FROM ALGORITHMS TO AGILITY

A QUANTITATIVE STUDY OF AI'S INFLUENCE ON DYNAMIC CAPABILITIES IN SWEDISH SMEs

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From Algorithms to Agility: A Quantitative Study of AI's Influence on Dynamic Capabilities in Swedish SMEs

Abstract:

This thesis explores the impact of Artificial Intelligence (AI) implementation on the dynamic capabilities (DC) of Swedish SMEs, focusing on the microfoundations of sensing, seizing, and transforming. Scholars agree that the DC conceptual framework needs to be validated through studies that explore the microfoundations of DC. Despite the burgeoning interest, empirical research on AI's effect on DC still needs to be expanded, particularly within the context of Swedish SMEs. This motivates this study to consider whether firms' AI implementation can give rise to DC. Survey data collected from 455 Swedish SMEs was analyzed through the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach, which provided sufficient basis to confirm that firms' AI implementation positively affects DC sensing, seizing, and transforming. The findings indicate that, within our model, AI significantly affects these DC, thereby supporting the theoretical proposition that AI can serve as a microfoundation for DC. This insight is of relevance to DC scholars as directionally indicative for future research, and managers in determining whether to invest in AI tools.

Keywords:

Dynamic capabilities, artificial intelligence, PLS-SEM, microfoundations

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Definitions

AI implementation (AII): Integrating AI technologies into business operations and strategies.

AI strategy and alignment (AIA): Setting goals, measuring effectiveness, aligning with business strategies, and adapting to technological changes.

AI organizational integration (AOI): Fostering cross-departmental collaboration and ensuring ethical use of AI.

AI operational execution (AOE): Mitigating risks, integrating AI into processes, and maintaining data governance.

Dynamic capabilities (DC): A firm's ability to adapt and reconfigure competencies in changing environments.

Sensing capabilities (SEN): Identifying and assessing opportunities and threats in the external environment.

Seizing capabilities (SEZ): Capturing and exploiting identified opportunities through strategic decisions.

Transforming capabilities (TRA): Reconfiguring resources and capabilities to maintain competitiveness.

Partial least squares structural equation modeling (PLS-SEM): A statistical method for modeling complex relationships between variables.

Competitive intensity (CI): The degree of competition within an industry.

Reflective-formative constructs: Constructs both influenced and formed by indicators.

Likert scale: A scale used in questionnaires to measure attitudes or opinions.

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1. Introduction

1.1. Background on dynamic capabilities

Within the realm of marketing, economics and management, researchers have long been interested in formulating a theory to explain firm performance (Ansoff, 1965; Kohli & Jaworski, 1990). It has become more important than ever to understand the drivers of success as business environments have become increasingly turbulent, with markets experiencing a higher rate of market shifts, or competitive intensity (Helfat & Peteraf, 2003). As such, academia's efforts have focused extensively on building the dynamic capabilities (DC) framework (Teece, 2014), which focuses on firm's ability to adapt to unpredictable shifts, integrate competencies, and reconfigure operational and strategic processes to become resilient to rising competitive intensity (Teece et al., 1997).

The framework's seminal paper is one of the most cited in business and economics and has grown to be one of the leading paradigms for understanding how firms can create a sustaining capacity for competition (Di Stefano et al., 2014; Schilke et al., 2018).

Notwithstanding its popularity, there remain gaps to be filled. The framework has long been criticized for lacking clarity on what capabilities are and how they ought to be measured (Schilke et al., 2018). This issue was compounded by the emergence of contrasting perspectives on the necessary boundary conditions under which DC arises, further complicating understanding (Di Stefano et al., 2014). However, theoretical developments have largely converged these perspectives and explicated conceptual underpinnings with more precise definitions and the integration of complementary frameworks, like the widely accepted resource-based view. These developments have been accompanied by more apt methodological practices, such as unified measurement scales, which have allowed for empirical work to produce contextual and practical insights into how DC behave (Eriksson, 2013; Schilke et al., 2018).

Much work has already been done to explore these microfoundations. There has been a wide array of literature produced on DC's relations with digital technologies (Macher & Mowery, 2009), organizational routines and culture (Bock et al., 2011; Felin et al., 2012), and the role of leadership (Kor & Mesko, 2013). Notable work on the role of

digital technologies in building DC has also been made (Steininger et al., 2021), marking it as a burgeoning research area with calls for pushing the DC framework into the internet frontier ever louder (Chen et al., 2023).

As globalization and the proliferation of digital technologies have intensified market volatility, the need for firms to nurture capabilities that adapt to these changes has intensified. This digital landscape has also allowed firms to become increasingly agile and rapid in responding to change (Teece, 2014).

