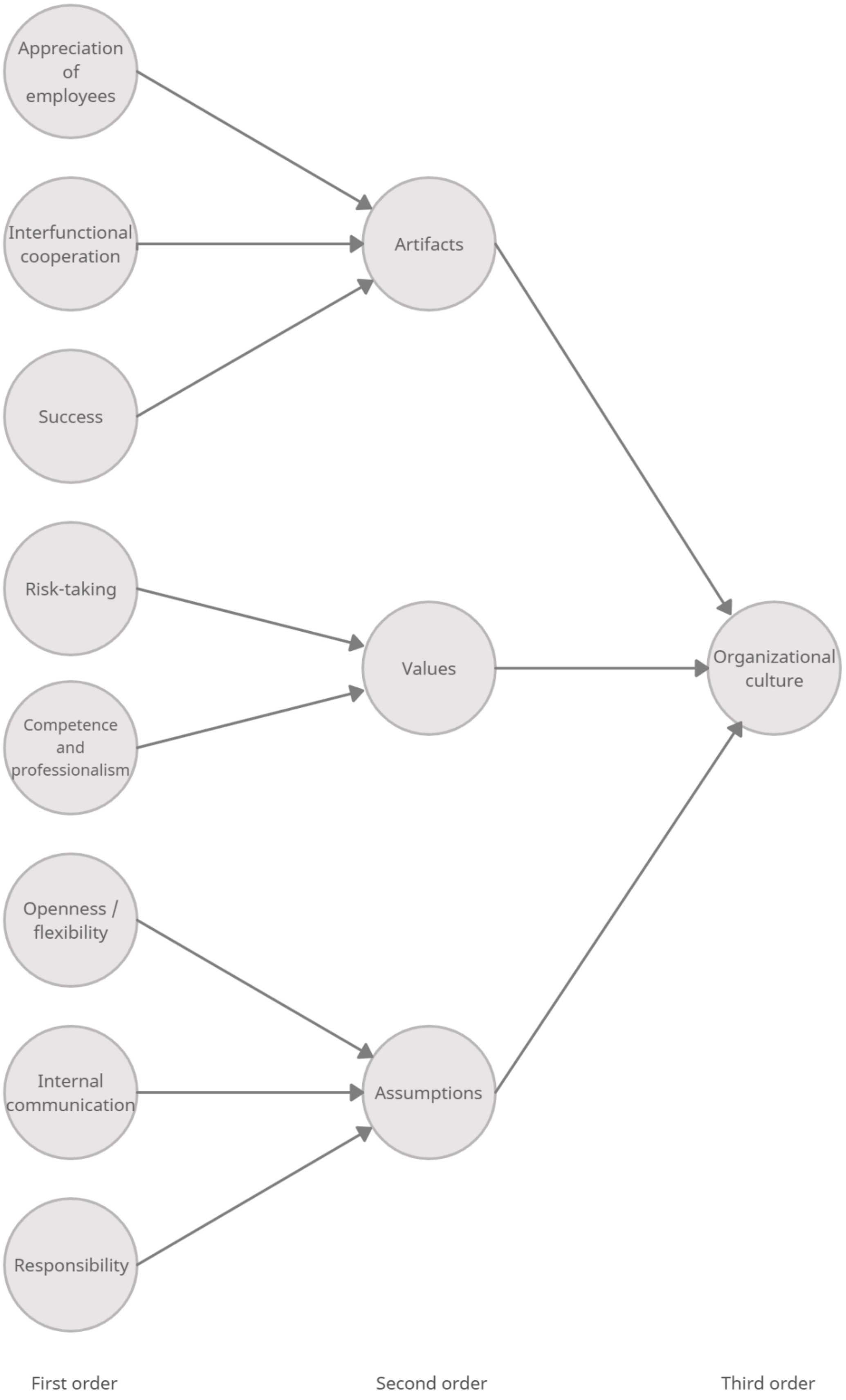

Figure 4. Organizational culture construct

Artifacts
The three dimensions measuring artifacts are presented below.

Appreciation of employees
Appreciation of employees is about how an organization values their employees and rewards them for their accomplishments towards the organization's goals. Appreciation of employees is measured by how an organization recognizes and rewards their individual employees and takes time to celebrate their work achievements.

Inter-functional cooperation
Inter-functional cooperation is about coordination and teamwork within the organization . Inter-functional cooperation is measured by how organizations value cooperation, coordination and sharing information among different work teams.

Success
Success is to which extent an organization strives for the highest standards of performance by encouraging employees to excel and reach for challenging goals. Success is measured by how an organization values success and performance, and that they aspire to be the best firm in their market.

Indicator	Question	Source
Inter-functional cooperation	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	
IFC1	Cooperation among different work teams is highly valued	(Hogan & Coote, 2014)
IFC2	This firm values integration and sharing among teams throughout the firm	
IFC3	We place great value on coordination among different work teams	
Appreciation of employees	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	
AE1	We place great value on recognizing and rewarding employees' accomplishments	(Hogan & Coote, 2014)
AE2	Taking time to celebrate employee’s work achievements is valued in this firm	
AE3	We place great value on showing our appreciation for the efforts of each employee	
Success	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	
S1	We value success in this firm	(Hogan & Coote, 2014)
S2	We aspire to be the best firm in our market	

S3	We place great value on our performance

Table 12. Operationalization of Inter-functional cooperation of employees and Success

Values
The two dimensions measuring values are mentioned below.

Risk-taking
Risk-taking is about how an organization values experimenting with new ideas and challenging the current status in the organization.
Risk-taking is measured by how an organization values willingness to experiment with new ideas and challenge the status quo.

Competence and professionalism
Competence and professionalism are how organizations value knowledge and skills among their employees. Competence and professionalism are measured by the organization's valuation of professional knowledge and skills among their employees, and if upholding the highest level of professionalism is valued in the organization.

Indicator	Question	Source
Risk-taking	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	
RT1	This firm values willingness to challenge the status quo	(Hogan & Coote, 2014)
RT2	This firm values a willingness to experiment with new ideas	
RT3	Valuing calculated risk-taking helped this firm get to where it is today	
Competence and professionalism	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	
CP1	We place great value on professional knowledge and skills	(Hogan & Coote, 2014)
CP2	We aspire to a high level of competence and professionalism	
CP3	Upholding the highest level of professionalism is valued within this firm	

Table 13. Operationalization of Risk-taking and, Competence and professionalism

Assumptions
The three dimensions measuring assumptions are presented below.

Openness and flexibility
Openness and flexibility are about how an organization values flexible approaches to problem solving and being open and responsive to new ideas. Openness and flexibility are measured by how an organization is open to new ideas, and how responsive they are to these ideas. And if they put great value on being flexible in the approach to problems.

Internal communication
Internal communication is about having open communication that facilitates information flows within an organization. Internal communication is measured by whether an organization values open and high-quality internal communication.

Responsibility
Responsibility is about how organization's value their employees being proactive and taking initiative and being responsible for their own work. Responsibility is measured by how an organization values their employees taking responsibility and using their initiative and being proactive in their role.

Indicator	Question	Source
Openness and flexibility	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	
OF1	We value openness to new ideas in this firm	(Hogan & Coote, 2014)
OF2	We are responsive to new ideas in this firm	
OF3	We place great value on being flexible in our approach for problems	
OF4	A willingness to show flexibility is valued within this firm	
Internal communication	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	
IC1	Open communication is valued highly within this firm	(Hogan & Coote, 2014)
IC2	We place great value on excellent internal communication within this firm	
IC3	Maintaining high quality internal communication is valued within this firm	
Responsibility	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	
R1	We place great value on every employee being proactive in his/her role	(Hogan & Coote, 2014)
R2	The firm values employees using their initiative	
R3	We value employees taking responsibility for their work	

Table 14. Operationalization of Openness and flexibility, Internal communication, and Responsibility

Operationalization of artificial intelligence capabilities
The constructs presented for AI capabilities are based on the constructs presented by (Mikalef & Gupta, 2021). They define AI capabilities as a third order construct that is divided into three dimensions; tangible resources, human resources, and intangible resources. We have adopted this construct. The construct is shown in figure 5.

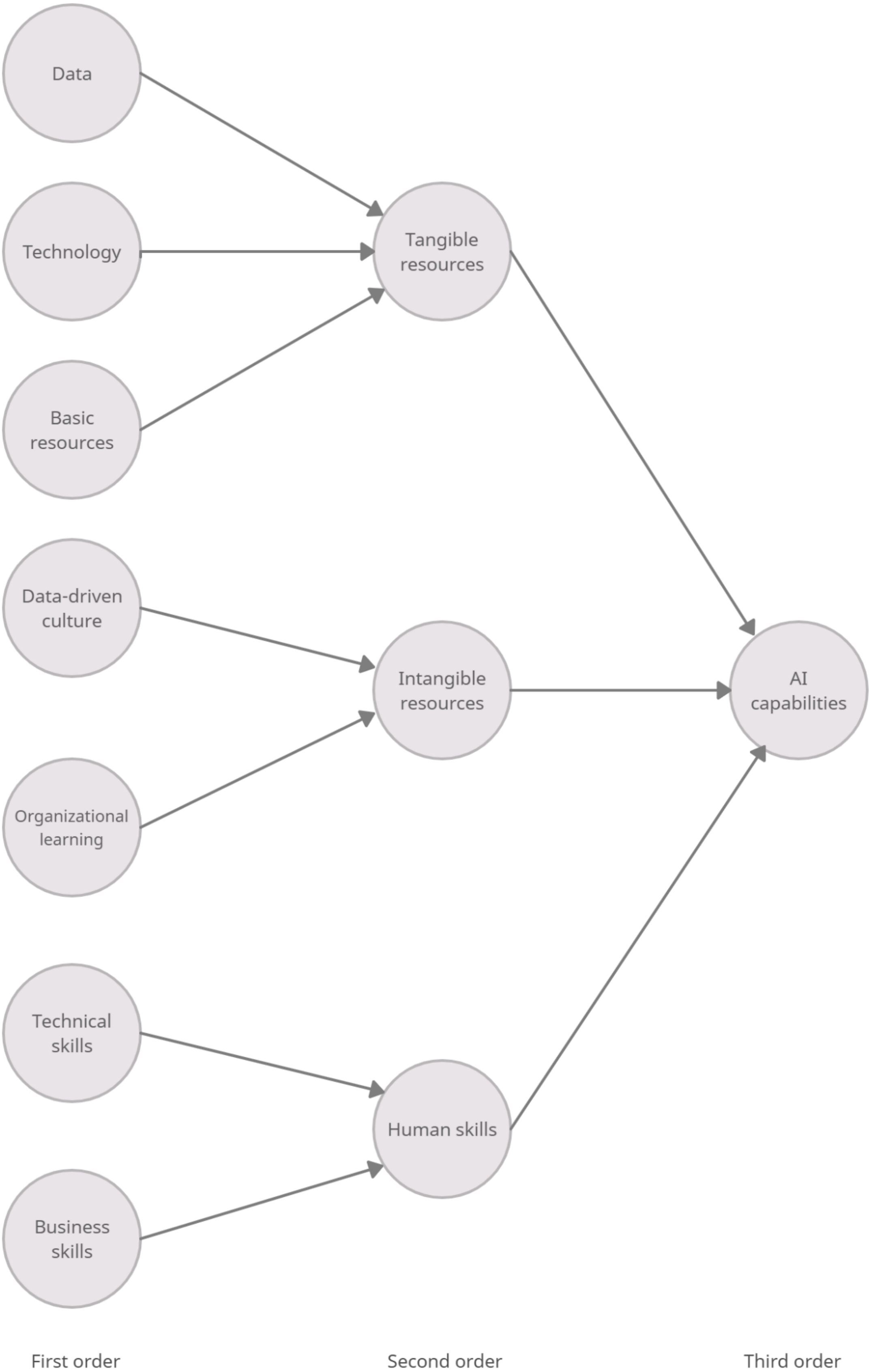

Figure 5. AI capabilities construct

Tangible resources
Tangible resources are resources that can be sold or bought in a market like physical or financial assets. The resources are divided into data, technology, and basic resources.. The questions are presented in table 15.

