The bond between AI ambitions and Organizational Capabilities

A Qualitative Study on the Interaction Between Incremental and Transformational Ambitions in AI Adoption and Organizational Capabilities in the Context of Client-Facing Work.

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Abstract

While Artificial Intelligence (AI) adoption to drive business value is a growing practice, not only for process or efficiency improvements and automation, but also to drive competitive advantage and differentiation, existing research on the topic of AI strategy and realized business value is scarce. A currently underexplored area is how ambitions in adopting AI influence the outcomes and business impact, and how these concepts are interconnected to organizational capabilities. Addressing the knowledge gap, this thesis aims to study: *How do transformative versus incremental ambitions practices in AI adoption interact with organizational capabilities in client-facing work?* Data gathering is obtained through a qualitative approach, with eight semi-structured interviews, which are conducted with different Nordic organizations that implemented AI in order to either improve their client-facing operations, or facilitate these operations with AI. The analysis is led by a combination of the Organizational Ambidexterity and Digital Dynamic Capability theory, enabling the explanation of how ambitions in AI adoption align with organizational capability building. Core findings of the study are that reaching satisfactory business results through AI adoption is highly influenced by having both high initial ambitions and strong capability building.. AI ambitions were mostly influenced by industry pressure and technology advancements, but the experimentation began both through top-down leadership or bottom-up trials. A key capability identified is the strong emphasis on Human-AI collaboration, rather than the creation of an independent substitution through digital transformation. Furthermore, the importance of the AI initiative not being treated as a stand alone project and becoming a core part of the business strategy, which is effected in turn by the ambition level. While strong capabilities for a successful AI implementation were crucial, the influence of the initial ambition on the outcomes was also pointed out during the interviews.

Keywords: Artificial Intelligence, organisational capabilities, transformational ambitions, incremental ambitions, customer relations

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Definitions

Artificial Intelligence (AI)	Artificial intelligence refers to computer systems that can perform complex tasks normally done by human-reasoning, decision-making, creating, etc. (NASA, 2024)
AI Adoption	AI adoption refers to the strategic integration of artificial intelligence technologies into organizational operations to enhance efficiency, productivity, and innovation (Fortinet, 2025).
Organizational Capabilities	The ability of an organization to perform a coordinated set of tasks, utilizing organizational resources, for the purpose of achieving a particular end result (Helfat & Peteraf, 2003, p. 999).
Ambition	A particular goal or aim : something that a person hopes to do or achieve (Britannica, 2025)
Incremental	Incremental Development is the practice of breaking the delivery of features or functions into small pieces that can be envisioned, built, tested, and delivered in a predictable, timeboxed period of time (Dalton, 2019)
Transformational	Able to produce a big change or improvement in a situation (Cambridge Business English Dictionary, 2025)

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1. Introduction

1.1. Background

Artificial Intelligence (AI) is a rising global phenomenon that started as a new technology experiment and grew into a core driver of business transformation. Digital technologies have a much greater influence on reshaping organizations through indirect effects that are overlooked by organizations (Orlikowski & Scott, 2023). AI doesn't only produce "waves" aimed at improving efficiency, but changes practices tied to decision-making and authority which bring fundamental shifts in industry norms (Orlikowski & Scott, 2023). AI is a force that reconfigures value through deeper, hidden and unintended consequences (Orlikowski & Scott, 2023). Thus, its importance lies beyond intended business impact, highlighting the significance of studying its dynamics in business contexts.

Reports by McKinsey and BCG show that AI adoption is widespread and evolving. McKinsey's 2025 global survey found an increase from 55% in 2024 to 78% of organizations using AI in at least one function, yet only 1% described their AI rollouts as "mature." BCG (2024) reported that 74% of firms struggle to achieve and scale tangible value, with only 4% classified as leaders. By 2025, many organizations are at a mature stage, experiencing real business benefits, including innovation, employee and customer satisfaction, and competitive differentiation (45–64% of companies), while fewer than 40% saw improvements in costs, profitability, or revenue growth (Figure 1).

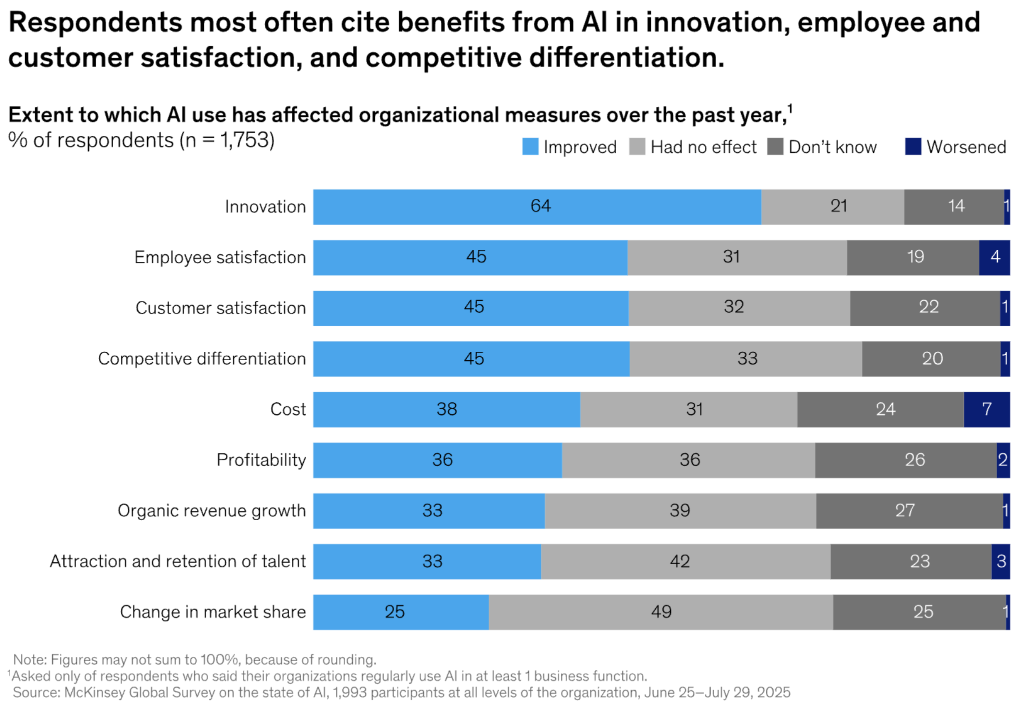

Figure 1. How AI affects organizational measures (McKinsey, 2025)

The "Artificial Intelligence and Business Strategy" research and publishing stream by MIT Sloan Management Review in collaboration with BCG is a series that tracks the evolution of AI in the business world, providing evidence-based insights on what thousands of companies worldwide hope to achieve their ambitions with AI and what capabilities they build to support it, as well as the outcomes. It is one of the most reliable tracking mechanisms for AI in business because of its long-term consistency and large scale. The data collected within several reports between 2017-2024 provide extensive evidence on the ambition-capability-outcome relationship in organizational AI adoption. Their 2019 survey of 2,500 executives revealed less than 40% realized measurable gains. By 2024, 90% of 3,000 respondents reported KPI improvements, showing a shift from operational improvement to redefining and automating KPIs. Successful adopters viewed AI as transformational, driving market differentiation, revenue, innovation, and making it central to business strategy. Organizations using AI for incremental efficiency gains improved operations but achieved little long-term change (Ransbotham et al., 2019). Those redefining strategic success with AI were three times more likely to achieve substantial financial growth (Schrage et al., 2024).

Correspondingly, McKinsey's 2025 survey found 80% of ~2,000 participants aimed at efficiency, while 50% had growth and innovation goals. Among high achievers, 79% started AI with transformative intentions, achieving benefits like customer satisfaction, competitive differentiation, profitability, and revenue growth (Figure 2). Organizations with goals beyond efficiency reimagined their businesses and scaled AI use more successfully.