1.2. Background on artificial intelligence

Driven largely by the public's increased access to artificial intelligence (AI) through the release of large language models (LLMs) like OpenAI's ChatGPT and Google's Gemini, much enthusiasm has recently surrounded AI (Eloundou et al., 2023). This has brought attention to AI's broader capabilities, which extend from automating routine tasks to facilitating complex decision-making processes, thereby reshaping the strategic landscape of businesses globally (Mikalef et al., 2023). A recent U.S. government census indicated that the use of AI almost doubled between September 2023 and February 2024 (Bonney et al, 2024). During the same period, a Gartner report showed that 61% of surveyed firms experienced some degree of disruption as a consequence of the proliferation of LLMs like ChatGPT (Gartner, 2024).

Marketing teams have not been insulated from AI. An industry report found that 64% of respondents thought that "AI is either very important or critically important to the success of their marketing over the next 12 months" (Eloundou et al., 2023). In marketing, the benefits of AI implementation seem to be mostly found in AI's capability to handle large volumes of data. This enhanced capacity which has allowed marketing professionals to better analyze consumer behavior patterns and understand market trends substantial data has led to more effective marketing strategies, increased personalization in customer relationship management systems, and better decision-making through predictive analytics (Ledro et al., 2022; Davenport et al., 2021).

Despite the wide array of accounts heralding the benefits of AI in enhancing organizational efficiency, implementation efforts have not gone unencumbered. An MIT Sloan report showed that 4 out of 10 firms saw little to no business gain from significant investments in AI technologies (Ransbotham et al., 2019)**.** Similarly, a Deloitte survey found that only a minority of firms are seeing significant efficiency gains (Deloitte, 2024). Brynjolfsson et al. (2017) attribute this to implementation lags and the need for complementary technologies necessary for effective integration. To overcome these difficulties and realize the potential of AI, firms may invest in skill development and, through thoughtful management practices, ensure careful planning and deployment. Notwithstanding these hurdles, the prevailing optimism about AI's potential remains robust, as noted by various reports which underscore that beyond the learning curve exists real tangible business value waiting to be captured (Deloitte, 2024; McKinsey, 2024).

1.3. Purpose and expected contribution

AI's potential to generate business value has garnered significant attention. AI implementation has been heralded as a transformative resource for firms to sustain competitive advantage in increasingly digital markets in the face of increasing competitive intensity. Exploring these claims is of interest to DC scholars as it might provide insight into the microfoundations of sensing, seizing, and transforming (Vo Thai et al., 2024). This work might be of interest to the marketing domain as elucidation of the interaction between AI and DC allows for insights which can direct future scholarly work on understanding the nature of the impact of AI implementation on marketing activities.

Yet, perhaps due to adoption still being in its early stages, research on a firm’s use of AI is still nascent, as is its effect on DC. This gap presents an opportunity to contribute to the field by potentially elucidating some of the underlying mechanisms that allow for DC to foster and, by extent, for value to be realized and competitive advantages to accrue (Mikalef et al., 2023). Furthermore, whilst the DC framework's conceptual

development has grown rich since its inception, several authors have called for further empirical work in new settings (e.g. Ambrosini, 2009; Schilke et al., 2018).

In studying Swedish SMEs' implementation of AI and its effect on DC, this study aims to contribute to the conceptual literature on DC by exploring AI microfoundations and extending the scope to Swedish SMEs. In line with its purpose, this study's research question has been formulated to be:

Does AI implementation affect dynamic capabilities in Swedish firms?

1.4. Delimitation

The ontology of interpretivism, which runs counterfactual to the objectivism adopted for this thesis, is the most preferred method in efforts to understand the building blocks of DC. This is elaborated upon in this paper's methodology section. Similarly, it is research of a qualitative or longitudinal nature that might allow for the production of insights tied to the microfoundations of DC. The authors of this study acknowledge that as a consequence of adopting a quantitative approach, there is a loss of depth and detail. This choice suits this paper's exploratory as a quantitative approach allows for investigating the existence of any meaningful relationship by looking at broad patterns.

Furthermore, quantitative DC research has focused on examining the effects of DC as an independent variable - most often firm competitive advantage, performance, or sales. Whilst DC was considered as a moderator and an antecedent in the model, they were due to practical considerations. Additionally, measuring competitive advantage, or similar constructs, would require soliciting the subjects for information, which could introduce bias. As such, due to practical considerations, these delimitations were adopted so that the limited scope of the study could be on the precision of the DC field.