Data
Data is a key factor for leveraging the potential of AI (Ransbotham et al., 2018). This measures the organization's access to data, how they are managing integration of data from multiple internal and external resources.

Technology
Technology is required to be radically new in order to handle the modern forms of data. It is about how organizations need to have some type of database management systems to adopt AI in their business. This is measured by how willing they are to explore or adapt to different computing approaches, visualization tools, services, software, and databases.

Basic resources
Basic resources include time and financial resources. This will be measured in order to measure the strength of the organization's concepts and basic resources when investing in AI initiatives and giving the investments sufficient time to grow. These questions are changed to fit our research.

Indicator	Question	Source
Data	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	
D1	We have access to Big Data (very large, unstructured, or fast-moving data) for analysis	(Gupta & George, 2016; Jeble et al., 2018)
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	
Technology	We have explored or adopted __ (1- totally disagree, 7- totally agree)	
TEA1	parallel computing approaches (e.g. Hadoop) to big data processing	(Gupta & George, 2016; Jeble et al., 2018)
TEA2	different data visualization tools	
TEA3	cloud-based services for processing data and performing analytics	
TEA4	new forms of databases such as NotOnlySQL (NoSQL) for storing data	

Basic resources	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	
BR1	Our AI projects are adequately funded	Based on: (Gupta & George, 2016; Jeble et al., 2018)
BR2	Our AI projects are given enough time to achieve their objectives	

Table 15. Operationalization of Data, Technology, and Basic resources

Human resources
Human resources address the human capital of an organization. It addresses the employees and managers skills, knowledge, experience, leadership qualities, vision, communication and collaboration competencies, and problem-solving capabilities (Mikalef & Gupta, 2021). The resources are divided into technical skills and business skills. The questions are presented in table 16.

Technical skills
These are the skills required to deal with implementation and realization of AI algorithms (Mikalef & Gupta, 2021). Measuring technical skills will provide an overview of an organization's ability to provide and own the skills to emphasize AI. These questions are changed to fit our research.

Business skills
Business skills are a necessary skill for managers in order to realize business value of AI investments. To drive such a large-scale change, leaders need to have a real understanding and commitment. It is important that leaders get familiar with AI technologies and its potential (Mikalef & Gupta, 2021). This is measured by how the AI managers understand and appreciate, ability to work, coordinate, and anticipate the needs of other functional managers, suppliers, and customers.

Indicator	Question	Source
Technical skills	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	
TS1	We hire people that already have AI skills	Based on: (Gupta & George, 2016; Jeble et al., 2018)
TS2	Our AI analytics staff has the right skills to accomplish their jobs successfully	
TS3	Our AI analytics staff has suitable education to fulfill their jobs	
TS4	Our AI analytics staff holds suitable work experience to accomplish their jobs successfully	

TS5	Our AI analytics staff are provided with the required training to deal with AI applications	
TS6	Our AI analytics staff are quite capable of using AI technologies	
TS7	Our AI analytics staff are effective in data analysis and processing	
Business skills	Our analytics managers __ (1- totally disagree, 7- totally agree)	
MS1	Understand and appreciate the business needs of other functional managers, suppliers, and customers	
MS2	Are able to work with functional managers, supplier and customers to determine opportunities that big data might bring to our business	
MS3	Are able to coordinate big data-related activities in ways that support other functional managers, suppliers, and customers	(Gupta & George, 2016; Jeble et al., 2018)
MS4	Have a good sense of where to apply big data	
MS5	Are able to understand and evaluate the output extracted from big data	

Table 16. Operationalization of Technical skills and Business skills

Intangible resources

Intangible resources are those resources that are difficult for other companies to replicate and in an uncertain market are regarded as of high importance. These resources are difficult to identify (Mikalef & Gupta, 2021). Intangible resources are data-driven culture and intensity of organizational learning. We have left the three other intangible resources out of the questions as these are widely measured by the organizational culture questions. The questions are presented in table 17.

Data-driven culture

Data-driven culture refers to the extent to which all managers and employees within an organization base their decisions on data. Data-driven culture is considered as critical in big data initiatives (Gupta & George, 2016). This is measured by looking at to what extent organizations use data versus intuition decisions.

Intensity of organizational learning

In order to cope with an uncertain and changing market, organizations need to make efforts to exploit their existing knowledge and explore new knowledge. As knowledge does not necessarily wear out, new technology can cause knowledge to become outdated. Firms with a high intensity of organizational learning are likely to have higher organizational knowledge (Gupta & George, 2016). This can be assumed to create a higher level of AI capabilities. The question measures the organization's ability to acquire new knowledge and how they utilize their existing knowledge.

Indicator	Question	Source
Data-driven culture	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	
DDC1	We considered data a tangible asset	(Gupta & George, 2016)
DDC2	We base our decisions on data rather than on instinct	
DDC3	We are willing to override our own intuition when data contradict our viewpoints	
DDC4	We continually assess and improve the business rules in response to insights extracted from data	
DDC5	We continuously coach our employees to make decisions based on data	
Organizational learning	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	
OL1	We are able to search for new and relevant knowledge	(Gupta & George, 2016)
OL2	We are able to acquire new and relevant knowledge	
OL3	We are able to assimilate relevant knowledge	
OL4	We are able to apply relevant knowledge	
OL5	We have made concerted efforts for the exploitation of existing competencies	
OL6	We have made concerted efforts for the exploitation of new knowledge	

Table 17. Operationalization of Data-driven culture and Organizational learning

Operationalizing of firm performance

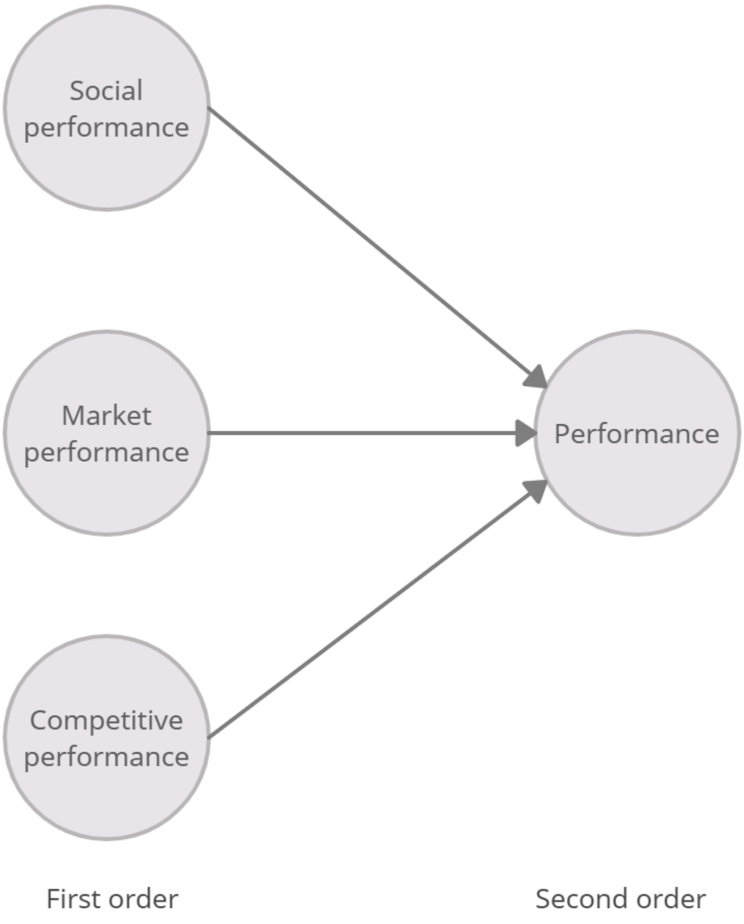

Figure 6. Performance construct

Firm performance refers to the performance of a firm in the different dimensions of performance. Performance is divided into three dimensions; Social performance, market performance and competitive performance. The construct is shown in figure 6.

Social performance
With modern technologies, there are many opportunities for increasing social performance, something AI technology has a positive impact on (Bag et al., 2020; Hong et al., 2021). Social performance construct is often an issue in developing countries. To create awareness of this issue, organizations have started to develop and share their responsibility report (Jeble et al., 2018). This construct is included to measure the social performance awareness in European based organizations and their focus on these issues. The questions are measuring gender equality, workers and their family's health, poverty, and level of nutritional focus.

Market performance
Market performance is related to an organization's ability to attract and retain customers, and obtain market growth (Ahmed et al., 2017; Hogan & Coote, 2014). The questions measure

the organization's ability to satisfy their clients, the firm's ability to keep current and attract new clients, ad their desire to grow.

Competitive performance
Competitive performance relates to the consequences of an organization's strategic position, and to which degree the organization is performing (Sambamurthy et al., 2003). The questions measure strategic advantage, market share, successfulness, EBIT (earnings before interest and taxes, ROI (return of investment) and ROS (return on sales).