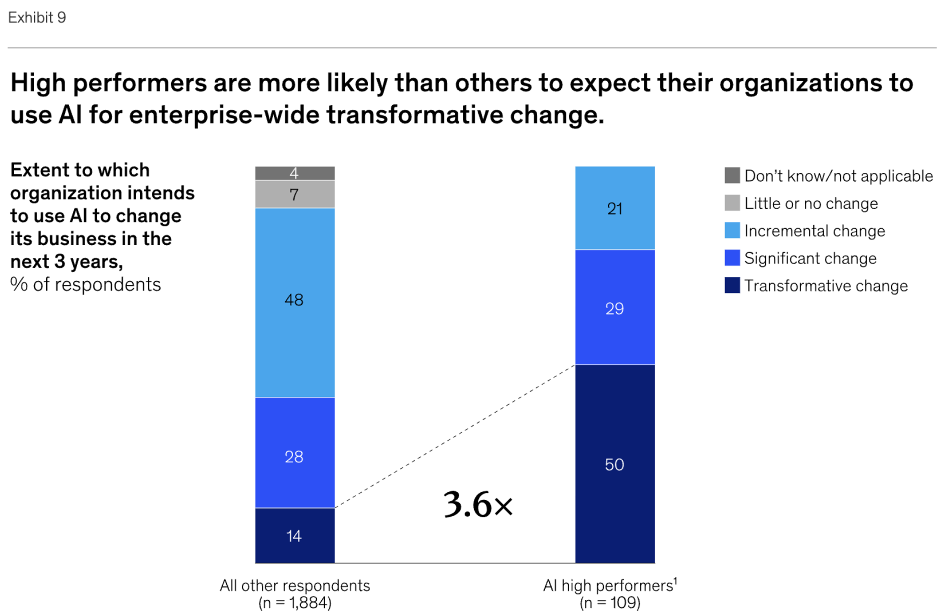

Figure 2. Intention to use AI for business change (McKinsey, 2025)

MIT-BCG's 2024 report showed firms that recreated KPIs with AI leveraged strong data systems, collaboration between data experts and business departments, and refined feedback loops (Schrage et al., 2024). Earlier reports (MIT-BCG, 2020) emphasized that organizational capabilities mediate the link between AI ambition and outcomes. Firms adapting processes, redesigning workflows, and using human-machine learning bridged ambition and results, gaining 2–3 times more value than incremental adopters. McKinsey (2025) also found high performers nearly three times as likely to have redesigned workflows, highlighting the importance of talent and technology in scaling AI for business impact.

In summary, these industry leaders (McKinsey, BCG, MIT Sloan Review), found that having high, transformational ambitions in AI adoption is one of the biggest factors that leads to satisfactory business impact.

They also discovered a correlation between building strong organizational capabilities and the relationship between high ambitions and high outcomes in AI adoption.

1.2. Aim and Research Question

The thesis aims to provide a deeper understanding of the interconnection between AI ambitions and outcomes in the context of client-facing operations, and their interaction with organizational capabilities. Understanding the interconnection between AI adoption goals, outcomes and capability development is crucial for theory and practice. From a theoretical point of view, it can bring new insights into capabilities building in the context of customer-facing AI adoption, as the main focus of current theories lies in operations and manufacturing contexts and into how ambition interacts with capability-building processes. From a practical view, it can help organizations strategize AI adoption by balancing high and low ambition while targeting the improvement of specific organizational capabilities.

This leads us to the following research question:

How do transformative versus incremental ambitions practices in AI adoption interact with organizational capabilities in client-facing work?

1.3. Main Focus and Delimitations

This thesis examines how organizations set ambitions in AI adoption, how they perceive the consequent outcomes and capabilities in client-facing work, in the Nordic region of Europe. The study will categorize ambitions as transformative and incremental ambitions. The research is bounded by qualitative case evidence concentrated on leaders and managers who shape the organizations' AI ambitions and drive the adoption. Therefore, the focus is on strategic perspectives and organizational factors, rather than technical AI aspects. These delimitations ensure a focused analysis that aligns with the research aim.

2. Literature Review

The Literature Review in structured into understanding: (1) what drives and motivates organizations to adopt AI and how scholars categorize ambitions; (2) how AI is used in client-facing contexts and how it relates to the ambitions; (3) the organizational capabilities that are needed for AI adoption; (4) a discussion of the existing knowledge; and (5) and identification of the research gap and the contribution of this thesis to the limitations in academic knowledge in the topic.

2.1. AI adoption: drivers and ambitions

Artificial Intelligence is defined as a technology that simulates human learning and other capabilities such as problem solving, decision-making and creativity (IEEE, 2018). Its core functionality is to replace human intelligence by learning, making recommendations and acting autonomously (IEEE, 2018). While this definition of attributes provides an indirect explanation of why AI is increasingly adopted to generate business value, academic researchers identify both drivers and ambitions behind AI adoption in different contexts.

The primary motives organizations adopt AI are: achieving competitive advantage and future strategic opportunity, in other words, gaining business value (Enholm et al., 2021). As evidence, a survey found that more than 84% of 3000 business executives think that AI will enable their companies to obtain or sustain competitive advantage (Lee et. al, 2019). In accordance, added business value is categorised into: (1) financial and efficiency gains - increased revenue, cost reduction, improved business efficiency - and (2) decision and process improvement - through automation, improved decision-making and collaboration (Enholm et al., 2021).

A similar study found that a core driver of AI adoption in organizations is achieving a more data-driven and evidence-based decision-making to better understand their costs, sales potential and emerging opportunities and to achieve new levels of competitive advantage (Smit et al., 2023). In practice, to leverage its technical functions through process automation: cognitive, task, and decision-making automation (Smit et al., 2023). Moreover, a Research Paper that explores factors influencing organizational adoption of AI highlights two types of strategic ambition related to AI adoption: short-term, measurable gains and long-term financial success (Pai & Chandra, 2022). A global survey in the same article showed AI's immediate impact on profitability and efficiency through cost optimization and revenue increase (Pai & Chandra, 2022). These short-term goals show AI's effectiveness in streamlining and automating operations and processes, enhancing customer-experience, personalized marketing and more accurate decision-making such as sales forecasting and identifying new market opportunities. Besides short-term economic profitability, AI is also used for financial effectiveness and strength (Pai & Chandra, 2022).

Hence, several studies across academic research illustrate the same pattern of categorization of ambitions in AI adoption. The first broad motivation that most scholars found is efficiency improvement ambitions and, the second, growth and innovation ambitions. These can be translated into transformational and incremental ambitions. Transformational ambitions refer to the organizational goals that aim to achieve lasting changes by focusing on radically redesigning business models, creating new customer experiences and fundamentally altering organizational capabilities (Xu et. al, 2021). On the other hand, incremental ambitions refer to the goals that aim to achieve gradual and continuous improvements within existing business models, processes and customer experiences in order to enhance current knowledge, technology and capabilities (Xu et. al, 2021). Thus, while incremental ambitions prioritize efficiency gains through step-by-step processes, transformational ambitions seek radical change by revolutionizing the organization's capabilities. However, while research shows that there is a difference and categorization of AI ambitions, there is little knowledge on the direct outcomes and business value created in relation to each type of ambition - incremental or transformational.

2.2. AI Adoption: ambitions and organisational capabilities

Organizational capability is defined as the collective result of a firm's coordinated routines across the organization that rely on individual employee skills (Dosi et al., 2008). AI is highly relevant to businesses through the optimization of several organizational capabilities, skills, processes, resources, and routines that help a company achieve its goals, such as improved operational efficiency by streamlining tasks, enhanced decision-making through predictive analytics, fostered innovation via personalized recommendations, cost savings and increased productivity through automation, and elevated customer experience via chatbots and virtual assistants (Oyekunle & Boohene, 2024).

Scholars have researched which organizational capabilities are needed in AI adoption and why. Weber et al. (2022) identify four key capabilities addressing two core AI adoption challenges. The first, inscrutability, refers to the difficulty in understanding and trusting AI outputs. Two capabilities to address this are AI project planning, identifying and prioritizing AI initiatives by understanding possibilities and limitations, and co-development of AI systems, integrating diverse expertise and facilitating cross-collaboration. The second challenge, data dependency, requires proper data foundations and continuous adjustments. Capabilities to address this are data management and AI model lifecycle management, ensuring the right data foundation and maintaining AI models after deployment.