Furthermore, the survey's sampling was limited in scope. Swedish SMEs were in focus. Specifically, target interviewees encompass CEOs, CIOs, marketing managers, and other departmental heads. Higher-level positions will provide a broader understanding of the company's business model and strategic development and, thus, are deemed to be

able to more easily gauge the level of implementation and the manifestations of different DC.

2. Theory and hypothesis development

2.1. Dynamic capabilities theory

As markets become global and new technologies promote increasingly volatile market conditions, Teece et al. (1997) posited that existing strategic management theories, such as the resource-based view (RBV) and Porter's Five Forces, did not extend beyond explaining how firms might build competitive advantages in static market conditions, and did not account for how firms ought to adapt to new environments (Cordes-Berszinn, 2013). They proposed the DC framework to create a conceptual body of work that could explain how firms could not only build, but also retain competitive advantages. The DC theory was formulated to explain the need for how firms, over time, strategically adapt their organization, underlying capabilities and resources to stay competitive. Firm performance is contingent on their ability to nurture the three principal parts of DC: sensing, seizing, and transforming (Teece, 2014).

Integrating AI across organizational units has been shown to break down silos and facilitate the flow of information, thereby allowing firms to **sense** their external environment and identify emerging opportunities and threats (Steininger et al., 2021). AI technologies, which monitor the external environment through advanced data analytics and machine learning models, have allowed trades to be executed by real-time price adjustments in financial markets (Boukherouaa et al., 2021). This capability enables firms to **seize** opportunities or preempt threats by proactively engaging in decision-making and deploying resources accordingly. Furthermore, the transformative impact of AI extends to the **transformation** of organizational processes and capabilities, ensuring that firms are not only reactive but also adaptive to changes (Steininger et al., 2021).

2.2. Competitive intensity

Though preceding the DC framework (Porter, 1985), the notion of competitive intensity is a central tenet in the theory (Schilke et al., 2018)**.** Competitive intensity refers to the degree of competition within an industry characterized by the presence of rivalries, velocity of market entry, and frequency of disruptions (Teece, 2007). There was long contention in the DC literature about whether the mere possession of DC leads to competitive advantages, or if the creation of DC is mostly actualized under competitive intensity (Di Stefano et al., 2014).

For research on DC's microfoundations, it is vital that this aspect of competitive intensity is captured as it is salient to explore how the foundational elements of DC are affected by competitive intensity in relation to what they purport to build (Steininger et al., 2021; Warner & Wäger, 2019). This is the principal motivation of including competitive intensity in the model as a moderator.[1] It was measured through the variable c*ompetitive intensity* (CI) which was adopted from Wilden et al. (2013) as a complement to the other DC measurements proposed and adopted by Kump et al. (2019). This construct was measured to capture the degree of competitive pressure experienced by firms. Respondents evaluated competitive intensity on a 7-point Likert scale (1 – Not intense at all, 7 – Extremely intense).

2.3. Microfoundations of DC

There seems to be wide consensus in the literature that the directional nature of future DC empirical work should be towards furthering the understanding of its microfoundations (Durán & Aguado, 2022; Herath & Harrington, 2022; Huy & Zott, 2018). This domain is the subject of increasing attention by substantial contributors to the DC domain and the wider scientific community alike as the number of studies has, in recent years, increased rapidly. Perhaps because it is still an emerging field, it has

[1]Competitive intensity is widely accepted to moderate the effect of DC. Whilst existing literature is cohesive on its importance on the formulation of DC, there lacks conceptual clarity and empirical basis to model competitive intensity as a moderator from microfoundations to DC. According to Söderlund (2023), the inclusion of moderators should be consistent with theory, and, as such, the moderator *competitive intensity* is of exploratory nature, and hopes to uncover insights around the contextual nature of the effects of competitive intensity. (Söderlund, 2023)

been subject to fragmentation, much like the uncoordinated developments of the DC framework in the years after its genesis (Schilke et al., 2018). Not until 2023, was it afflicted by the absence of a cohesive literature review. In less than two years, it received over 200 references, signaling the broad interest in a synthesis of knowledge in the area. Besides providing a foundational basis of knowledge around DC's microfoundations, they identified how past methodologies used to study DC microfoundations were transposed from RBV theory. This misalignment failed to account for the very essential conditions under which DC are formed (Chen et al., 2023).