Indicator	Question	Source
Social performance	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	
SP1	Our firm believes in gender equality	(Jeble et al., 2018)
SP2	Our firm pays significant attention to the nutritional status of the meal served in the canteen	
SP3	Our firm believes in poverty reduction	
SP4	Our firm support healthy working conditions	
Market performance	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	
MP1	Our firm is achieving client satisfaction	(Hogan & Coote, 2014)
MP2	Our firm is able to keep the current clients	
MP3	Our firm is attracting new clients	
MP4	Our firm is attaining desired growth	
Competitive performance	Answer the questions by reflecting on your own experience in your organization. (1- totally disagree, 7- totally agree)	
CA1	We have gained strategic advantages over our competitors	(Schilke, 2014)
CA2	We have a large market share	
CA3	Overall, we are more successful than our main competitors	
CA4	Our EBIT (earnings before interest and taxes) is continuously above industry average	
CA5	Our ROI (return on investment) is continuously above industry average	
CA6	Our ROS (return on sales) is continuously above industry average	

Table 18. Operationalization of Social, Market, and Competitive performance

Questionnaire validity
In order to develop the questionnaire, we based the questions on peer-reviewed articles to make sure the measurements were previously tested and used. We also got input from our supervisor, who reviewed the questionnaire for quality insurance.

Content validity
By using questions from previous literature that was read and analysed during the systematic literature review and additional research, we secured the validity of the questionnaire. Doing this ensured that the different variables we had in our constructs was accurately measured in the questionnaire. All questions collected from previous literature that measured the different variables were evaluated in cooperation with our supervisor to choose the most suitable questions. After finalizing the survey, we ended up with 88 questions.

Construct validity
To ensure that we measured our assumptions and wanted to measure, we chose questions from previous literature that were connected to their respective variables. Choosing variables that are connected to the different constructs, as well as connected to our construct model, we increased the quality of the questionnaire. Further, we examined the literature to find out whether there had been any problematic encounters in connection with the questions.

4.5 Method for collecting data

In this section, we explain the methods used in the study. We will explain the methods used for data collecting, analysis and how reliability and validity for the analysis were secured.

Population selection
When discussing how to collect a suitable population, we decided on different characterizations of the organizations that had to be met. We saw the number of respondents as an important factor for completing a statistical analysis of collected data, and therefore had to make sure we collected a sufficient number of respondents. According to (Jacobsen, 2015), the number of less than 100 respondents will make it difficult to implement a reasonable analysis, as well as the margin of error is likely to be high. The more respondents collected, the less is the margin of error. After discussing with the supervisor to decide on a reasonable number of respondents to achieve a reliable statistical analysis, we ended up with a target of 300-350 respondents.

After settling on an acceptable number of respondents, we investigated other demographics of our population. Due to AI in a business context being a relatively new phenomenon, we were aiming towards European based organizations. This is decided because of the availability of respondents, we are likely to get a larger respondent rate. Most respondents have been based in Norway, due to personal relationships to different organizations in various industries and the availability of contact information. Having a population that spreads across several borders may cause problems as different contextual factors that may influence the organizational culture, AI capabilities or performance construct. Our respondents were mainly based in Scandinavian or western European countries. Arguably, this does not differ significantly in this topic as companies often do business across borders within the same regions.

The topic of the thesis focuses on AI capabilities and organizational culture, which is measurable in different levels of employment. With this in mind, we chose our target population to be executive managers of big data and AI solutions, as well as employees that are directly connected to AI solutions within the organizations. Since we also wanted to capture the use of AI tools, we reached out to employees likely to use AI tools in their daily work. For those responding that they do not use AI in their organization, we asked if they saw a potential for use of AI in their firm. This was done to capture their view on use of AI in organizations. Based on these requirements, most of our respondents worked in IT or consulting organizations.

4.5.1 Data collection method

We primarily aimed at medium and large business, but with some additions of small businesses if they suited for the population criteria. The reason for mainly targeting medium and large businesses was the uncertainty of the population size and the challenge of finding which organizations were actively using AI. In advance of the data collection process, we assumed that organizations actively using AI would be willing to contribute to a master thesis within the field they actively take part in. This assumption is based on previous experience where organizations have been forthcoming in taking part in university projects and research. In order to find organizations within the population criteria, we mainly looked at publicly available lists of technological organizations and researched the organizations' websites. In addition, we reached out to personal connections with a connection to people within suitable organizations. Further, we used the social platform LinkedIn to reach out to our targeted population. After collecting potential respondents, we plotted the contact information into a spreadsheet to systematically reach out to the respondents.

In the beginning we contacted the organizations through e-mails, mostly found through the organization’s websites. We firstly experienced a low respondent rate during our first distribution, about 4-5%, an unexpected result. Through feedback from some of the receivers of the survey we changed the e-mail template to ensure the legitimation of the survey. We then sent out a reminder and in addition added more respondent e-mails to our spreadsheet, this was a continually ongoing process during the data collection process. By changing the e-mail template and continuously adding new respondents whilst sending out reminders resulted in a higher respondent rate. Additionally, we used snowball sampling techniques (Taherdoost, 2016), where we asked the respondents to distribute the survey to other co-workers or acquaintances that could be relevant. Snowball sampling proved to be an effective technique, but also could have a negative outcome, as it is harder to have complete control of the respondents.

4.5.2 Methods of analysing the collected data

To analyse our data, we used a method called Partial Least Squares Path Modelling (PLS-SEM), which is a type of Structural Equation Modelling (SEM). The PLS-SEM method is recommended when testing complex and less established theories (J. Hair et al., 2014). To perform the data analysis, we used a software called SmartPLS. This software allowed us to visualize the conceptual model with our variables and hypotheses.

Reliability and validity
To evaluate the conceptual model, we used PLS calculations. By using these calculations, we could ensure the quality of the model by removing measurement errors such as poorly formulated questions.

First, we did an evaluation of the outer model. The outer model loadings are the focus in reflective models, they are representing the paths from a factor to its representative indicator variables. The outer loadings represent the contribution of the indicator to the definition of its latent variable (Garson, 2016). Then we conducted an evaluation of the inner model, meaning the paths between the latent variables (J. Hair et al., 2014). The conceptual model has both reflective and formative constructs. This is represented with the direction the arrows are pointed in the model. If the arrow is pointed from the first order construct to the indicator, it is reflective, and if it is pointing from the indicator to the construct, it is formative.

To ensure that we checked the reliability and validity in the best possible way in terms of our analytical results we have been reading at the textbook by Garson, 2016. And examined previous master's theses that have been using quantitative methods has been of great help. Additionally, we have watched different video lectures by Professor James Gaskin to do the calculations, and we have been given guidance by our supervisor.

Analysing the outer model

The outer model consists of all measurements of the latent variables. Our model has multi ordered constructs, this means that we will include the measurements of the second and third order constructs in this section.

Formative measures

To ensure the reliability and validity of our outer model we started evaluating the formative measurements. The formative measures consist of evaluating the significance and relevance of outer weights. This evaluation was done by looking at the t-values and p-values using the bootstrap algorithm in SmartPLS. To see if the formative constructs represent multicollinearity, we did a collinearity diagnostic. This was done by investigating the Variance Inflation Factor (VIF). For formative measures it is debated what the maximum VIF value is before multicollinearity becomes a problem. (Diamantopoulos & Siguaw, 2006) states that values below 3.33 is accepted, but (J. F. Hair et al., 2014) states that values below 10.00 is accepted.

Reflective measures

The reflective measures are evaluated with different techniques compared to those used for formative measures. We evaluated the reflective measures by checking the reliability, convergent validity, and discriminant validity.
We started by looking at Cronbach's alpha, composite reliability, and discriminant validity. According to (J. Hair et al., 2014) the Cronbach's alpha and Composite reliability should both have a value that is above 0.708, and each indicator loading should also have a value above 0.708. To evaluate the convergent validity, we looked at the AVE values (average variance extracted). (J. Hair et al., 2014) explains that these numbers should be above 0.50. We evaluated the discriminant validity by checking if the outer loading on the reflective indicators was higher on the constructs it was measuring than on all the other constructs (J. Hair et al., 2014). By using the Fornell-Larcker criterion we checked that the square root of the AVE of each construct was higher than any of the inter-factor correlations. In addition to the Fornell-Larcker criterion to measure discriminant validity we checked the heterotrait-monotrait ratio (HTMT). This is regarded as a better method for assessing the discriminant validity (Henseler et al., 2015).

Analysing the inner model

When analysing our inner model, we had to perform our measurement with the two-stage approach. The regular approach for second order constructs would be the repeated indicator approach, due to our model being a mixed model with reflective-formative and formative-formative constructs the two-stage approach is needed. If not, the repeated indicators in the second-order construct would be perfectly predicted by the first-order constructs, which also contain those indicators. This means that all other potential effects from other predictors are effectively swamped out, and the r squared for the second-order construct is 100% (Lowry &

Gaskin, 2014). With the two-step approach it is possible to overcome this problem. To do the two-step approach we did create the measurement model and obtained the latent variable scores for the second order constructs, and all the other top-level constructs. We extracted the latent variable scores to a new dataset and made a new model that used the latent variable scores as indicators of the constructs (Lowry & Gaskin, 2014).

To evaluate the reliability and validity of the inner model we analysed the VIF value. The value should be below 10.00 according to (J. F. Hair et al., 2014), but this is debated among researchers. Then we looked at the path coefficient and the associated t-values and p-values. According to (Kline, 2011), the path coefficient weights indicate the following;

path coefficient weights < 0.10 indicates a small effect

path coefficient weights < 0.30 indicates a medium effect

path coefficient weights < 0.50 indicates a large effect

These weights work as guidelines for new research areas, and the numbers should not be interpreted to the extent where weights for 0.49 and 0.51 are treated differently.

4.6 Research ethics

Our study have provided a lot of information from employees working within different organizations. To gather as many respondents as possible and at the same time avoid conflict, we chose to make the survey anonymous. This could also be regarded as a weakness to the study, but we decided that conducting the survey anonymously increased the chance of gathering a sufficient number of participants. All participants were informed about the nature of the study and that all data would be handled anonymously. They were also free to decline to participate or just partially finish the survey without any consequences.

To avoid any plagiarism, we have done our utmost to credit the researchers' work by referring them according to the APA 7th standard. This is also to acknowledge the respective authors of their work and research.

5.0 Analysis and results

In this chapter we present the result of our analysis. In the first part we present the results of the quantitative survey results, including demographic data, reliability and validity, and hypothesis testing. Finally, we present a summary of this section.

5.1 Survey analysis and result

In this section, we present the outcome of our analysis, which was done to test if our hypotheses would be supported.