Another perspective categorizes capabilities into enabling, foundational skills and routines before AI adoption, e.g., data readiness, technical expertise, cultural acceptance, and enhancing, skills created by AI, e.g., improved market sensing, accelerated product development, better decision quality (Gama & Magistretti, 2022). Most literature focuses on enabling capabilities, leaving a gap in understanding the capabilities created by AI, even though many organizations are at a mature AI adoption stage. McKinsey's 2025 survey found 62% of organizations are piloting or experimenting with AI, and 38% are scaling or fully scaled.

2.3. Knowledge Synthesis

Academic research offers an extensive comprehension of the motivations that drive AI adoption in different contexts and industries. The first type of motivations that most respective studies mention are related to short-term efficiency gains, automation of processes and more data-based decision-making, which can be translated into incremental ambitions. The second category of motivations focus on long-term growth, new business models and innovation, and can be translated into transformational ambitions. While numerous researchers study and categorize these different types of drivers and ambitions, few scholars offer insights into how each ambition translates into business outcomes.

Researchers also study the capabilities that organizations need and build in order to adopt and implement AI initiatives. The capabilities that are mentioned the most and can be found in all studies related to organizational capabilities in AI adoption are data and technical capabilities, such as data readiness and management or technical infrastructure. Other popular and thoroughly discussed capabilities are organizational learning and skilled workforce. The least examined organizational capabilities in the context of AI adoption are those related to strategic alignment i.e. the alignment of AI initiatives with business strategy.

2.4. Research Gap and Contribution

Existing research on AI adoption and organizational capabilities largely focuses on advanced technical infrastructure, data availability, and information management. These studies contribute to understanding AI adoption at an organizational level but lack insights into AI ambition and implementation in specific departments, such as customer-facing work. There is a lack of qualitative, peer-reviewed research exploring why organizations with better technical infrastructure sometimes struggle to realize business value through AI, while organizations with limited technical knowledge succeed. As a result, literature does not sufficiently clarify the relationship between an organization's AI strategy and its technical readiness.

This study contributes to knowledge on AI implementation and organizational capabilities by providing a qualitative, interview-based perspective on customer-facing work and how AI ambitions translate into capability development across industries. It extends the literature by examining the processes through which AI capabilities are built in customer-facing work. Using the Digital Dynamic Capability framework and Ambidexterity theory, the study explores how different AI ambition levels, incremental and transformational, relate to sensing, seizing, and reconfiguring capabilities in sales, customer service, and marketing. The research provides empirical insight into how organizational capabilities are developed, how approaches vary across organizations, and why similar AI ambitions can lead to different outcomes in customer-facing implementations.

3. Theoretical Framework

The analysis investigates how organizations utilize Artificial Intelligence in its customer facing work to receive a certain business benefit, more specifically what capabilities they develop using AI. Moreover, the main objective is to explore missing capabilities that divide the ones who reach their AI ambition goal and those who do not. Demonstrating this will be done using *Digital Dynamic Capabilities (DDC) Framework (Ellström, 2022),* investigating the capabilities needed, and *Organizational Ambidexterity Theory (Tushman and O'Rilley, 2013),* focusing on the strategy ambition.

3.1. Digital Dynamic Capability (DDC)

The first central framework that this study will make use of is the *Digital Dynamic Capability (DDC)* Framework for digital transformation (Ellström., 2022), which builds upon the dynamic capability view (Teece, 2007) but adds a digital element to the previous theory. According to the DCV, the core advantage does not only come from simply possessing the resources but through the firm's ability to change and innovate by managing the change (Teece, 2007). The main focus of the theoretical framework is on the DDC, however, which focuses more on the capabilities that are needed for the digital transformation (Ellström., 2022), similar to as in the implementation of AI in customer facing work. The DDC consists of 3 core capability categories: Sensing, seizing, and reconfiguring (Ellström., 2022). Sensing capability is focused on the firm's capability to recognize the digital opportunities in the environment. More specifically for AI in customer facing work, it involves the firm's ability to see new AI technologies or disruptive competitive moves based on signals (Ellström., 2022). Seizing capability involves the firm's capability to use resources to explore the digital opportunity from the sensing phase (Ellström., 2022). For specifically AI, this phase involves exploring and utilizing new processes or offerings that use AI onto the customer-facing work, which could include the customer service, marketing channels, sales channels, ensuring that the new digital resource can be managed effectively. Reconfiguring capability phase is the part where the actual change or redesign is occurring, where processes, structures, and assets are changed or improved to sustain the advantage from the new opportunity (Ellström., 2022). Within the AI and the customer facing work perspective, changes into the operational routines, as well as adjusting employee roles, and securing the necessary resources are essential.

The DDC frameworks contributed to the study by providing guidelines for identifying capabilities, especially digital capabilities, that are existing in the successful firms or missing in those who are unsuccessful in reaching their ambition.

Figure 3: Digital Dynamic Capability Theory (Stoica & Andersson, 2025)

3.2. Organizational Ambidexterity Theory

The *Organizational Ambidexterity Theory* will focus on the strategic intent of the companies. It allows the study to categorize the companies into the present efficiency (incremental) and future innovation (transformational ambition). The theory consists of two core parts, exploitation and exploration. The exploitation focuses on efficiency (Tushman and O'Rilley, 2013) and will be linked to incremental improvements and low ambition. This involves changing existing competencies and capabilities for the better. In order to efficiently gain a short-term return, this also involves improvement in technologies and knowledge (Tushman and O'Rilley, 2013). This core part of the theory corresponds to the low-ambition incremental strategy regarding AI and customer-facing work, where the focus is mainly on optimizing existing customer-facing processes, and this can be through giving quicker response rates or improving the efficiency of the processes for a certain business benefit. The exploration part focuses on innovation and discovery (Tushman and O'Rilley, 2013). This will be tied to the transformational ambition, thus the high ambition. This factor involves searching for new knowledge and competencies rather than refining existing ones. The exploration factor is similar to the high-ambition transformational strategy, where the AI in the customer-facing work is used as a tool for change, rather than refining current processes. This could include establishing a new type of service that is highly personalized.

3.3. Combined Model

The study employs a combination of the two theories, where the model begins with the organizational ambition level for the AI implementation in the customer-facing work, focusing on O'Reilly's and Tushman's 2013 Explorational and Exploitational Concepts, where the higher ambition will be categorized into Explorational and the lower ambition will be categorized Exploitational. Then, based on the AI ambition level, we'll look into the organizational capabilities that the organization develops using Elström's 2022 model, where we'll look into three core categories of organizational capabilities, sensing, seizing, and reconfiguring. Moreover, we'll look into the outcome, whereas the companies were satisfied or not satisfied with the outcome of the AI implementation, and the initial business value that was intended. The model allows us to look at the gaps between the companies at different ambition levels, what capabilities they have developed, and what the outcomes were regarding satisfaction. The Combined Theoretical Model is used as an analytical tool to examine how organizations convert AI ambitions into organizational capabilities in the customer-facing work context. Rather than using it as a predictive model of success within the AI implementation, the model supports a comparative analysis of how different ambition levels are associated with varying approaches to sensing, seizing, and reconfiguring organizational capabilities. It enables the study to explore variations across organizations in different industries without assuming a single organizational capability configuration to be optimal.