Microfoundations are the individual-level processes that underpin DC. Studies have focused on exploring specific actions and behaviors, technological use, or deployment of human capital (Felin & Foss, 2011). Without a clear understanding of the micro-level elements that make up DC, it is bound to receive critiques of vagueness. Thus, researchers have endeavored to explore these so that the conceptual framework might provide detailed and actionable insights into how DC might be cultivated. In line with recommendations of literature reviews (Schilke et al., 2018), the conceptualizing of AI has shown that by integrating data-driven insights into the adjustment of organizational processes, AI can deliver value by differentiating the organization's capabilities from that of competitors (Steininger et al., 2021; Helfat & Peteraf, 2003).

Exploring AI as a microfoundation in the context of DC is beneficial as it provides an understanding into how firms can actualize value from AI investments within the conceptual framework of DC. As such, it informs research that can evaluate AI as a critical resource to sustain competitive advantages in volatile markets. This approach not only enhances the empirical relevance of the DC framework by extending applicability but also offers practical insights for leveraging technology effectively in dynamic environments. Such an investigation enriches our understanding of the strategic implications of AI in business.

2.4. Conceptualisation of AI implementation

2.4.1. AI and DC

As previously described, scholars have become increasingly occupied with understanding which microfoundations allow DC to be operationalised. Not surprising given this digital age, much effort has been channeled towards exploring how information systems, digital literacy, technological penetration in firms, use of new technologies, innovative management, and other aspects of technological implementation can affect firms' long-term prosperity (Li et al., 2018; Palmié et al., 2021; Scuotto et al., 2023; Steininger et al., 2021; Zahoor et al., 2023).

Not until recently has firms' AI implementation been of notable interest to DC researchers. Advancements in this area have particularly been made by Patrick Mikalef, of Norwegian University of Science and Technology, and co-authors in their work to understand the intersection of AI and DC in different contexts and under varying circumstances. Their research has emphasized how AI technologies can enhance firms' ability through AI-driven insights, which facilitate strategic decision-making and operational efficiency in organizations (Mikalef & Gupta 2021, Mikalef et al., 2023; Steininger et al., 2021). Recognising the potential AI implementation may hold for firms as suggested by research done thus far, they, and others, continue to propagate for further study in this novel field (Schilke et al., 2018; Steininger et al., 2021).

2.4.2. Definition of AI and AI implementation

Lately, AI has often been used interchangeably with the narrower definition of generative AI, specifically with Large Language Models (LLMs) such as ChatGPT that use machine learning to understand text and image prompts to which it responds in a human-like manner (Lamarre, 2024). The actual definition of AI can, in broad terms, be defined as computer systems’ capacity to mimic human capabilities of problem-solving. Still, what is actually meant when the phrase artificial intelligence is used is not immediately clear. As such, it can generally be considered a general-purpose technology.

Having established what the use of AI in this paper refers to, it is important to note that it is not only the *implementation of AI,* as such, which is of interest, but *AI*

implementation. The subtle difference is that the former focuses on putting AI technologies to use, whilst the latter includes far-reaching strategic and organizational implications for firms, hoping to extract value from the use of AI technologies. Thus, this study's broad definition of AI implementation includes the planning of AI integration, the alignment of strategy and communicating that strategy within the firm, the building of feedback loops, and ensuring effective deployment (Ångström et al., 2023)**.** It is crucial to include the surrounding practices and processes as they facilitate the operationalisation of AI, as this thesis hypotheses that AI implementation, as a microfoundation, allows for DC to be operationalised (Brynjolfsson et al., 2017; Mikalef & Gupta, 2021).

2.4.3. AI implementation construct and segmentations

For the structural model, AI implementation (AII) was hypothesized as a Type II second-order reflective construct composed of three first-order formative constructs (Jarvis et al., 2003). This proposed composition of AI implementation is consistent with the guidelines from Diamantopoulos and Winklhofer (2001). The formative nature includes first-order constructs being theoretically distinct and contributing to a unique aspect of the second-order construct. As such, AI implementation was measured and assessed through the three AI-related constructs - *AI strategy and alignment*, *AI organizational integration,* and *AI operational execution* - which, in turn, was measured through the questionnaire. These were formulated with the hope of capturing the broad definition of AI implementation as described in the previous segment.

The antecedent variable of *AI strategy and alignment* (ASA) encompasses factors that ensure that AI is leveraged effectively within the scope of the organization's wider mission. The deployment and adoption of AI technologies need to be precipitated by thoughtful coordination between strategy and operations (Brynjolfsson et al., 2017; Ångström et al., 2023). Such organizational alignment is critical in markets with high competitive intensity (Kiron et al., 2023).