5.1.1 Demographic

Our selected population consists of a wide range of organizations in different industries. The geographical focus was Scandinavian based organizations, but some respondents were residents or working out of other countries. This was due to many organizations participating having offices across borders. Due to the use of the snowballing method techniques, the survey was distributed to an unknown number of organizations. Further, the survey was distributed in groups through the social media platform LinkedIn. We ended up with 326 respondents, and about 250 partially answered the survey. Those who partially answered were all cases dismissed as not usable data. Further, of those 326 respondents, 157 did answer that they do not currently use AI in their organization. 27 of those who do not use AI answered that they did not see any potential for use of AI in their organization. We have therefore in this study chose to remove those participants who do not use or see any potential for AI.

Dimension	Population
Type of company	
Private	240
Public	30
Profit	25
Non profit	4
Company size	
0-9 employees	26
10-49 employees	70
50-249 employees	114
More than 250 employees	89
Industry	
IT	100
Consultant	43
Other	33
Energy	19
Construction industry	18
Media	15
Retail	13
Finance	10
Aquaculture	10
Education	9
Service	7
Real estate	7
Medical technology	4
Subsea	3
Agritech	3
Health sector	2
Game development	2
Offshore	1
Country of residence	
Norway	289
Sweden	3

Ireland	2
North Macedonia	2
Denmark	1
Wales	1
USA	1

Table 19. Demographic data

5.1.2 Reliability and validity

In our study we have used a deductive approach. All variables and indicators are extracted from or based on previous peer-reviewed literature. The variables and indicators were developed along with our supervisor assistance to ensure the quality of the variables and indicators. To make sure the testing of the variables and indicators was accurate, the development consisted of reviewing earlier research using these variables and indicators. The variables and indicators have been previously tested, however they have not been tested in our model and could have a different outcome.

Evaluation of measurement models (outer model)
In this section we present the evaluation results. All indicators that have been used were collected from peer reviewed articles that are published in journals.

Formative measures
To measure the formative measures, we used the tool SmartPLS 3.0 (*SmartPLS*). In order to establish the validity and reliability of the outer model we calculated t-values of all the formative indicators as a two tailed test. Further we checked the p-values, that should be below 0.05. We also used SmartPLS to calculate the path coefficients (weights). Lastly, we looked at the VIF measurements top check if they were below 10.
The results from the first, second and third order constructs are illustrated in table 20 and 21.

Latent variable	Indicator	Weight	T-Value	P-Value	VIF
Basic Resources	BR1	0.864	6.518	p<0.000	7.598
	BR2	0.144	**1.032**	**p<0.302**	7.598
Data	D1	0.392	4.577	p<0.000	2.208
	D2	0.312	3.003	p<0.003	3.558
	D3	0.393	3.885	p<0.000	3.526
Technology	TEA1	0.369	5.188	p<0.000	2.311
	TEA2	0.270	3.606	p<0.000	2.661
	TEA3	0.333	4.517	p<0.000	2.364
	TEA4	0.203	2.644	p<0.008	2.462

Table 20. Formative indicators value

Constructs	Measures	Weight	T-Value	P-Value	VIF
Artifacts	Appreciation	0.317	15.655	p<0.000	2.261
	Inter-functional cooperation	0.352	19.374	p<0.000	2.170
	Success	0.473	20.060	p<0.000	2.609
Values	Risk-Taking	0.645	26.398	p<0.000	1.591
	Competence	0.512	20.680	p<0.000	1.591
Assumptions	Openness	0.412	13.434	p<0.000	3.358
	Internal communication	0.337	14.347	p<0.000	2.434
	Responsibility	0.372	16.167	p<0.000	2.484
Org- Culture	Artifacts	0.339	16.215	p<0.000	4.858
	Values	0.369	18.462	p<0.000	4.216
	Assumptions	0.343	15.328	p<0.000	5.495
Intangible	Org. learning	0.553	22.302	p<0.000	1.478
	Data-driven culture	0.604	20.830	p<0.000	1.478
Tangible	Data	0.399	17.385	p<0.000	2.626
	Technology	0.351	15.564	p<0.000	3.059
	Basic Resources	0.397	18.692	p<0.000	1.622
Human skills	Technical skills	0.417	15.080	p<0.000	1.264
	Business skills	0.747	28.550	p<0.000	1.264
AI capabilities	Intangible	0.590	17.045	p<0.000	2.849
	Tangible	0.270	7.039	p<0.000	2.398
	Human Skills	0.222	6.119	p<0.000	1.990
Social perf.	AI capabilities	0.578	11.406	p<0.000	1.000
Market perf.	AI capabilities	0.499	8.598	p<0.000	1.000
Competitive perf.	AI capabilities	0.479	9.642	p<0.000	1.000

Table 21. Formative measurements second and third order construct

There is one insignificant value between the indicator first order latent variable (BR2). Due to the importance of the indicator in the construct, we have decided keeping the indicator. This is supported by (Cenfetelli & Bassellier, 2009) who explains that models with several formative constructs and many indicators, the insignificant indicators may be retained if the researcher can justify the contribution of the constructs.

Reflective measures

We have measured composite reliability, Cronbach's alpha, and indicator reliability. According to (J. Hair et al., 2014), composite reliability and Cronbach's alpha and composite reliability should have a value above 0.708. Our reflective measures are illustrated in table 22.

Latent Variable	Indicator	Loadings	Cronbach's Alpha	Composite Reliability
Appreciation of employees	AE1	0.919	0.918	0.948
	AE2	0.935		
	AE3	0.927		
Business skills	MS1	0.920	0.977	0.982

	MS2	0.962		
	MS3	0.972		
	MS4	0.968		
	MS5	0.962		
Competence and professionalism	CP1	0.924	0.920	0.949
	CP2	0.950		
	CP3	0.911		
Competitive performance	CA1	0.756	0.907	0.928
	CA2	0.718		
	CA3	0.856		
	CA4	0.839		
	CA5	0.893		
	CA6	0.887		
Data-driven culture	DDC1	0.665	0.897	0.926
	DDC2	0.886		
	DDC3	0.888		
	DDC4	0.910		
	DDC5	0.858		
Inter-functional cooperation	IFC1	0.923	0.910	0.943
	IFC2	0.940		
	IFC3	0.897		
Internal communication	IC1	0.907	0.927	0.953
	IC2	0.947		
	IC3	0.947		
Market performance	MP1	0.864	0.887	0.922
	MP2	0.894		
	MP3	0.895		
	MP4	0.802		
Openness / flexibility	OF1	0.886	0.919	0.943
	OF2	0.897		
	OF3	0.913		
	OF4	0.892		
Org. learning	OL1	0.907	0.952	0.962
	OL2	0.929		
	OL3	0.918		
	OL4	0.927		
	OL5	0.862		
	OL6	0.850		
Responsibility	R1	0.936	0.936	0.959
	R2	0.957		
	R3	0.932		
Risk-taking	RT1	0.891	0.845	0.907
	RT2	0.910		
	RT3	0.819		
Social performance	SP1	0.762	0.768	0.851

	SP2	0.809		
	SP3	0.641		
	SP4	0.848		
Success	S1	0.907	0.891	0.932
	S2	0.892		
	S3	0.919		
Technical skills	TS1	0.718	0.967	0.973
	TS2	0.958		
	TS3	0.935		
	TS4	0.918		
	TS5	0.937		
	TS6	0.964		
	TS7	0.959		

Table 22. Composite reliability, Cronbach's alpha ad Indicator reliability

Discriminant validity was established by creating an overview of the cross loadings and checked that the indicators were measuring the correct measures. This is illustrated in table 23.