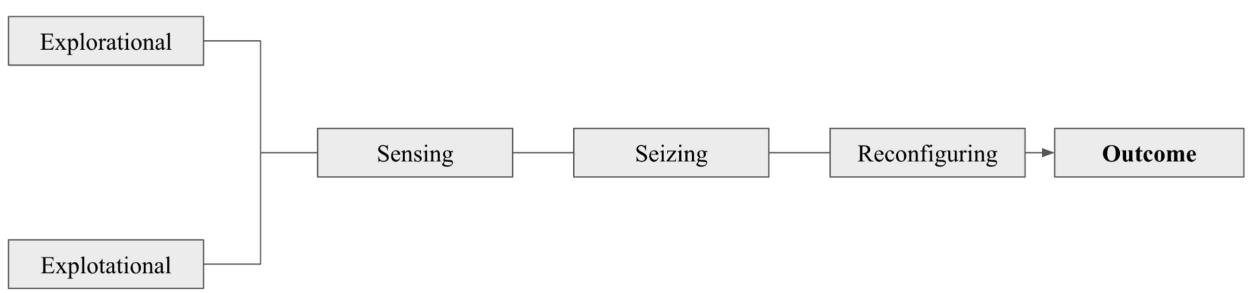

Figure 4: Combined Model: Organizational Ambidexterity Theory and Digital Dynamic Capability Theory (Stoica & Andersson, 2025)

3.4. Applicability

The two frameworks complement each other in this study. The ambidextrous theory and the digital dynamic capability theory are applicable to the study as it addresses two central aspects within the study's research, being the AI ambition and the organizational capability development within the organizations. The ambidexterity theory serves as a strategic framework, distinguishing between explorational and explorational ambition levels.

While the dynamic capability theory focuses on the operational component. Together, these two theories allow the study to explore how different AI ambition levels are visually surfaced in the organizational approaches to capability developments without assuming a specific implementation path or outcome as a result Does this framework aid well in the study's qualitative analysis, aiming for a deeper understanding of the variation in how organizations implement AI in a customer-facing work context.

3.5. Theory Discussion

The theories of Organizational Ambidexterity and Digital Dynamic Capabilities are integrated to specifically explore the strategic ambition and the capabilities necessary to achieve said strategic ambition. The limitations of the Organizational Ambidexterity Theory is the lack of specific digital focus. The Digital Dynamic Capabilities framework was specifically chosen for the study of digital focus and ability to complement a less digital focused model. The limitations of the Digital Dynamic Capabilities framework is that it explains the change but does not explore the strategic ambition. The two theories are chosen to cover the two core core themes of the study, strategic ambition and capability development, and for the two to complement each other.

For this study, the theories are not used as prescriptive models for predicting successful AI implementation and the outcomes of it. Rather, they are used as an analytical lens to look deeper into how different levels of AI ambition are translated into different organizational capabilities and how they are developed within the customer-facing work. By using the ambition as the starting point and the digital dynamic capabilities as the process part, the combined model allows for a clear examination of variation in how organizations build, change, and align different capabilities when implementing AI tools within the customer-facing work context.

4. Methodology

4.1. Research Approach

4.1.1. Research Paradigm

This study will adopt an interpretivist paradigm, focusing on a subjective review (Saunders, 2023. p177). The interpretive paradigm builds upon the notion that humans differ in Physical phenomena since they actively create meanings (Saunders, 2023), and the interpretivist paradigm research focuses on studying these meanings. This paradigm requires adopting an empathetic stance to understand the participants' social worlds from their own points of view (Saunders, 2023). This study will align with Phenomenology, which focuses on studying existence, with particular focus on participants' lived experience and their interpretations of the events. More specifically, it is the recollection or interpretations of the experiences that the participants (Saunders, 2023). In the case of this study, it will collect the recollection and interpretation of the journey of AI implementation in the customer facing work.

4.1.2. Research Approach

An abductive approach will be adopted for the research. This approach's logic is based on moving between the theory and data (Saunders, 2023 p. 185). This approach has a relevant fit to the research a s it allows for making comparisons across empirical cases (Saunders, 2023), as the research will in regards to the development of capabilities. This allows the research to follow a theoretical framework while still being open to new insights in the empirical data (Saunders, 2023).

4.2. Research design

4.2.1. Qualitative approach

The study uses a qualitative research approach, as it studies participants' meaning and the subjective nature or organizations as the meaning is obtained from words, and not numbers. (Saunders, 2023 p.213) The design of the study is appropriate due to the early stages of the AI research. There is difficulty identifying standard performance metrics regarding ambition and capabilities developed in connection with the AI. Moreover, the qualitative approach allows for non-standardized data to be analysed and structured using themes before analysis (Saunders, 2023 p. 213).

4.2.2. Semi structured-interviews

The data collection method is semi structured interviews. This form of interview allows probe questions to a response (Saunders, 2023 p.477), additionally it offers the flexibility for the conversation to deviate into areas not considered beforehand but still valuable for understanding (Saunders, 2023 p. 477). Moreover, this flexibility allows for altering the questions based on the participants professional role and knowledge based on the role.

There is a risk with semi-structured interview design, which involves the potential risk of quality of the information related to reliability and dependability risk, due mainly to its lack of standardization (Saunders, 2023). One big risk is interviewer bias, where the interviewer's phrasing of the questions might affect the participants' responses, where the interviewer applies their own beliefs and frame of reference (Saunders, 2023).

4.2.3. Interview question design

The design of the interview questions concentrate on three core factors. 1)the ambition level for their use of AI in their customer facing operations, 2) The capability development and the skills the organizations developed 3) The perceived business benefit associated with the AI tool and satisfaction level. The structure of the questions moved from the role of the participator, into the core themes that contribute to the empirical data.

4.3. Data Collection

4.3.1. Sample selection

The participation selection was based on a criterion-based purposive sampling (Nyimbili, 2024). This strategy was employed to ensure participants possessed the relevant knowledge to contribute to the data. Three core criteria were established regarding the sample participants (appendix A), 1) the firm must have relevant experience engaging and employing Artificial Intelligence in their customer facing work 2) firms were to fall into one of two ambition groups: Transformational (high) or Incremental(low) 3) Participants were picked based on professional role and if they were likely, based on the role, to possess knowledge that could effectively contribute to the empirical data. The participants were contacted via email or Linkedin. In total, eight interviews were conducted, and the interviews reached saturation at participant 6. Although the number of participants is relatively small and limited, this is consistent with qualitative research that focuses on the saturation and the information power, (Malterud, 2016), rather than focusing on the sample size itself. Information power was considered high for this study due to the narrow focus on AI and its user-customer-facing perk. Moreover, participants mainly held managerial and executive roles, Possessing information, broader information about the organisation and its use within AI and customer-facing work, spanning to different departments in the organisations, which contributed to early saturation in the interviews, with the last interviews reinforcing the early interviews themes rather than providing new themes. Small details and differences, but no real new themes were identified in the later interviews.

4.3.2. Interview process

All of the interviews were done over online services, Microsoft Teams or Google Meet based on the preference of the participants. Conducting the interviews online were chosen for the convenience of the participants (Bryman, 2016). The interview duration will last around 30-45 minutes to ensure adequate data is collected, while still being convenient for the participant. Moreover, the recordings were conducted through iphone voice memo or Microsoft Copilot. Most of the interviews were conducted in English, while some in Swedish. All quotes will be translated and assessed in English.

4.4. Thematic Analysis

The analysis of the empirical data will use a deductive thematic analysis. The categories for sorting data into quadrants originate directly from the integrated theoretical frameworks (Saunders, 2023), the digital dynamic capabilities, and ambidexterity theory. This approach is used because the research is not trying to identify new ideas, but rather lets the existing theories, DDC and ambidexterity, guide the sorting of participants. A deductive thematic analysis is therefore suitable, as the analysis is guided by established frameworks rather than generating new themes.

Firstly, all interviews are transcribed and the data prepared. Secondly, data is sorted by participant, categorized based on strategy, exploration, or exploitation of the ambition level, and by strategic capability, sensing, seizing, or reconfiguring, including the specific capabilities, skills, and actions mentioned in the interviews. After core coding, the main analytical technique used is pattern matching (Saunders, 2023). Expected outcomes, i.e., the capabilities required for a successful project, are identified first. Then, a comparison is made between the actual capabilities of firms that have not reached their ambition level and the expected outcomes based on the theories. The difference between these two factors is called the capability gap, i.e., the missing digital dynamic capabilities explaining why the project or AI use failed.