Firms' ability to effectively utilize AI is reflected in the absence of friction between AI tools and the function of other employees, ways of working, processes and practices; this is contingent on the firm's ability to effectively integrate (Mikalef et al., 2022). The conditions which allow for smooth integration is measured through the antecedent

variable of *AI organizational integration* (AOI), which inquires into the level of cross-departmental collaboration which leverages diverse expertise, and optimized resource utilization; the effective communication of the benefits of AI use to different vestiges in the firm; and ethical usage which mitigates risk and long-term sustainability (Chatterjee et al., 2021).

In order for firms AI implementation to be effective, it is of consequence to inquire into the nature of firms enactment and implementation. As such, the antecedent variable of *AI operational execution*, which encompasses several critical factors. It measures the integration of AI into business processes and in so measures how AI tools function within existing workflows and systems. Furthermore, it covers the presence of robust practices on risk mitigation which is important due to the black box nature of AI. As such, it is crucial that there is strategy in place which ensures the safety and ethicality of AI systems towards the wider organization (Mikalef et al., 2022; Peretz-Andersson et al., 2023)

2.5. Hypotheses

In the context of the DC framework, this study aims to explore the influence of microfoundations of DC, disaggregated into sensing, seizing, and transforming capabilities, by the sample firm's AI implementation. The motivation for this study is rooted in the potential of AI to enhance business value and sustain competitive advantage, a topic that has garnered attention but remains underexplored in the DC literature (Mikalef et al., 2023; Ågerfalk, 2020). These hypotheses are further designed based on the scope of Swedish SMEs. As such:

- H1: AI implementation (AII) has a positive effect on sensing capabilities (SEN).
- H2: AI implementation has (AII) a positive effect on seizing capabilities (SEZ).
- H3: AI implementation has a (AII) positive effect on transforming capabilities (TRA).

2.5.1. Hypothesis generation

Our conceptual framework, as shown in Figure 1, includes the hypothesized effects of H1, H2, and H3, as well as competitive intensity as a moderating variable. As

explained, it is a moderator of exploratory nature and its inclusion is, as such, reflective of a tentative conceptualisation.

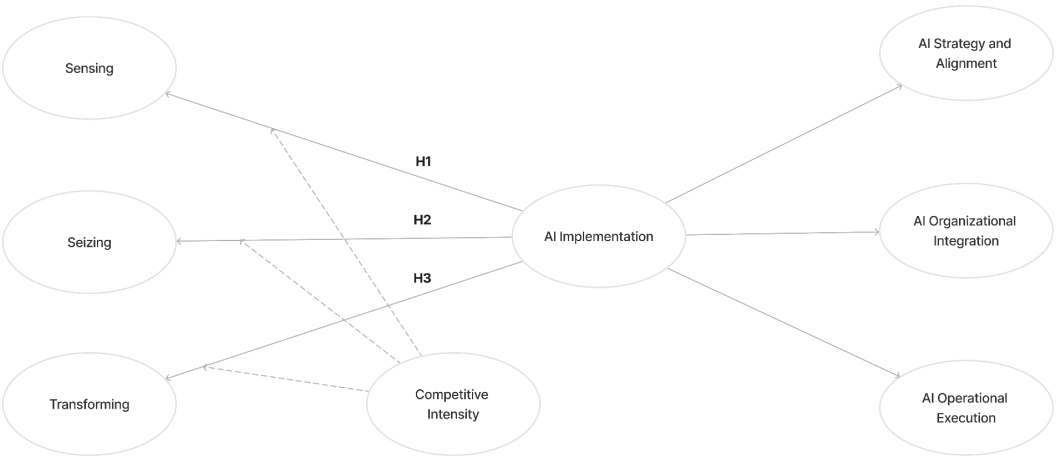


Figure 1: Conceptual Measurement Model

3. Methodology

3.1. The scientific approach to research design

This paper's motivation to explore how AI implementation might build DC was the guiding north star in deciding how our research would be conducted. The nature and the degree of a firm's AI implementation, as well as the level of DC at the firm, are, for this study, assumed to manifest in the social and objective fabric of reality. As such, this study was ontologically designed based on the tenets of the objectivist paradigm. Objectivism makes the assertion that reality can be reliably observed, which can create empirics to be used to further understand that reality. This, in turn, prescribes an epistemology of positivism (Bell et al., 2022).

This aligns with the study's purpose so that observations might be deductively used to assess the hypotheses, i.e., AI's effects on DC. This paper's authors conducted a cross-sectional study to gather quantitative survey data. This descriptive research is underscored with the positivist aim for findings to be generalisable as the qualitative method applied through surveys allowed for gathering substantial data, which might then be used to identify patterns and effects. The quantitative research design allowed for statistical analysis to model the relevant relationships, hoping that the research outcome would allow for applicability and the deriving of explanatory value. The described approach for the research design is found in AI and DC research, as in the literature with a foot in both domains (Schilke et al., 2018; Steininger et al., 2021).