	Appreciation of employees	Competitive performance	Competence and professionalism	Data-driven culture	Internal communication	Inter-functional cooperation	Market performance	Business skills	Openness / flexibility	Org. learning	Responsibility	Risk-taking	Success	Social performance	Technical skills
AE1	**0.902**	0.387	0.575	0.378	0.580	0.589	0.504	0.223	0.589	0.481	0.689	0.564	0.668	0.557	0.098
AE2	**0.879**	0.394	0.534	0.374	0.536	0.552	0.483	0.296	0.551	0.506	0.643	0.526	0.637	0.534	0.245
AE3	**0.968**	0.375	0.518	0.425	0.600	0.588	0.474	0.306	0.566	0.481	0.664	0.557	0.613	0.607	0.112
CA1	0.423	**1.001**	0.537	0.388	0.488	0.492	0.706	0.299	0.553	0.448	0.465	0.554	0.616	0.448	0.050
CA2	0.205	**0.706**	0.278	0.283	0.258	0.235	0.442	0.251	0.220	0.236	0.136	0.266	0.349	0.385	0.181
CA3	0.311	**0.805**	0.348	0.346	0.383	0.365	0.584	0.241	0.373	0.308	0.244	0.402	0.426	0.421	0.151
CA4	0.322	**0.606**	0.335	0.245	0.350	0.246	0.517	0.174	0.295	0.271	0.232	0.299	0.361	0.398	0.077
CA5	0.379	**0.725**	0.354	0.300	0.366	0.294	0.545	0.185	0.365	0.331	0.262	0.365	0.427	0.434	0.072
CA6	0.371	**0.766**	0.352	0.316	0.382	0.301	0.556	0.212	0.381	0.329	0.254	0.370	0.390	0.441	0.086
CP1	0.498	0.430	**0.963**	0.293	0.569	0.500	0.618	0.169	0.625	0.538	0.623	0.520	0.719	0.494	0.038
CP2	0.531	0.411	**0.989**	0.325	0.553	0.500	0.627	0.192	0.663	0.595	0.710	0.586	0.796	0.495	0.058
CP3	0.604	0.445	**0.950**	0.320	0.596	0.525	0.636	0.249	0.586	0.562	0.618	0.521	0.789	0.557	0.111
DDC1	0.355	0.301	0.309	**0.734**	0.319	0.332	0.266	0.516	0.324	0.508	0.368	0.389	0.338	0.393	0.216
DDC2	0.366	0.304	0.279	**0.934**	0.301	0.346	0.246	0.503	0.323	0.419	0.345	0.362	0.340	0.392	0.159
DDC3	0.351	0.335	0.301	**0.830**	0.400	0.362	0.347	0.494	0.381	0.465	0.341	0.406	0.342	0.455	0.170
DDC4	0.333	0.357	0.272	**0.960**	0.343	0.357	0.272	0.553	0.370	0.453	0.326	0.385	0.296	0.423	0.203
DDC5	0.368	0.331	0.253	**0.906**	0.319	0.330	0.249	0.500	0.316	0.442	0.310	0.348	0.312	0.378	0.263
IC1	0.552	0.437	0.608	0.379	**0.909**	0.671	0.616	0.261	0.733	0.520	0.588	0.653	0.619	0.559	-0.002
IC2	0.563	0.430	0.543	0.365	**0.985**	0.671	0.521	0.278	0.637	0.456	0.561	0.587	0.591	0.515	0.012
IC3	0.621	0.432	0.580	0.389	**0.915**	0.727	0.550	0.305	0.675	0.476	0.612	0.648	0.649	0.545	0.093
IFC1	0.556	0.364	0.544	0.358	0.675	**0.965**	0.514	0.230	0.703	0.449	0.618	0.675	0.661	0.505	0.098
IFC2	0.612	0.394	0.522	0.390	0.685	**0.914**	0.536	0.255	0.693	0.436	0.620	0.673	0.649	0.563	0.152
IFC3	0.541	0.365	0.433	0.390	0.665	**0.940**	0.468	0.255	0.581	0.420	0.527	0.622	0.547	0.478	0.148
MP1	0.502	0.540	0.642	0.249	0.503	0.492	**0.723**	0.203	0.596	0.451	0.546	0.518	0.689	0.573	0.062
MP2	0.442	0.608	0.602	0.285	0.529	0.507	**0.838**	0.239	0.585	0.491	0.494	0.518	0.650	0.528	0.114
MP3	0.477	0.592	0.566	0.334	0.555	0.499	**0.933**	0.298	0.593	0.474	0.506	0.580	0.694	0.530	0.117
MP4	0.374	0.628	0.502	0.249	0.456	0.385	**0.755**	0.190	0.482	0.418	0.383	0.451	0.578	0.486	0.013
MS1	0.295	0.310	0.253	0.533	0.288	0.296	0.311	**0.905**	0.319	0.476	0.286	0.333	0.316	0.328	0.404
MS2	0.300	0.266	0.213	0.623	0.275	0.253	0.277	**0.949**	0.294	0.475	0.243	0.340	0.269	0.391	0.429
MS3	0.288	0.275	0.209	0.646	0.299	0.280	0.269	**0.983**	0.315	0.486	0.252	0.354	0.286	0.381	0.449
MS4	0.285	0.269	0.208	0.614	0.304	0.257	0.248	**0.965**	0.288	0.473	0.260	0.324	0.272	0.352	0.463
MS5	0.298	0.282	0.198	0.609	0.314	0.243	0.264	**0.943**	0.297	0.482	0.252	0.315	0.274	0.362	0.418
OF1	0.545	0.404	0.654	0.381	0.674	0.622	0.634	0.268	**0.924**	0.576	0.680	0.732	0.709	0.523	0.078
OF2	0.552	0.403	0.564	0.446	0.604	0.640	0.507	0.321	**0.835**	0.576	0.615	0.797	0.632	0.474	0.151
OF3	0.548	0.376	0.606	0.317	0.655	0.653	0.608	0.255	**0.953**	0.528	0.676	0.777	0.667	0.424	0.106
OF4	0.557	0.472	0.589	0.332	0.676	0.671	0.620	0.255	**0.861**	0.501	0.657	0.720	0.691	0.489	0.077
OL1	0.475	0.365	0.583	0.523	0.460	0.394	0.503	0.480	0.590	**0.929**	0.593	0.588	0.606	0.472	0.208
OL2	0.472	0.398	0.600	0.482	0.492	0.404	0.573	0.450	0.593	**0.893**	0.596	0.571	0.613	0.457	0.206
OL3	0.427	0.346	0.550	0.464	0.454	0.409	0.484	0.443	0.556	**0.939**	0.538	0.526	0.575	0.414	0.221
OL4	0.464	0.365	0.545	0.476	0.469	0.424	0.519	0.431	0.568	**0.949**	0.546	0.561	0.565	0.445	0.186
OL5	0.546	0.346	0.537	0.514	0.486	0.482	0.437	0.404	0.516	**0.862**	0.502	0.552	0.520	0.484	0.193
OL6	0.516	0.383	0.523	0.535	0.476	0.494	0.433	0.451	0.509	**0.872**	0.494	0.551	0.514	0.463	0.153
R1	0.676	0.323	0.623	0.377	0.603	0.663	0.529	0.246	0.730	0.564	**0.922**	0.653	0.763	0.488	0.104
R2	0.693	0.316	0.668	0.393	0.624	0.619	0.540	0.258	0.726	0.584	**0.988**	0.687	0.773	0.486	0.081
R3	0.682	0.329	0.710	0.380	0.558	0.550	0.542	0.243	0.632	0.552	**0.873**	0.595	0.787	0.549	0.075
RT1	0.551	0.399	0.572	0.417	0.600	0.685	0.576	0.295	0.747	0.529	0.642	**0.963**	0.684	0.506	0.169
RT2	0.499	0.409	0.522	0.387	0.603	0.619	0.525	0.307	0.793	0.543	0.563	**0.983**	0.642	0.442	0.128
RT3	0.445	0.396	0.367	0.334	0.490	0.497	0.426	0.249	0.576	0.470	0.507	**0.701**	0.530	0.324	0.162
S1	0.678	0.463	0.697	0.332	0.585	0.593	0.686	0.222	0.684	0.538	0.762	0.647	**0.961**	0.534	0.088
S2	0.490	0.509	0.754	0.309	0.566	0.557	0.700	0.260	0.640	0.529	0.673	0.651	**0.793**	0.521	0.057
S3	0.671	0.474	0.769	0.397	0.620	0.659	0.669	0.287	0.692	0.589	0.742	0.679	**0.973**	0.630	0.179
SP1	0.520	0.365	0.550	0.273	0.466	0.473	0.533	0.241	0.491	0.427	0.527	0.390	0.596	**0.639**	0.053
SP2	0.424	0.362	0.388	0.432	0.390	0.394	0.419	0.297	0.365	0.355	0.416	0.426	0.471	**0.782**	0.211
SP3	0.258	0.357	0.175	0.252	0.293	0.231	0.325	0.228	0.201	0.210	0.153	0.225	0.253	**0.501**	0.132
SP4	0.515	0.402	0.437	0.405	0.483	0.480	0.483	0.279	0.437	0.408	0.388	0.384	0.457	**0.773**	0.160
TS1	0.148	0.032	0.081	0.133	0.014	0.113	0.083	0.312	0.128	0.243	0.125	0.155	0.122	0.041	**0.730**
TS2	0.170	0.142	0.074	0.273	0.032	0.151	0.100	0.438	0.113	0.195	0.087	0.192	0.119	0.206	**0.957**
TS3	0.142	0.094	0.061	0.201	0.020	0.133	0.096	0.409	0.085	0.178	0.073	0.167	0.111	0.207	**0.949**
TS4	0.143	0.106	0.058	0.238	0.026	0.129	0.070	0.397	0.088	0.170	0.071	0.150	0.102	0.197	**0.882**
TS5	0.157	0.140	0.087	0.247	0.067	0.133	0.079	0.423	0.111	0.211	0.078	0.165	0.117	0.216	**0.949**
TS6	0.147	0.139	0.051	0.246	0.039	0.147	0.080	0.438	0.109	0.200	0.079	0.180	0.111	0.195	**0.952**
TS7	0.174	0.137	0.084	0.235	0.041	0.143	0.108	0.460	0.124	0.219	0.100	0.181	0.137	0.222	**0.971**

Table 23. Cross loadings

The Fornell-Larcker criterion was calculated and extracted from SmartPLS. The results are illustrated in table 24. We also checked the values of the Heterotrait-Monotrait ratio (HTMT).

The threshold for establishing discriminant validity is 0.90 (Gold et al., 2001). All our values are acceptable, as they are below 0.90. This is illustrated in table 25.

Fornell-Larcker	**Appreciation of employees**	**Business skills**	**Competence and professionalism**	**Competitive performance**	**Data-driven culture**	**Inter-functional cooperation**	**Internal communication**	**Market performance**	**Openness / flexibility**	**Org. learning**	**Responsibility**	**Risk-taking**	**Social performance**	**Success**	**Technical skills**
Appreciation of employees	**0.927**														
Business skills	0.293	**0.957**													
Competence and professionalism	0.562	0.216	**0.928**												
Competitive performance	0.402	0.278	0.443	**0.827**											
Data-driven culture	0.402	0.601	0.321	0.369	**0.846**										
Inter-functional cooperation	0.594	0.265	0.523	0.391	0.391	**0.920**									
Internal communication	0.594	0.298	0.594	0.446	0.385	0.706	**0.934**								
Market performance	0.498	0.269	0.641	0.657	0.310	0.522	0.571	**0.864**							
Openness / flexibility	0.588	0.303	0.646	0.444	0.391	0.689	0.701	0.626	**0.897**						
Org. learning	0.515	0.488	0.595	0.393	0.528	0.461	0.507	0.519	0.593	**0.899**					
Responsibility	0.696	0.262	0.680	0.331	0.387	0.621	0.609	0.540	0.709	0.588	**0.942**				
Risk-taking	0.548	0.322	0.541	0.440	0.415	0.662	0.625	0.555	0.781	0.575	0.635	**0.874**			
Social performance	0.549	0.337	0.502	0.459	0.429	0.504	0.520	0.549	0.481	0.456	0.486	0.439	**0.769**		
Success	0.651	0.280	0.784	0.509	0.364	0.638	0.628	0.715	0.712	0.596	0.777	0.674	0.560	**0.906**	
Technical skills	0.161	0.446	0.073	0.118	0.236	0.141	0.037	0.090	0.113	0.213	0.091	0.172	0.180	0.120	**0.916**

Table 24. Fornell-Larcker criterion

HTMT	**Appreciation of employees**	**Business skills**	**Competence and professionalism**	**Competitive performance**	**Data-driven culture**	**Inter-functional cooperation**	**Internal communication**	**Market performance**	**Openness / flexibility**	**Org. learning**	**Responsibility**	**Risk-taking**	**Social performance**	**Success**	**Technical skills**
Appreciation of employees															
Business skills	0.310														
Competence and professionalism	0.611	0.229													
Competitive performance	0.426	0.289	0.467												
Data-driven culture	0.445	0.644	0.354	0.399											
Interfunctional cooperation	0.649	0.282	0.570	0.410	0.435										
Internal communication	0.643	0.313	0.643	0.471	0.422	0.769									
Market performance	0.552	0.287	0.711	0.714	0.345	0.579	0.627								
Openness / flexibility	0.640	0.320	0.702	0.463	0.431	0.751	0.758	0.693							
Org. learning	0.551	0.506	0.635	0.407	0.574	0.496	0.539	0.563	0.634						
Responsibility	0.750	0.274	0.732	0.338	0.424	0.670	0.653	0.594	0.764	0.621					
Risk-taking	0.620	0.353	0.606	0.482	0.476	0.748	0.702	0.635	0.879	0.640	0.710				
Social performance	0.637	0.388	0.576	0.549	0.508	0.586	0.606	0.660	0.555	0.520	0.553	0.526			
Success	0.717	0.300	0.866	0.546	0.408	0.705	0.690	0.806	0.786	0.645	0.850	0.772	0.659		
Technical skills	0.172	0.458	0.079	0.133	0.252	0.152	0.047	0.096	0.121	0.225	0.098	0.192	0.206	0.128	

Table 25. Heterotrait-Monotrait ratio (HTMT)

Evaluation of the structural model (Inner model)
Reliability and validity of the structural model (inner model) was established by looking at the VIF (variance inflation factor). This was calculated by SmartPLS. Further, we checked the path coefficient and its t-values and p-values. The relevant paths are referring to the constructs used to establish the hypotheses. See table 26 for illustration.