4.5. Method Discussion

4.5.1. Method Validation

Validity ensures that the measures are measuring what they are intended to do. The construct validity (Saunders, 2023) focuses on ambition and the digital dynamic capabilities directly from the theoretical definitions. To make sure that the questions are measuring what they are intended to do, they are designed to inquire about resource allocation in the sense of capabilities and expected outcomes directly. The internum validity is ensured by employing pattern matching , where we will be able to make comparisons to the observed digital dynamic capabilities in our empirical data against the theoretically predicted capabilities and see if there is a match or not (Saunders, 2023). To ensure reliability of the data collection, the interview questions will be standardized based on a semi structured model, ensuring that there is a consistent core set of questions. Moreover, additional measures are implemented to ensure the reliability of the data collected. For mitigating the participant risk the following is implemented, we schedule the interviews based on the participants' convenient times to avoid participation error due to time constraints. To avoid participants giving false answers is minimized by guaranteeing anonymity and confidentiality for all responses, including both those in the individual person as well as the organization they are representing (Saunders, 2023). To mitigate the researcher risks, the following implementations are made. To ensure the research remains objective, only the categories already defined in the theories will be used. Moreover, a final check with the participant will be done to verify that their meaning has been captured throughout the interview.

4.5.2. Ethical considerations

To ensure the participants feel safe and to ensure the integrity of the research, ethical considerations were upheld. Participants received information regarding the objective of the study, as well as the methods and methods to ensure informed consent (Saunders, 2023. p.284). Moreover, each participant had to sign a GDPR form that conformed to guidelines of Stockholm School of Economics. The participant upheld the right to choose not to answer a question. The participants of the interviews had full anonymity, including both the company, individual person, and any sensitive data related to the individual or company. Furthermore, any collected data are stored securely and will not continue being stored after the study is completed.

4.5.3. Use of AI in the research process

Artificial intelligence was used to some extent, including only administrative tasks and no alterations to the core research or analytics of the research were done by AI. Microsoft Copilot was used for recording as well as transcribing the interviews. Perplexity, Gemini (Bard) and Scite was utilised as assistance in finding relevant research articles and books And ChatGPT was used for grammatical assistance and to refine language. Accuracy was verified with all use of AI in assistive or administrative tasks, especially regarding the accuracy of transcription. Checks were done by reading and listening to the interview recording in order to ensure accuracy.

5. Empirical Findings

In this chapter, the empirical findings from the study will be presented from the multiple companies that participated in the study. These findings are a key part for answering the capability gap between the different quadrants And we'll focus on the relationship between the strategic ambition with the AI and the capabilities and skills that were developed.

5.1. How AI Ambitions are perceived

Interviews indicated that organizations focus mainly around operational efficiency for their AI ambitions. Moreover, more than efficiency, organizations seek to create uniform information across the organizations and quality improvements in the customer interactions:

> *"And what actually happens is that everyone answers correctly... different answers... person-dependent..." - P1*

> *"That it would be easier and faster to obtain the information..." - P5*

> *"That is where AI comes in: they compile the information and make it understandable for the user or customers." -P5*

Other ambitions such as cost reduction were also present:

> *"Coding tools $200 a month... replaced that entire team..." -P3*

The participants differed in whether they used the AI tools to improve the existing work or something that fundamentally changes the business operations within the customization work:

> *"It's entirely transformational because... bigger project... client timelines..." - P3*

> *"One is that maturity across anybody involved in knowledge work has increased. And the second is the costs. It used to be hundreds and thousands of man-hours, and now you can buy that capability at very low cost. So, algorithmic capability is a commodity." - P6*

The integration of AI into the business is something that they aim to have as an everyday work, as a normal embedded tool that is natural to work with; A central piece in the employees' everyday lives, not a separate project:

"Because this is an integral part of the business. So it's not something you do on the side, this is the business. This is the strategy." - P1

"... it has automatically become a standard way of working. I've been working with AI for the last 25 years." - P3

5.2. How ai ambitions are initiated

The approaches explained in the interviews were a mix of top-down support and bottom-up experimentation. In most cases, the initiative and commitment came from top-down leadership, while a lot of interviews also suggested that the inspiration and the use also comes from bottom-up:

"I went to MIT to learn the basics. I think it's important that CEOs understand this. If CEOs don't understand it, it won't work." -P1

"Above all, the need must come from the staff. It doesn't come from above. Instead, it goes around the department, goes to the finance department, and asks what tasks are very repetitive and time-consuming." -P1

Throughout the interviews, there was a pattern of the organizations starting out in a voluntary pilot and then moving over into mandatory adoptions in phases throughout the departments and organizations.

"We asked them, would you like to volunteer and test ChatGPT? And everyone just said, yes, yes, I said. So we had a group of maybe ten people from different departments. " - P1

"And then if the data was positive, they would try to spread it out to more and more teams. " - P2

Internal training and workshops were used, as well as peer demonstrations, to create interest and spread the adoption throughout organizations, as well as formal training for expertise:

> *"What we also did was hold monthly inspiration seminars where people in the organization got to present to everyone else. Everyone was invited. We started with a salesperson in the UK and Sweden... And now this fall, we've been doing CoPirot training every other week. It's really just to inspire and raise overall competence. " - P1*

> *"Skills wise, I sent everyone for training. So I found a company that was offering these kinds of like AI crash courses where you actually get hands-on, you build things. And yeah, people had to do that as a part of their job. " -P3*

Most of the participants expressed that they pursued AI in customer-facing work partially for the competitive advantage, but many followed the overall industry trend and customer interaction tendencies that were growing within the industry:

> *"But it's also true that there's a wave of AI implementation sweeping through the insurance industry internationally. So I can also see a trend washing over the entire industry." -P4*

> *"The way that industry typically works is that if someone who's a leader [...] they do something that's a very powerful driver of people doing things. Some people [...] define what good looks like, but others follow [...] 80% followers. Role models is a core driver.""- P6*

Many companies implement a very experimental approach to its AI initiative:

> *"A year ago, we didn't know that an AI agent would help with customer service. It has emerged and helped improve implementation and business benefits. We didn't know from the start how we would do it [...] it's more a case of running, thinking, and acting as you develop it." - P1*

There was also a large focus on human-AI collaboration across organizations:

> *"and we must again certify in the system that we have read it, but that I, as the medical risk assessor, am responsible for the decision." -P4*

5.3. Capabilities: needed and developed

Organizations develop themselves or acquire the capabilities. But both camps expressed a need for the capability in the organization to efficiently structure and gather data between the departments in the organizations, due to the data training and cloud storage of the data. Within the customer-facing operations, privacy and compliance capabilities in combination with AI were perceived as very important, hence the use of an internal cloud for storage.

> *"...data is the most critical hygiene factor. Without having a good data strategy and structure, then it just won't be possible. " - P7*

> *"And on the technology side, a lot of it has to do with having what we frame as an efficient data flow [...] ingesting data, preparing data, applying AI, and making sure it's used. To summarize, efficient data flow." - P6*

Some already had the competences prior to adoption:

> *"We had the technical competence in-house already. And the raw data that exists is quite good...*
> *And that makes it easier when you're going to get some benefit from it later. " - P5*

While in the incremental cases, where use of generative AI was more used, the expertise was different:

> *"When it comes to generative AI, it's interesting because the models ... they've got the capability of understanding human language and can translate that into code ... we don't need data scientists ... However, to scale them effectively, we need technical talent." -P7*

Experimental and pilot learnings were crucial and continue to be with the changing environment in AI:

> *"So we were sort of the Guinea pigs in the beginning and they were trying to gather what? Went well, what did not go well and then moved forward using that data. " - P2*

Cross functional collaboration became important due to the data input required from all departments:

"We can't get away from the matrix organization, but it's moving towards crossfunctional teams ... But that's not to say you wouldn't have, say, a customer service department ... it's more pushed in that direction." - P6

"Our team dynamics processes were constantly changing because of our AI chatbots... we also used the chatbot among teams... it helped us understand shortcomings in cross-collaboration and how to improve efficiency." - P8