3.1.1. Alternative approaches

As described, this study's research design assumes that AI implementation and DC can be observed. It is this assumption's extension to DC which is worthwhile discussing. It is important to note that the theoretical literature on DC, starting from Teece et al.'s (1997) seminal paper to the wealth of work that has been produced since, is in broad agreement that DC should be inferred and sought to be understood through an analysis of a firm's processes and. This suggests that DC research should be designed through an interpretive paradigm and with longitudinal and case studies such as described by

Akwei (2007) in their important work on methods to measure DC. In their study, they explore qualitative methods for measuring DC and highlight their value in understanding contextual factors that might otherwise be missed through quantitative methods (Akwei, 2007). Nevertheless, they and others appreciate the importance of quantitative methods in determining effects on and of DC across contexts to develop and validate the conceptual framework. Furthermore, there exists consensus among researchers regarding the need for research which demonstrates the operationalisation of DC (Steininger et al., 2021).

These elements of this study research and study design are devised based on unified and standardized methodologies used by studies which make up the broad empirical literature of DC (Karna et al., 2016; Kump et al., 2019). Furthermore, literature reviews and meta-studies which synthesize DC work show that this paper's design is of a widely accepted fashion (Steininger et al., 2021).

It should be noted that this particular study design was further motivated by limitations imposed by time considerations and scope, which made, e.g., longitudinal or mixed methods studies impractical. Whilst other qualitative approaches could have been adopted, this study's quantitative method is motivated as it allows for the current understanding of DC's effects to be extended to this study's novel purpose in exploring AI implementation in the context of DC. To that end, the nature of the research and study design is crucial to develop insights and explore the conceptual framework's applicability in a new domain (Bell et al., 2022).

3.2. Survey design and assessment

The survey was designed in accordance with the study's aim to assess how the implementation of AI affects the DC, sensing, seizing, and transforming, as well as the study's scope of Swedish SMEs. As such, it sought to understand these two separate constructs of DC and AI which are often latent and not observable. To that end, multiple indicators for each latent variable were designed to ensure more reliable and substantial measurements. Furthermore, questions were designed, where possible, in accordance with the literature and standardized measurements.

3.2.1. Data collection and distribution

We employed the online survey platform Qualtrics to collect empirical data needed to support our research model. The survey was sent to 2,343 C-suite executives across Sweden via email, containing a concise introduction, study objectives, and a link to the survey. This approach is defined by Bell et al. (2022) as convenience sampling, targeting respondents readily available within our network.

The survey began with a detailed explanation of its purpose and an explicit invitation to give GDPR consent; those who did not consent were automatically excluded from the survey. The questionnaire comprised 15 main questions divided into three sections that explored AI implementation (16 subquestions), DC (14 subquestions), and competitive intensity (Figure 2).

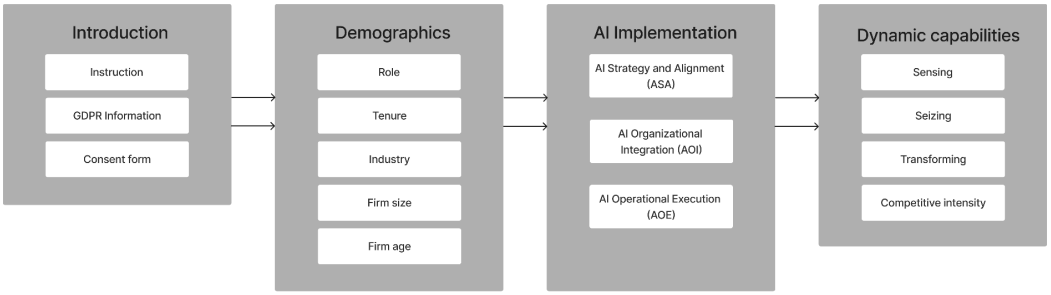


Figure 2: The survey's main components and the survey flow

3.2.2. Data quality

When survey responses were no longer being collected, this methodology yielded 455 usable responses. Qualtrics recorded that a total of 538 recipients had opened the survey; out of those, 499 had actually completed the survey. 120 respondents only partially answered the survey. These were not removed as the missing values were categorized as missing not at random (MAR). This was to avoid introducing bias in the data, as participants who chose not to answer specifically may have different characteristics than participants who did. Their inclusion was made possible by the fact that SmartPLS can be used to handle missing values (Ringle et al., 2024).