Paths	Weight	T-Value	P-Value	VIF
AI capabilities -> Competitive performance	0.459	9.570	p<0.000	1.000
AI capabilities -> Market performance	0.472	9.423	p<0.000	1.000
AI capabilities -> Social performance	0.515	10.767	p<0.000	1.000
Org. culture -> AI capabilities	0.619	15.601	p<0.000	1.000

Table 26. Inner model value paths

5.1.3 Testing the hypotheses

Hypotheses were tested after the reliability and validity of the complete research model were established. Our four hypotheses were constructed in order to test if there is correlation between; *Organizational culture ->AI capabilities (H1), AI capabilities->Social performance (H2), AI capabilities->Market performance (H3)* and *AI capabilities->Competitive performance (H4)*. The effect of path coefficient weights can be divided into three values of effect; <10 indicates a small effect, around 0.30 indicates a medium effect and $\geq$ 0.50 indicates a large effect (Hair et al., 2011). In the following section we present each hypothesis and their weighting in order to establish if they are supported. In figure 7. Our research model including additional measures is shown. A summary of the hypotheses and the supporting data is shown in table 27.

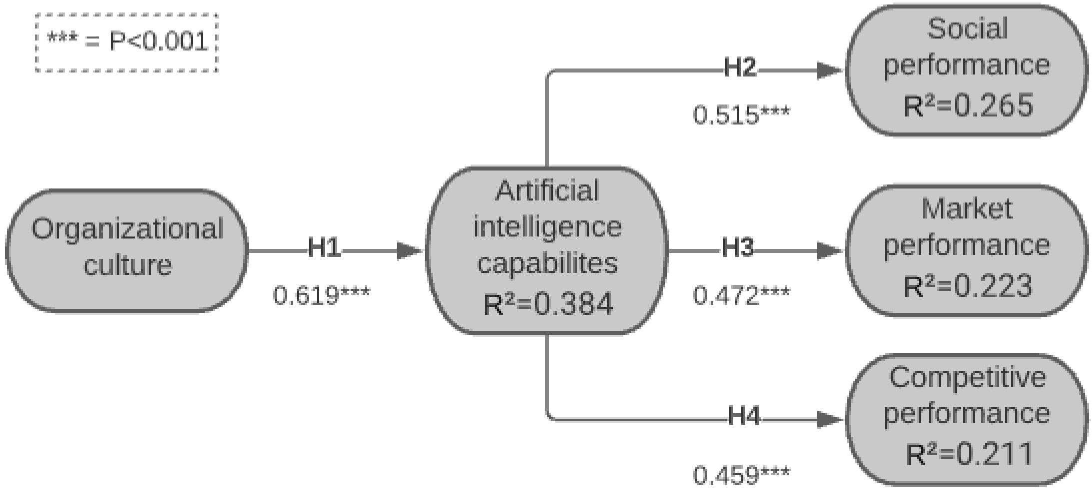

Figure 7. Research model, weights, P-values, and R^2

Hypothesis 1: "Organizational culture has a positive effect on artificial intelligence capabilities"
Hypothesis 1 has a strong effect of 0.619. The hypothesis is supported with a T-value of 15.601, which is significantly above 99.9 percent, and a P-value below 0.001. The reliability and validity were acceptable, which confirms that hypothesis 1 is **supported**.

Hypothesis 2: "Artificial intelligence capabilities has a positive effect on social performance"
Hypothesis 2 has a strong effect of 0.515. The hypothesis is supported with a T-value of 10.767, which is significantly above 99.9 percent, and a P-value below 0.001. The reliability and validity were acceptable, which confirms that hypothesis 2 is **supported**.

Hypothesis 3: "Artificial intelligence capabilities has a positive effect on market performance"
Hypothesis 3 has a strong effect of 0.472. The hypothesis is supported with a T-value of 9.423, which is significantly above 99.9 percent, and a P-value below 0.001. The reliability and validity were acceptable, which confirms that hypothesis 3 is **supported**.

Hypothesis 4: "Artificial intelligence capabilities has a positive effect on competitive performance"
Hypothesis 4 has a strong effect of 0.459. The hypothesis is supported with a T-value of 9.570, which is significantly above 99.9 percent, and a P-value below 0.001. The reliability and validity were acceptable, which confirms that hypothesis 4 is **supported**.

Hypothesis	Independent Variable	Dependent Variable	Weight	T-Value	P-Value	Conclusion
H1	Org.Culture	AI Capabilities	0.619	15.601	p<0.000	Supported
H2	AI Capabilities	Social performance	0.515	10.767	p<0.000	Supported
H3	AI Capabilities	Market performance	0.472	9.423	p<0.000	Supported
H4	AI Capabilities	Competitive performance	0.459	9.570	p<0.000	Supported

Table 27. Hypotheses

6.0 Discussion

In this chapter we will discuss our findings and compare those with earlier studies and literature on the topic.

Our study is based on previous research and can therefore be viewed as confirmation on the measurements of AI capabilities, as well as the connection between AI capabilities and firm performance. Based on our literature review and our knowledge, the connection between organizational culture and AI capabilities has not been empirically tested in the past. In addition, to our knowledge, there are no similar studies mainly focusing on Scandinavian organizations.

In this section we begin by summarizing our findings in our research study. Next, we discuss our four hypotheses and the research question.

6.1 Summary of research

The main concern of the study was mainly explaining how organizations can develop and exploit AI capabilities by changing their organizational culture. This was measured through social performance, market performance and competitive performance. AI as a tool is relatively new and interesting introduction to the business world that has received a lot of attention recently. Previous research has often focused on the technical aspects of AI or adoption of AI where organizational culture only is mentioned as one of several factors for successful AI implementation. Less research is focusing on how to achieve value from AI in the context of organizational culture. Earlier studies mentioned organizational culture as an important non-technical factor for successful AI adoption, we wanted to provide a deeper understanding of this.

During the literature review we identified research gaps that briefly were discussed in several articles. Mainly that organizational culture needs to be prioritized in order to realize the value of AI adoptions. An organization adopting AI needs to work to a data-driven culture, and not only focus on the technical aspects of AI adoption.

To test our hypotheses, we chose a quantitative approach. We gathered a total of 299 participants, mainly Norwegian residents. Further we then analysed the results using Partial Least Squares Structural Equation Modeling (PLS-SEM). This was done by using the software tool SmartPLS.

6.2 Discussion of the RQ and hypotheses

In order to answer our research question; *"To what extent does organizational culture affect an organization's ability to adopt and use AI?"*, we looked at organizational culture's effect on AI capabilities. This resulted in the first hypothesis (H1). This hypothesis was significant and had high path coefficient values. Further it is well established that organizational culture has a positive effect on AI capabilities. The three other hypotheses (H2, H3, H4), were developed to measure organizational culture's impact on AI capabilities through the firm's performance. These three hypotheses were significant and had a high path coefficient, where they can be valued as confirmed.

The following subsections are structured in accordance with the hypothesis, where we discuss our interpretation of the findings. This is based on the path coefficients that link the hypothesis latent variables and if their relationships are significant or affected by other factors.

Hypothesis 1: "Organizational culture has a positive effect on artificial intelligence capabilities"

The analysis shows that hypothesis 1 is strongly supported with a significant ($p<0.001$) path coefficient weight of 0.619, which indicates a large effect. This matches our pre-conceptions of a positive correlation effect between organizational culture and AI capabilities. In a fast moving and rapidly changing business market due to the fast development of technology it is key for organizations to keep up with the market, to stay competitive. In order to achieve this, organizations are constantly adopting new technological tools such as AI. This finding can help organizations to understand what factors are important to utilize the value of AI, by showing that organizational culture has an important effect on AI capabilities. It is very unlikely that technical factors alone will increase performance. Organizations also need to consider the organizational factors to increase their performance.

Hypothesis 2: "Artificial intelligence capabilities has a positive effect on social performance"

The analysis shows that hypothesis 2 is strongly supported with a significant ($p<0.001$) path coefficient weight of 0.515, which indicates a large effect. This matches our pre-conceptions of a positive correlation between AI capabilities and social performance. Earlier studies and literature agree that AI capabilities will increase a firm's performance. This study suggests that AI capabilities will increase firms' social performance.

Hypothesis 3: "Artificial intelligence capabilities has a positive effect on market performance"

The analysis shows that hypothesis 3 is strongly supported with a significant ($p<0.001$) path coefficient weight of 0.472, which indicates a large effect. This matches our pre-conceptions of a positive correlation between AI capabilities and market performance. We suggest that AI capabilities will increase firms' market performance. AI capabilities will help organizations to keep their clients satisfied and also attract new clients. This finding could help organizations to increase their growth, by showing the importance of AI capabilities on market performance.

Hypothesis 4: "Artificial intelligence capabilities has a positive effect on competitive performance"

The analysis shows that hypothesis 4 is strongly supported with a significant ($p<0.001$) path coefficient weight of 0.459, which indicates a large effect. This matches our pre-conceptions of a positive correlation between AI capabilities and competitive performance. This study suggests that AI capabilities increase a firms' competitive performance. In order to gain strategic advantages over competitors, this finding could help organizations to do so by showing the importance AI capabilities have on competitive performance.

6.3 Discussion of other findings

This research provided us with a big amount of data and can be a source for further analysis. In this section we present a short summary of two of our other findings.

1. Even though we reached out to technology companies or companies using technology (analysing etc.), 27 of our respondents answered that they do not use AI and cannot see any potential for use of AI in their organization. Based on our assumption that AI technology could lead to any organization being more efficient and gaining value from AI, having close to 10 percent answering that they see no potential for AI was surprising. This may be due to the fact that these respondents may not be working with technology in their daily work. Some respondents also came back to us with implications of understanding the questions. This was especially connected to the questions regarding the technology. The lack of terminology knowledge could also be a factor for why some respondents do not see any potential for AI in their organization.
2. As mentioned in point 1, several of our population had a hard time understanding the technological terminology. This could be due to the fact that they do not actively use technology in their work, but work in a company that does. Gathering data from these

respondents is also valuable for this research, as it paints a picture of the organizational culture within the respective organizations.