The organization developed the workflow and capability of human-AI combination within the customer facing work, specifically how to use them:

"AI is helpful, but only up to a point. When the customer situation gets complicated, the system struggles, and that's where human judgment is still essential." - P8

"Humans possess unique qualities such as relationship-building, curiosity, adaptability, and continuous learning, which are difficult for AI to replicate. As AI automates routine cognitive tasks, these human strengths become even more critical." - P7

Credibility checks to verify the AI output in an efficient way was crucial:

"....to make it legally sound, the organization has that text in our case management system [...] we must certify in the system that I, as the medical risk assessor, am responsible for the decision." -P4

Organizations built AI literacy throughout the employees, including the management teams, integrating it into the organizations training:

"Basic training we've received—because of special guidance on risk assessment—has been very good [...] and we also have intranet campaigns for everyone to learn more about AI." -P4

"From a leadership point of view, it becomes more important to be technically proficient ... You need that in the future of leadership." - P7

Change management capabilities to drive specifically the AI adoption through voluntary and inspirational pilot into implementing it as a mandatory practice:

> *"We started with volunteer groups... So it became an exclusive group." - P1*

> *"Then we forced everyone to make their AI plan... Stepped up gradually." - P1*

> *"Senior staff associate AI with loss of control; need to address trust and governance... Younger staff are eager to experiment; seniors need proof of ROI." - P3*

> *"...one thing to build AI systems, another to scale and transform how we work." - P7*

A special skill was the ability to understand where AI fits into their business strategy, to ensure it is integrated effectively, and the ability to actually integrate it effectively into the existing systems:

> *"So that's the most important one. Also, keep focus on the two, three big things, not just the functional level... consider corporate vulnerabilities from AI changes." - P7*

> *"You have to understand AI to see its benefits... AI is part of the business." - P1*

Continuous impact tracking:

> *"And then one thing to emphasize, because it's typically underemphasized, is the ability to track incremental impact. Because when there's so many things moving and no humans in the loop, having that, the ability to measure is one of the key capabilities." - P6*

5.4. Outcomes

There was a pattern in some but not all interviews the AI tools implemented frequently producing inaccurate output that had to be checked by human to verify accuracy of information:

"And it's always the case that an AI assistant like this hallucinates. That is, it makes things up that aren't there. And when I encounter that, I say... This is a clear example of why I need to report this error and why we need to teach the assistant to learn correctly again. "- P4

Causing scepticism or frustration in some organizations:

"While others might see it as, "God, how bad it is, you can't trust it," and get tired of it pretty quickly and give up on it. And they don't understand that this is a learning process for AI as well. " -P4

"... but then when people spent more and more time correcting the mistakes it made, the enthusiasm dropped for sure." - P2

Organizations using private data clouds had problems with limited data training sets:

"I would say the training data set used was very limited, so I would say it wasn't able to answer a lot of questions ... .With the amount of detail that I wanted it to answer and. Again, because of the limited data set, it was quite limited in what it could do and what it could not do ". - P2

5.4.1. Limitations

AI tools within the customer facing operations often produce inaccurate outputs that need to be verified by humans:

"The problem of hallucination was still there, the inaccuracy. I wasn't able to understand the context of the whole project. That's why I had to do it file by file. " - P2

Even though there was a difficulty, people viewed it positively, more like a challenge that could help the tool learn and get better, rather than a limitation:

"And it's always the case that an AI assistant like this hallucinates ... It makes things up that aren't there. When I encounter that, I say... This is why I need to report this error and teach the assistant to learn correctly again. I say it as something positive ... it was good that this was discovered and now we can do this well." - P4

Despite the AI tools existence, there was adoption resistance:

"I would say there was an initial enthusiasm that I saw in the team when we started using it, but then when people spent more and more time correcting the mistakes it made, the enthusiasm dropped for sure. " - P2

"Yes, but I would say that I know that not everyone uses the AI assistant as frequently as they could. So the goal is for everyone to use it 100% of the time in cases where it can be used. "-P4

The resistance was sometimes worsened by technical issues:

"And then, as soon as there is a glitch in the AI assistant or something goes wrong... Then it takes over and becomes a reason not to open it next time, creating a higher threshold. These hallucinations and teething problems become more serious for someone like that than for me, who just thinks, okay, I saw this, I'll report it, and let's hope it's fixed by next month." - P4

Several interviews touched upon a critical barrier being the lack of understanding by the higher ups, not that commitment was a problem, rather the understanding

"I think it's important that CEOs understand this. If CEOs don't understand it, it won't work. I think that's the challenge: getting CEOs to be at the forefront. Because this is an integral part of the business. " - P1

Some organizations struggles with scaling up the operation after initial experimental phase:

"And so today we have perhaps 100 different use cases within generative AI. Most are just experimental. We have a few that deliver value, and a substantial number with proven value, but not scaled up yet... So it's one thing to build these AI systems, another to scale them and make the transformation." - P7

5.4.2. Examples of outcomes

Some organizations experienced efficiency and quality improvement within their customer facing work, mainly time efficiency improvements:

"And tests have been done in the US, where they have these really large pools of medical records. And there, they've been able to... achieve a time saving of 30%." - P4

"So it's going to take us one day to build this tool, 30 minutes to load it, and then three days for the AI to help provide all these structured analyses. If done manually, it would have been four to six weeks with at least 100 to 120 separate documents." - P3

Consistency and quality improvements:

"And what actually happens is that everyone answers correctly. Before, when you called someone, there were different answers, so we could sometimes give one answer there, but on the website there was a different answer." - P1

Cost reduction:

"$200 a month with Claude has replaced that entire team in India for me. " - P3

Customer success:

"AI helped us understand customer pain points better and find patterns in their issues, as they were often repeating. It also opened insights to new problems we were not aware of." - P8

Competitive advantage:

" And so we have promised the deliverable and we've promised it with the price. And that's where they're going to hold us to... that's a big differentiator for us when we can go to a client and we know we have that capability which is very different from others. " - P3

5.4.3. Satisfaction and outcomes

Several organizations expressed positive attitude towards the result that the AI adoption in the customer facing operations had displayed:

"Yes, it has definitely helped us to improve our implementation and what we want to do. " - P1

"In large, we are a big group. So for some, not as much as we would hope. For others, more than we could even think of at that time. Overall, we're very happy with that. " - P7

"...somewhere between four and five [on 1-5 maturity scale]. " -P3

"Absolutely, but as I said, the Co-pilot agents were a clear target. There, we simply had to make things easier for the user, or for the customer. " - P5

While other are not yet satisfied, mainly due to not succeeding in scaling to a satisfactory level, or because of technical challenges in the tool itself:

" I think that some people may still feel most comfortable not involving the AI assistant, so the goal is not something I would like to see greater efficiency and 100% use of, 100% of all cases with medical records. " - P4

"....there was an initial enthusiasm that I saw in the team when we started using it, but then when people spent more and more time correcting the mistakes it made, the enthusiasm dropped for sure. " - P2

6. Analysis

This chapter analyzes how AI and ambition levels are associated with differences in the development of organizational capabilities in the customer-facing operations. The analysis builds on a combined theoretical framework which integrates organizational ambidexterity (O'Rilley and Tushman, 2013) and dynamic digital capabilities (Ellström, 2022), but the focus on sensing, seizing, and reconfiguring capabilities.The AI Ambition Levels are used as a tool to separate between organizations that focus on different explorational or exploitational ambition within the ambidexterity framework and examine how these differences relates, associates with, associates to capability development and the organization's own perceived outcome of AI implementation, satisfaction or not.

6.1. Ambition levels

6.1.1. High Ambition - Transformational

High Ambition Organizations, (P1, P3, P7) integrated AI adoption into their core business strategy. The strategic positioning allowed them to create the conditions needed for the capability development during implementation, mainly because it allowed them to allocate resources to the initiatives, especially for the experimental phase over time. P1's CEO attended MIT training and made several changes that made the AI initiatives mandatory across all departments, not only focusing on one but scaling up to the entire organization, moving from voluntary pilots and inspirational seminars to require mandatory adoption both on top level and employee level. This reflects the progression within sequential ambidexterity (O'Reilly and Tushman, 2013), where exploration, trying new things, gradually shifts into exploitation, where use becomes systematic.