The total response rate was 23%, and of these participants, the completion rate was 92%. See Appendix A for full details of the respondent's characteristics and demographics.

3.2.3. Data analysis

For analyzing purposes, the data collected from the survey was exported into SmartPLS as SmartPLS can handle a wide variety of reliability and consistency measures (Ringle et al., 2024). PLS-SEM is particularly effective for dealing with complex models and accounting for a range of interactions. This makes PLS-SEM an especially apt choice for DC research, as complex interactions can be modeled through both formative and reflective latent variables, which enables researchers to more granularly evaluate construct relationships. Moreover, as PLS-SEM explicitly incorporates error terms, the significant effects are explained (Hair et al., 2017).

3.2.4. GDPR

The empirical data collected has been handled according to the information on General Data Protection Regulation (EU Regulation 2016/679, 2016). In accordance with the guidelines of GDPR, we only collected relevant and necessary personal data, and participants were asked to give explicit consent before proceeding with the survey.

3.2.5. Questionnaire and measurements

Independent and dependent variables

As this study is concerned with the implementation of AI's impact on DC, *sensing, seizing,* and *transforming* are used as dependent variables. *AI implementation* was created as an index of the three AI constructs: *AI strategy and alignment, AI organizational integration,* and *AI operational execution*. These three are seen as the reflective constructs of the formative second-order construct *AI implementation* which is used as the independent variable. Furthermore, *competitive intensity* is seen as an exploratory moderating variable that is not included in the hypothesis testing.

Questionnaire measurements

The questions used in this survey were both created and adopted from previous research. The DC questions were adopted from Kump et al.'s (2019) paper and Wilden et al.'s (2013) research, while the AI implementation questions were adapted and created from a wider arrangement of previous research due to the lack of a unified measurement scale. All measurements but demographics were assessed on a 7-point Likert scale with anchoring at every point, from *strongly disagree* (1) to *strongly agree* (7). A summary of the constructs used and their adaptations and adaptations can be seen in Table 1 while the complete set of questionnaire items can be found in Appendix B.

Construct	Description
AI strategy and alignment (ASA)	Assessed as a reflective first-order construct comprising four key aspects: (1) establishing clear goals and objectives, (2) effective measurement through key performance indicators (Mikalef & Gupta, 2021), (3) ensuring alignment with business strategies, and (4) conducting regular reviews and updates (Mikalef et al., 2023). Adapted from Jankovic & Curovic (2023) and Mikalef et al. (2023).
AI organizational integration (AOI)	Measured as a reflective latent variable composed of three dimensions: (1) fostering cross-departmental collaboration, (2) communicating AI benefits effectively, and (3) ensuring ethical usage of AI. Adapted from Chatterjee et al. (2021), and Mikalef et al. (2023).
AI operational execution (AOE)	Evaluated as a reflective first-order construct comprising three elements: (1) systematic risk mitigation, (2) integration of AI into core organizational processes, and (3) maintaining robust data governance and automation practices. Adapted from Mikalef et al. (2022) and Peretz-Andersson et al. (2023).
Sensing	Measured through survey questions designed to assess activities such as monitoring technological advancements, customer needs, and market trends. Adopted from Kump et al. (2019).
Seizing	Measured through questions examining strategic decision-making processes based on insights from sensing activities, focusing on transforming sensed opportunities into actionable strategies and innovations. Adopted from Kump et al. (2019).
Transforming	Assessed through questions evaluating adaptation to current market conditions and proactive measures to shape the organization's future trajectory. Adopted from Kump et al. (2019).

Competitive intensity	Adopted from the activity-based survey proposed by Wilden et al. (2013) to capture the degree of competitive pressure experienced by firms.
Demographics	Participants were asked to submit firm size, age, role, and tenure. Firm size was measured as an ordinal variable following the European Commission's size-class recommendations: micro (0–9 employees), small (10–49 employees), medium (50–249 employees), and large (> 250 employees). Adopted from Arend (2014) and EU Commission (2003).

Table 1: A summary of the measurements used in the survey

3.3. Reliability and validity

Before the hypotheses may be accepted or rejected, the reliability and validity of the underlying measurement model must be ensured. The measurement model's reliability and validity were rigorously assessed. Reliability ensures that the measures used are consistent and accurate, while validity checks whether the measures accurately capture the intended concepts (Saunders et al., 2009). The statistical significance of the measurement and structural model was evaluated through bootstrapping with 5000 subsamples (Hair et al., 2021; Streukens & Leroi-Werelds, 2016). Reflective models were analyzed to determine the contribution of each observable variable (outer loadings) and each indicator (outer weights) to their respective constructs, with loadings above 0.5 deemed acceptable (Calvo-Mora et al., 2005; Matsunaga, 2010). However, item Q7_1 in AI organizational integration and item Q14_3 in Competitive Intensity displayed loadings of 0.436 and 0.602 respectively and were thus removed (Appendix C).