6.4 Discussion of the research process

In this section, we discuss some of our thoughts regarding the research process conducted in this study.

Literature review
In our literature we focused on organizational culture within the field of AI. We chose to have this focus as organizational culture is considered as an important factor in AI capabilities. Also, most articles concerning implementation of AI mentioned organizational culture as important for gaining value from AI implementation. Further, there was a clear research gap within this field as many studies on organizational culture in a data-driven company context only focused on big data and not AI on its own.

Data collection process
When researching a field, the data collecting process can be the most time-intensive job. We tried to combine this process with other tasks while waiting for the respondents. But quickly found out that we needed to devote this time to gathering more respondents and refine our mail template in order to collect a sufficient number of respondents. This was a result of a small answer-rate after our first distribution and feedback from participants expressing their concern on whether the survey was legitimate. By changing the template based on the feedback to a more readable text that provided enough information and built confidence in the legitimation of the survey for the receiver of the email. We were able to increase our answer rate in the next distributions of the survey. Further, some time was used to answer different emails on questions from the participants regarding the survey. Often these questions regarded the legitimacy of the study. Even though we did not have the luxury to see who had answered the study or not, due to the study being anonymous. We felt that confirming the legitimacy of the survey by answering any concern from our university mail, provided us with more answers.

We also tried to distribute the survey through LinkedIn, where we reached out to our own connections and posted in relevant groups (e.g. Alumni). This provided us with some answers, but was also risky, as we did not know where the answers came from. During the data collection process, we decided that the most efficient way of collecting respondents was through sending out emails to relevant organizations. These emails were provided by the organization's public websites.

We do not know why the respondents who did not use AI or saw any potential for AI in the organizations completed the survey. As it was specified in the inviting email template that the survey was concerning organizational culture in the context of AI. In addition, this was specified on the first page of the survey, along with our definition of AI. In retrospect, we see that if a respondent answered NO to both using AI and seeing potential for AI use, we could have ended the survey. As these respondents were of no value for us.

Planning the analysis process
Using SmartPLS, or any other analysis tool, is something we have very limited experience with. As a result of this we used more time on getting to know the software than necessary. This could definitely be an improvement to avoid any unforeseen challenges. Also, during the

first algorithm runs, we were insecure on whether we did our analysis correctly or not in the software. This resulted in us doing the whole analysis from scratch in order to compare the results and confirm that we had not missed some things when we did it the first time. In addition, we consulted with our supervisor to confirm that our analysis was correct. Other improvements, like a trial survey could also benefit the study. But this would not fit in the timeframe of a master's thesis.

6.5 Research implications

In this study we have attempted to understand the use of AI in an organizational context. This study has some interesting findings that could be used in further research and in practical use.

Our research is providing a good foundation for understanding concepts as organizational culture, AI capabilities and organizational performance. By evaluating our definition of these concepts and models other researchers can refine or build upon our model and improve upon measurement methods. Further our study offers empirical support regarding the important role of organizational culture in adoption of emerging technologies such as AI.

Our research shows that there is a positive correlation between organizational culture and AI capabilities, and AI capabilities and social-, market- and competitive performance. This is the same result that (Mikalef & Gupta, 2021) achieved in their study. In their research, they found a significant positive correlation between AI capabilities and organizational performance. This study further supports this as we found a significant correlation between all AI capabilities and all constructs of competitive performance. Our findings should help organizations understand that to utilize their AI technologies, it could be necessary to look at the organization's culture and capabilities. Further, our study supports (Fehling et al., 2019), who in the MIT Sloan Management Review states that organizations looking at AI in an organizational perspective, rather than as a technological aspect, are more likely to derive value from AI. Our study also contributes to (Pappas et al., 2018), which states that developing a data-driven culture, fostering technical and managerial skills, and promoting organizational learning are critical factors in realizing value when going through a digital transformation.

A practical usage of this is that organizations could look at our constructs of organizational culture and AI capabilities to see what improvements they could make in order to achieve performance gains from their AI technologies. An example of this could be an organization that has invested in tangible resources, but still has a lack considering the organizational culture. By using the constructs, a Chief Information Officer (CIO) could identify the weak resources and take necessary actions. These constructs could also be used to evaluate the culture and AI capabilities of an organization, and thereby evaluate if they have an organizational culture that is ready for AI technology adoption.

By explaining the process of how this research has been completed we believe this research could be valuable for others who want to go through with a similar research approach or who wants to build upon this research. Further this study could provide researchers with a deeper understanding of AI capabilities and their relation to organizational elements.

6.6 Limitations and future work

There are some limitations to our study. Although our constructs are based on previous research, our research model as a whole is complex. To achieve even more significant values, both the performance constructs and organizational culture constructs can be refined and improved.

As a part of the data collection process, we chose to use several methods. Both using LinkedIn and using the snowball effect by asking participants to forward the survey, gives us less control of the respondents. This is because we cannot track who has received the survey and completed it as the survey was anonymously. By choosing to use these two methods along with email distribution, the data we collected can be less reliable. However, these participants constituted a small number of the participants.

The survey contained several questions with a technical context and terms that could be difficult for participants with limited technical knowledge. Since we wanted to capture a broad range of employees within the organizations to achieve a better understanding of the organizational culture, the issue with understanding the technical questions occurred. Further, the way participants interpret the 1-7 scale can be seen as a limitation. Rating a question seven is supposed to mean totally agree. Some participants may see rating a question seven means that they see it as perfect and based on this instead pick six as their answer. We have specified this in each of the questions this applies to but have no way to control if each respondent has interpreted this correctly. This could also come down to whether some prefer extreme or middle values. Also, the survey was quite big, some of the questions we included were not used in our model. The size of the survey leads to the survey taking some time to complete. This may have led to several participants not completing the survey. The complete survey can be seen in the appendix.

Having chosen a quantitative approach using a survey, instead of a mixed-method where we in addition conducted additional interviews, can be seen as a limitation of the study. A mixed-method approach could have provided more insight on organizational culture and how for example high-level executives sees organizational cultures' relation to AI. The present study can be extended by employing Fuzzy-Set Qualitative Comparative Analysis (fsQCA) (Ragin, 2009), which allows to get deeper insight into the data as it enables us to identify the necessary and sufficient conditions for an outcome to occur (Pappas & Woodside, 2021; Woodside, 2017). Further, fsQCA allows us to go back to the cases to get a richer understanding of the data (Pappas, 2018; Pappas & Woodside, 2021), thus future studies may compare and complement results from SEM analysis with fsQCA.

As we got several participants that answered no to both using AI and seeing potential for using AI in their organization, it would be interesting for future research to look into why they do not see any potential of AI. This could be done through interviewing these specific participants. It would also be interesting to see a study that integrates moderating factors as environmental factors in the survey. This is because it is proven that the environmental factors have an impact on the use of AI, similar to the digital divide.

Our study is mostly limited to Norwegian organizations. It would be interesting to see the study being extended to a larger demographic. A larger demographic would capture the organizational culture differences between countries, as it is proven in earlier research that work ethics and organizational culture differs from countries and especially continents. It has been shown that there are different preferences for adopting technology in different countries (Arenas-Gaitán et al., 2011).

To sum-up, we think future research could be:

1. Refine the model
2. Extend the survey, using mixed-method approaches
3. Interview those who do not see potential for use of AI
4. Include environmental factor
5. Extend the survey to a larger demographic

These can provide a better understanding of organizational culture in the context of AI.

7.0 Conclusion

The aim of this study has been to shed light on the importance of organizational culture in the context of AI capabilities and the ability of organizations to successfully adopt AI by answering the following research question:

"To what extent does organizational culture affect an organization's ability to adopt and use AI?"

The research question was answered based on data collected in a survey with 299 responders with different roles within technology companies mainly in the Scandinavian region. Then the data was analysed by using Partial Least Squares Structural Equation Modeling (PLS-SEM) in the software tool SmartPLS.

Prior to the analysis we conducted a systematic literature review in order to increase our knowledge on the topic, form a foundation for the study and create a conceptual model. Further, we distributed a survey to relevant participants to collect data. Then we analysed the collected data and tested the hypotheses.

Our analysis showed significant support for all four hypotheses, as they all had a strong path coefficient weight. Based on this we can conclude that organizations with a strong focus on organizational culture, will have an easier time developing and utilizing AI capabilities. In a constantly changing market, organizations with a good understanding of the organizational cultures' impact on AI are more likely to succeed.

In response to our research question, organizational culture has a clear impact on AI adoption in organizations. This can indicate that organizations that are planning to implement AI or are seeking to realize more value from AI might want to redirect their focus to organizational culture instead of the technology itself.

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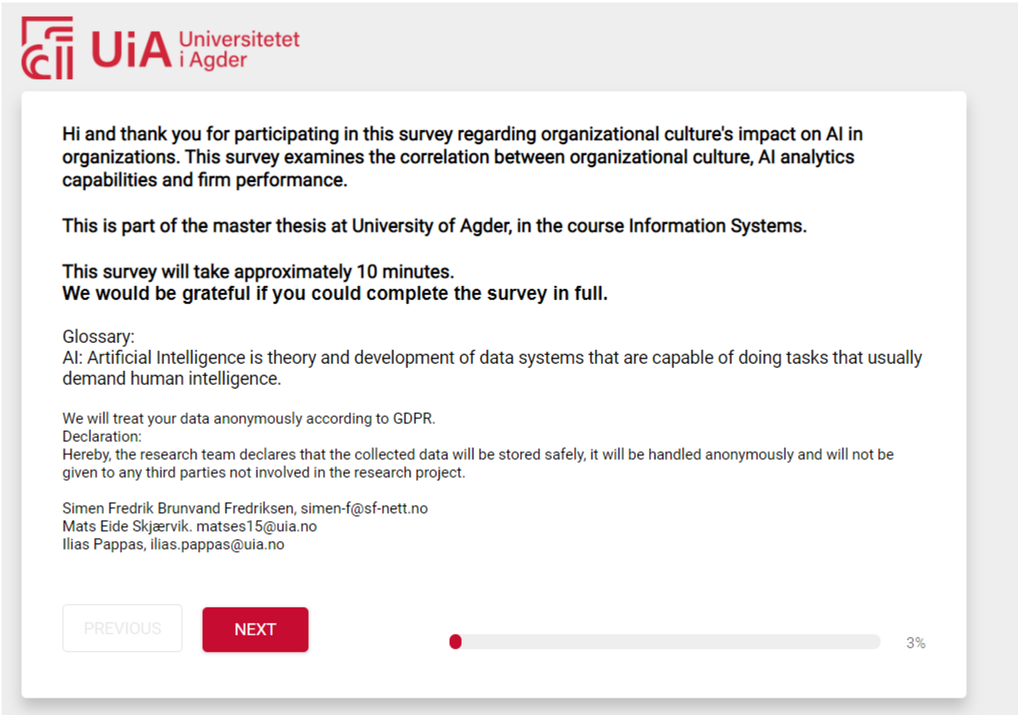
9.0 Appendix

9.1 Appendix 1 Original survey

Figure 8 Original survey exported



UiA Universitetet i Agder

Hi and thank you for participating in this survey regarding organizational culture's impact on AI in organizations. This survey examines the correlation between organizational culture, AI analytics capabilities and firm performance.