6.1.2. Low Ambition - Incremental

The low-ambition organizations (P2, P4, P6) use AI mainly in existing processes to optimize them. P4 described a wave of AI implementation within their industry, suggesting the motivation came from external pressure rather than internal ambition. The lower ambition created resource constraints, not because of a lack of funds, but because they needed an efficiency improvement metric specified before implementation to justify investment in experimental resources, halting initial capability development in the experimental phase. This pattern indicates the ambition level determines whether organizations develop capabilities or simply implement the tool within customer-facing work. The low ambition restricted AI to existing processes, preventing the sensing, seizing, and reconfiguring (Ellström, 2022) capabilities from taking place in the necessary manner for transformation in customer-facing work and AI adoption. This suggests ambition influences the effectiveness of the capabilities, and whether systematic capabilities such as sensing, seizing, and reconfiguring develop at all, compared to ad-hoc problem-solving (Winter, 2003, cited in Ellström et al., 2022).

Hence, high-ambition organizations can be framed as those that invest early in enabling capabilities like AI skills, data infrastructure, and cultural acceptance (Gama & Magistretti, 2022). Committing to experimentation and mandatory training can be interpreted as systematic building of enabling capabilities that later drive enhancing capabilities (Gama & Magistretti, 2022), in mature phases of AI implementation. However, as low-ambition organizations focus mainly on operational efficiency, they never build the enabling capabilities deeply enough for enhancing capabilities to emerge. Thus, the "ambition level" can be presented as the mechanism that undermines whether enabling capabilities mature into enhancing capabilities.

6.2. Sensing capabilities

Sensing capabilities, identifying and scanning for new opportunities (Ellström et. al, 2022), differed between the bitter levels. High-ambition organizations developed a sensing routine through test pilots, inspiration seminars, and mandatory AI planning sessions, successfully implementing systematic experimentation protocols across departments (Ellström et al., 2022). Ellström et al. identify framing as identifying external opportunities, yet some of the most satisfied high-ambition organizations discovered their most valuable AI opportunities through internal experimentation. Thus, sensing can also be generated through exploration within organizations. Traditionally, sensing in Ellström et al. (2022) assumes scanning for external opportunities. However, these findings suggest that in AI contexts, not all opportunities pre-exist; many emerge through experimentation, and external opportunities may not always fit the organization. This demonstrates that even for sensing capabilities, it is important in the AI context to have interpretation ability and continuously evaluate experimentation findings and implement them effectively.

In connection to Weber's et. al (2022) concept of inscrutability, an organization with limited AI Project Planning and Co-Development of AI Systems equals to having low sensing capabilities, having limited understanding of AI's strengths, limitations, and value potential, making it difficult to evaluate or trust AI-generated insights, which was a pattern identified in the study findings.

Among the low-ambition organizations, there was a pattern of ad-hoc problem-solving—finding small and temporary solutions rather than having a sensing routine. These organizations practiced a more passive form of sensing, looking for an external case to imitate to achieve their improvement or business benefit. They know what could make customer-facing operations more efficient but struggle to discover applications that would transform this benefit, since they search for existing external use cases. There is also a failure difference between sensing in high- and low-ambition organizations. The AI use often required correcting mistakes, creating frustration and negative feedback. Without routines or resources to interpret this as learning instead of tool failure, they struggled to learn from mistakes. Within sensing capability, Ellström emphasizes interpreting opportunities, focusing on understanding external trends and the environment. Rather than recognizing these challenges as learning opportunities, many low-ambition organizations were given no guidelines for treating uncertainty and turning it into insight, instead viewing it as a failure of the tool.

6.3. Seizing

Seizing capabilities refer to the ability to utilize the resources necessary for the opportunities identified in the sensing phase (Ellström, 2022). Interestingly, some of the highest-ambition and highest-satisfaction organizations committed substantial resources before knowing what opportunities would emerge, mobilizing resources for experimentation before the core opportunity had been identified. This reframes the seizing capability from being a value capturer based on known opportunities to a proactive capability-building process through experimentation. Seizing becomes the capability to discover the opportunity rather than only seize an already known one. A key difference among high-ambition organizations was that some invested only in experimentation, while others combined efficiency gains to capture immediate value with potential future capabilities such as AI engineering training.

Low-ambition organizations committed to more operational and tactical improvement. They were able to seize the opportunities sensed through external proven use cases. However, without generating their own sensing, they had no large opportunity to justify substantial resource investment, resulting in limited sensing justified only through external cases. This limited seizing, which prevented continuous development and improvement of the sensing capability. An example is P4, which recognized accuracy barriers but could not invest in verification capabilities, resulting in individuals verifying the information manually. Moreover, the limited resource commitment caused problems to persist far longer than in organizations with more resource allocation, which had the opportunity to correct mistakes and continuously improve the tool, creating a better experience in customer-facing operations.

6.4. Reconfiguring

Reconfiguring capabilities transform organizational routines, resources, and structure. Ellström (2022) describes reconfiguring as renewing the transformation. This pattern connects to the concept of data dependency emphasized by Weber et al. (2022), the need for strong data foundations and ongoing AI model maintenance. Study findings show that organizations engaging in deeper reconfiguration were better positioned to overcome data dependency, as building new infrastructures, workflows, and skill bases enabled stable and scalable data pipelines for high-performing AI.

The degree of transformation matters. Most highly satisfied organizations created entirely new systems, such as knowledge management infrastructure, where AI became core within service delivery, especially in customer service. The difference lies in whether components are restructured or entirely swapped. The degree of transformation often determines if AI becomes part of core service delivery or remains a separate project. Creating new infrastructure or organizational parts makes the AI initiative closely integrated with the business strategy.

Many companies invested heavily in AI training, making it a core part of the organization, which increases the cost and risk of reversing the initiative and makes the transformation more likely to succeed. Low-ambition organizations avoid such commitment by keeping AI implementation reversible, preventing deep infrastructure changes. Ellström's (2022) framework implies that organizations sense opportunities, seize resources, and then reconfigure to exploit them. In customer-facing AI, reconfiguration is required before actual value capture, particularly as human-AI collaboration needs transformation for AI to deliver its true value.

6.5. Ambidexterity

Organizational ambidexterity focuses on balancing exploration and exploitation (O'Reilly & Tushman, 2013), which this study shows is essential for AI capabilities and development. The findings reveal ambidexterity as a transformational mechanism for AI within customer-facing operations. O'Reilly and Tushman (2013) distinguish between structural and contextual ambidexterity, where either separate units or the same unit use different activities.

The study shows that initial temporary exploration phases must eventually be integrated throughout the organization, as AI adoption needs organization-wide integration to deliver business value. Organizations that kept units separate failed to scale and did not achieve the desired value. Two cases focusing only on exploration or only on exploitation failed to scale, suggesting that separate units must eventually merge to effectively integrate AI organization-wide.

Most cases preferred predetermined business value and outcomes before allocating resources. However, transformational AI value is fundamentally unpredictable, emerging through exploration, and cannot be fully specified beforehand. O'Reilly and Tushman (2013) frame exploration as searching for "known unknowns," but AI adoption is more extreme, as opportunities are difficult to determine even in experimental phases. The study shows that the most valuable AI applications cannot be predicted, yet resource allocation is still required during exploration. High ambition enables both exploration and exploitation, while low ambition enables only exploitation.

In low-ambition organizations, exploitation dominates. This limits what the organization can do with AI. P4 recognized hallucination issues requiring solutions that would have emerged from the exploratory phase. Jumping directly to exploitation without exploration means core capabilities for managing AI are missing, leading to more challenges with the tool and lower satisfaction with outcomes.

6.6. Ambition capability development

The analysis reveals patterns that AI ambition levels are a central factor in capability development. The findings indicate ambition comes before capability development choice. High ambition allowed for resource allocation without specific predetermined business value outcome, only a general direction, low ambition requires efficiency metrics, eliminating the essential exploration. High ambition treats setbacks as learning opportunities for a better tool, while low ambition organizations view them as inefficient. Resource investment before knowing the outcome, compared to traditional order.

7. Conclusion

7.1. Limitations of the Study

Despite its contribution to academia, the study is prone to several limitations that need to be acknowledged. Firstly, as a qualitative study approach based on interviews, the participant's subjective interpretations shape the data and findings. As the study greatly focuses on founders and leaders in strategic and management positions who are involved in shaping AI strategies and adoption, the data is affected by social desirability bias. Furthermore, the study is only centered on interview data and lacks further quantitative observations and validation, restraining the strength and validity of findings. Another key constraint is the limited size of eight interviews that were chosen through purposive sampling. Although saturation was reached after six interviews that were equally balanced into organizations with incremental and transformational AI ambitions, the sample size limits the generalizability of findings. Finally, AI adoption is a fast-changing practice that rapidly evolves, hence, the findings may change as technologies and adoption of digital transformation in organizations develop.

7.2. Recommendations for Future Research

We have several recommendations for future research. Firstly, we suggest conducting industry-specific studies, as each industry portrays unique capabilities. Rather than spreading the research across multiple varied industries, having a focused approach can improve the strength of findings and reduce study limitations. Secondly, gathering data from multiple perspectives within the same organizations can offer more insights into how leaders, managers and frontline employees view ambition and capability building in the context of AI adoption. A variety in the data gathering in terms of participants' roles can offer divergent and less biased insights. Thirdly, we strongly recommend the investigation of the enhancing capabilities - the capabilities that emerge after AI adoption. Current research displays a strong focus on foundational capabilities for driving a successful AI adoption, but less on the capabilities that AI adoption itself builds in the organization.

7.3. Concluding Remarks

The study highlights AI ambition as fundamental in capability development, and as a key differentiator. Patterns in findings show how high-ambition organizations invest in exploration and experimentation, which helps them integrate AI into core business strategies, and low-ambition organizations have a limited ability of developing transformative capabilities as they focus on incremental improvements. In the end, ambition doesn't only drive resource allocation and capability development, but also organizational learning. It determines how organisations learn and treat failures in AI adoption, embracing AI in their routines.

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9. Appendices

9.1. Appendix 1: Interview Guide

Research purpose
This interview is part of a bachelor thesis at the Stockholm School of Economics, titled:
"The bond between AI ambitions and organizational capabilities."

We are studying how organizations' ambitions when adopting Artificial Intelligence (AI) , whether aiming for incremental improvements or transformational change - shape the skills, processes, and ways of working that companies develop to make AI successful in customer-facing work. The goal is to understand what organizations aimed to achieve with AI, what they built to make it happen, and what outcomes they have seen so far.

Key Concepts:

Artificial Intelligence (AI): tools or systems that can analyze data, make predictions, or perform tasks that usually require human judgment: such as chatbots, virtual assistants, recommendation engines, or predictive analytics.

Organizational capabilities: the combination of skills, tools, processes, and routines that enable a company to make its ambitions work in practice.
Examples: employee training, new workflows, integration between AI and human agents, or data systems that support decision-making.

Ambitions:

- *Incremental*: focused on improving existing processes (e.g., faster response times, partial automation).
- *Transformational:* aiming to fundamentally change how the company operates or interacts with customers.

Interview format

- Duration: ~45 minutes
- Style: Semi-structured, conversational
- Focus: Your perspective and experiences, there are no right or wrong answers.
- Confidentiality: All responses will be anonymized. You may skip any question or stop at any time.

Background

1. Can you tell me a bit about your role and involvement in AI-related projects?

2. How long has your organization been using AI in customer-facing work, and what kind of tools or applications do you use?

3. What motivated your company to start using AI, efficiency, innovation, customer experience, or something else?

4. Before starting with AI, how ready was your organization in terms of data, technology, and skills? Which capabilities existed before AI, and which emerged afterward?

- Did you already have systems, expertise, or resources in place, or did you have to build them from scratch?

Ambition & Goals

5. When your organization first started using AI, what were the main goals?

- What did "success" look like at that time?

6. Which statement best describes your original ambition level?

- Incremental: "We wanted to optimize existing processes." (step by step)
- Transformational: "We wanted to fundamentally reinvent customer service." (Larger change consistent of many steps)

7. On a scale of 1–5, how ambitious were these goals overall?

- 1 = Small efficiency improvements
- 5 = Complete transformation of customer interaction

8. What influenced your company to choose this level of ambition in the first place?

- Internal factors (leadership vision, resources, existing skills, budget)
- External factors (competitive pressure, customer expectations, regulation)

Capability Development

10. How does your organization identify new AI opportunities or decide which ones to pursue?
    - Who or what usually drives those ideas, leadership, customer feedback, or data?
11. Do you have any specific roles, systems, or routines that help you spot new AI opportunities?

11. What new skills or capabilities did your organization need to develop to make AI work in customer-facing settings?

- Technical capabilities: data analytics, machine learning, automation tools, API integration.
- Process capabilities: agile workflows, faster decision-making, data governance.
- Customer-related capabilities: managing AI–human interaction, maintaining trust, personalization.
- Learning capabilities: experimenting, internal training, knowledge sharing.

12. Which of these capabilities were the most critical for success?

- Can you recall one concrete example (a project, person, or decision) that helped you develop a key capability?

14. How has your organization changed or learned since implementing AI?

- Have you restructured teams, created new roles, or adjusted workflows?

15. Can you describe one critical turning point during implementation?

- What happened, how did you respond, and what was the outcome?

16. What organizational changes were required as a result?

- New roles created
- Employees retrained
- Processes redesigned

17. Which two capabilities made the biggest difference to your success, and which two missing capabilities are holding you back today?

Outcomes & Gaps

18. Compared to your original goals, where would you say you are today?

- Exceeded / Met / Partially met / Did not meet (satisfied or not)

19. Did you reach these results within the expected timeline, or did it take longer (or shorter) than planned?

- If it took longer, what caused the delay?

20. Can you point to any signs or examples that show progress or success?

- (Examples: improved customer satisfaction, faster service, cost savings, new service offerings.)

21. What were the main barriers or challenges you faced?

- (Examples: data quality, lack of skills, resistance to change, unclear strategy.)

22. What factors most enabled your success?

- (Examples: management support, clear vision, external partnerships.)

23. Do you think your current capabilities now shape your future AI ambitions? How?

Closing

26. Is there anything important about your AI experience or capability development that we haven't covered?

9.2. Appendix 2: Email to Interview Subjects

Hi,

I hope you're doing well. My name is Elisa Stoica/ Ebba Andersson, and I'm a BSc student at the Stockholm School of Economics currently writing my bachelor thesis on how organizations use AI to improve customer-related work and what new capabilities or changes that creates inside the company.

I came across [Company Name]'s work in [specific area], and I believe your experience would provide valuable insights for my research.

The interview would take approximately 30-45 minutes, and will be held over Microsoft Teams or Google Meet. The goal is to understand how organizations set ambitions for AI, what capabilities emerge as a result, and what lessons are learned along the way. I can also share the interview questions beforehand to ensure everything is clear and aligned with your area of expertise.

Would you be open to participating in a short interview, or could you connect me with someone in your team who has been involved in AI implementation or digital transformation?

Thank you very much for considering this. I'd be happy to share a short summary of findings after the thesis is completed.

Warm regards,
Elisa Stoica/ Ebba Andersson
BSc in Business and Economics | Stockholm School of Economics

9.3. Appendix 3: Specifications of Interviews

Participant No.	Code	Ambition Category
1.	P1	Transformational
2.	P2	Transformational
3.	P3	Transformational
4.	P4	Incremental
5.	P5	Incremental
6.	P6	Incremental
7.	P7	Transformational and incremental
8.	P8	Transformational and incremental

Average Interview Length: Approx. 40:00

Interviews Locations: Microsoft Teams and Google Meet