This is part of the master thesis at University of Agder, in the course Information Systems.

This survey will take approximately 10 minutes.
We would be grateful if you could complete the survey in full.

Glossary:
AI: Artificial Intelligence is theory and development of data systems that are capable of doing tasks that usually demand human intelligence.

We will treat your data anonymously according to GDPR.
Declaration:
Hereby, the research team declares that the collected data will be stored safely, it will be handled anonymously and will not be given to any third parties not involved in the research project.

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PREVIOUS NEXT 3%

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1. Do your organization use AI tools?

- ❑ Yes
- ❑ No
- ❑ I do not know

1.1 Is there a potential for AI use in your organization?

- ❑ Yes
- ❑ No

1.2 Are you personally using AI tools?

- ❑ Yes
- ❑ No

1.2.1 Is someone in your team or someone you professionally collaborate with using AI tools?

- ❑ Yes
- ❑ No

1.4 What kind of AI tools are being used in your organization?

- ❑ Amazon Web Services
- ❑ Domo
- ❑ Google (Locker)
- ❑ IBM
- ❑ Microsoft
- ❑ Micro Strategy
- ❑ Oracle
- ❑ Qlik
- ❑ SAP
- ❑ SAS
- ❑ Tableau
- ❑ ThoughtSpot

- ❑ Other

What kind of AI tools are being used in your organization?

2. Type of company are you working for?

- ❑ Private
- ❑ Public
- ❑ Profit
- ❑ Non profit

3. What is the size of the company you are working for?

- ❑ 0-9 employees
- ❑ 10-49 employees
- ❑ 50-249 employees
- ❑ More than 250 employees

4. Country of residence

_____

5. What type of industry do you work in?

_____

6. Organizational culture
Openness/willingness
Answer the questions by reflecting on your own experience in your organization.

1- Totally disagree, 7 Totally agree

	1	**2**	**3**	**4**	**5**	**6**	**7**
We value openness to new ideas in this firm	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
We are responsive to new ideas in this firm	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
We place great value on being flexible in our approach for problems	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
A willingness to show flexibility is valued within this firm	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑

7. Internal communication

1- Totally disagree, 7 Totally agree

	1	**2**	**3**	**4**	**5**	**6**	**7**
Open communication is valued highly within this firm	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
We place great value on excellent internal communication within this firm	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
Maintaining high quality internal communication is valued within this firm	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑

8. Inter-functional cooperation

1- Totally disagree, 7 Totally agree

	1	**2**	**3**	**4**	**5**	**6**	**7**
Cooperation among different work teams is highly valued	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
This firm values integration and sharing among teams throughout the firm	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
We place great value on coordination among different work teams	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑

9. Risk taking

1- Totally disagree, 7 Totally agree

	1	**2**	**3**	**4**	**5**	**6**	**7**
This firm values willingness to challenge the status quo	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
This firm values a willingness to experiment with new ideas	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
Valuing calculated risk-taking helped this firm get to where it is today	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑

10. Competence and professionalism

	1- Totally disagree, 7 Totally agree						
	1	**2**	**3**	**4**	**5**	**6**	**7**
We place great value on professional knowledge and skills	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
We aspire to a high level of competence and professionalism	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
Upholding the highest level of professionalism is valued within this firm	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑

11. Appreciation of employees

	1- Totally disagree, 7 Totally agree						
	1	**2**	**3**	**4**	**5**	**6**	**7**
We place great value on recognizing and rewarding employees' accomplishments	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
Taking time to celebrate employee's work achievements is valued in this firm	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
We place great value on showing our appreciation for the efforts of each employee	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑

12. Responsibility

	1- Totally disagree, 7 Totally agree						
	1	**2**	**3**	**4**	**5**	**6**	**7**
We place great value on every employee being proactive in his/her role	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
The firm values employees using their initiative	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
We value employees taking responsibility for their work	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑

13. Success

	1- Totally disagree, 7 Totally agree						
	1	**2**	**3**	**4**	**5**	**6**	**7**
We value success in this firm	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
We aspire to be the best firm in our market	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
We place great value on our performance	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑

14. Social performance

	1- Totally disagree, 7 Totally agree						
	1	**2**	**3**	**4**	**5**	**6**	**7**
Our firm support gender equality	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
Our firm support in poverty reduction	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
Our firm pays significant attention to the nutritional status of the meal served in the canteen	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
Our firm support healthy working conditions	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑

15. Market performance

	1- Totally disagree, 7 Totally agree						
	1	**2**	**3**	**4**	**5**	**6**	**7**
Our firm is achieving client satisfaction	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
Our firm is able to keep the current clients	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
Our firm is attracting new clients	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
Our firm is attaining desired growth	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑

16. Competitive advantage

	1- Totally disagree, 7 Totally agree						
	1	**2**	**3**	**4**	**5**	**6**	**7**
We have gained strategic advantages over our competitors	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
We have a large market share	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
Overall, we are more successful than our main competitors	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
Our EBIT (earnings before interest and taxes) is continuously above industry average	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑

	1- Totally disagree, 7 Totally agree						
	1	2	3	4	5	6	7
Our ROI (return on investment) is continuously above industry average	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
Our ROS (return on sales) is continuously above industry average	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑

17. Data

	1- Totally disagree, 7 Totally agree						
	1	2	3	4	5	6	7
We have access to Big Data (very large, unstructured, or fast-moving data) for analysis	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
We integrate data from multiple internal sources into a data warehouse or mart for easy access	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
We integrate external data with internal to facilitate high-value analysis of our business environment	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑

18. Technology

We have explored or adopted:

	1- Totally disagree, 7 Totally agree						
	1	2	3	4	5	6	7
Parallel computing approaches (e.g. Hadoop) to big data processing	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
Different data visualization tools	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
Cloud-based services for processing data and performing analytics	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
New forms of databases such as NotOnlySQL (NoSQL) for storing	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑

19. Technical skills

	1- Totally disagree, 7 Totally agree						
	1	2	3	4	5	6	7
We hire people that already have AI skills	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
Our AI analytics staff has the right skills to accomplish their jobs successfully	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
Our AI analytics staff has suitable education to fulfil their jobs	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
Our AI analytics staff holds suitable work experience to accomplish their jobs successfully	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
Our AI analytics staff are provided with the required training to deal with AI applications	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
Our AI analytics staff are quite capable of using AI technologies	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
Our AI analytics staff are effective in data analysis and processing	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑

19. Technical skills

If your organization were using AI tools, we focus on:

	1- Totally disagree, 7 Totally agree						
	1	2	3	4	5	6	7
Hiring people that already have AI skills	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
That AI analytics staff has the right skills to accomplish their jobs successfully	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
That AI analytics staff has suitable education to fulfil their jobs	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
That AI analytics staff holds suitable work experience to accomplish their jobs successfully	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
That AI analytics staff are provided with the required training to deal with AI applications	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
That AI analytics staff are very capable of using AI technologies	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
That AI analytics staff are effective in data analysis and processing	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑

20. Managerial skills

Our big data analytics managers:

1- Totally disagree, 7 Totally agree

	1	2	3	4	5	6	7
Understand and appreciate the business needs of other functional managers, suppliers, and customers	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
Are able to work with functional managers, supplier and customers to determine opportunities that big data might bring to our business	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
Are able to coordinate big data-related activities in ways that support other functional managers, suppliers, and customers	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
Have a good sense of where to apply big data	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
Are able to understand and evaluate the output extracted from big data	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑

21. Basic resources

1- Totally disagree, 7 Totally agree

	1	2	3	4	5	6	7
Our AI projects are adequately funded	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
Our AI projects are given enough time to achieve their objectives	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑

22. Data-driven culture

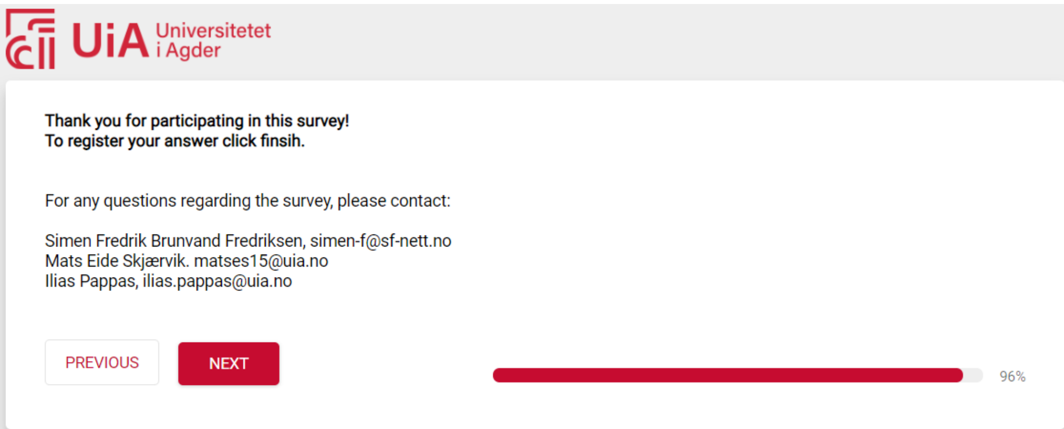
1- Totally disagree, 7 Totally agree

	1	2	3	4	5	6	7
We considered data a tangible asset	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
We base our decisions on data rather than on instinct	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
We are willing to override our own intuition when data contradict our viewpoints	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
We continually assess and improve the business rules in response to insights extracted from data	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
We continuously coach our employees to make decisions based on data	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑

23. Intensity of Organizational learning

1- Totally disagree, 7 Totally agree

	1	2	3	4	5	6	7
We are able to search for new and relevant knowledge	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
We are able to acquire new and relevant knowledge	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
We are able to assimilate relevant knowledge	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
We are able to apply relevant knowledge	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
We have made concerted efforts for the exploitation of existing competencies	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑
We have made concerted efforts for the exploitation of new knowledge	(1) ❑	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(7) ❑



9.2 Appendix 2 complete survey

Figure 9. Complete model