3.3.1. Reliability

Both Cronbach's Alpha (CA) and Composite Reliability (CR) for first-order reflective latent variables surpass the recommended threshold of 0.70, indicating strong reliability (Hair, 2021) (Table 2). Additionally, construct-to-item loadings were confirmed to be above 0.6, validating convergent validity (Hair et al., 2017; Malhotra et al., 2006; Shi & Maydeu-Olivares, 2019); see Appendix C for full details on loadings.

	Cronbach's alpha (CA)	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AI operational execution	0.86	0.87	0.90	0.55
AI organizational integration	0.77	0.78	0.86	0.68
AI strategy and alignment	0.90	0.90	0.93	0.78
Competitive intensity	0.83	0.88	0.88	0.64
Seizing	0.84	0.84	0.89	0.67
Sensing	0.87	0.88	0.91	0.66
Transforming	0.86	0.88	0.90	0.64

Table 2: Construct reliability and validity

3.3.2. Validity

The Average Variance Extracted (AVE) values for the constructs exceed the threshold of 0.5, confirming convergent validity (Fornell & Larcker, 1981), as previously seen in Table 2. In models employing formative indicators, such as AI implementation as a formative second-order construct, it is crucial to control collinearity among lower-order constructs to ensure stable estimates. The Variance Inflation Factor (VIF) for each construct is below the maximum accepted value of 5, indicating an absence of multicollinearity (Kleinbaum et al., 1988). These results are presented in Table 3.

	VIF
AI implementation -> Seizing	1.136
AI implementation -> Sensing	1.136
AI implementation -> Transforming	1.136
AI operational execution -> AI implementation	2.964
AI organizational integration -> AI implementation	2.171
AI strategy and alignment -> AI implementation	2.97

Age -> Seizing	1.628
Age -> Sensing	1.628
Age -> Transforming	1.628
Competitive intensity -> Seizing	1.148
Competitive intensity-> Sensing	1.148
Competitive intensity-> Transforming	1.148
Size -> Seizing	1.586
Size -> Sensing	1.586
Size -> Transforming	1.586
Competitive intensity x AI implementation -> Seizing	1.018
Competitive intensity x AI implementation -> Sensing	1.018
Competitive intensity x AI implementation -> Transforming	1.018

Table 3: Variance inflation factor (VIF) of constructs

Discriminant validity, which ensures distinctiveness among constructs, was verified using two methods: the Fornell-Larcker method and HTMT (Fornell & Larcker, 1981; Hair et al., 2014), with results detailed in Table 4, and Table 5.

	AOE	**AOI**	**ASA**	**AGE**	**CI**	**SEZ**	**SEN**	**SIZE**	**TRA**
AOE	**0.742**								
AOI	0.693	**0.824**							
ASA	0.785	0.707	**0.881**						
AGE	-0.204	-0.08	-0.184	**n/a**					
CI	0.331	0.182	0.245	-0.138	**0.802**				
SEZ	0.615	0.349	0.558	-0.349	0.39	**0.82**			
SEN	0.548	0.553	0.544	-0.175	0.405	0.54	**0.812**		
SIZE	-0.095	-0.091	-0.127	0.601	0.042	-0.24	-0.056	**n/a**	
TRA	0.374	0.208	0.342	-0.269	0.399	0.67	0.469	-0.149	**0.797**

Table 4: Fornell-Larcker Criterion

	AOE	AOI	ASA	AGE	CI	SEZ	SEN	SIZE	TRA
AOE									
AOI	0.848								
ASA	0.886	0.833							
AGE	0.239	0.22	0.159						
CI	0.4	0.252	0.288	0.191					
SEZ	0.709	0.409	0.641	0.349	0.484				
SEN	0.601	0.685	0.619	0.186	0.463	0.603			
SIZE	0.223	0.233	0.126	0.591	0.041	0.258	0.112		
TRA	0.43	0.249	0.389	0.296	0.496	0.769	0.495	0.158	
CI X AII	0.108	0.137	0.119	0.068	0.058	0.11	0.032	0.092	0.159

Table 5: Heterotrait-Monotrait (HTMT) criterion

4. Results

Before the hypotheses may be accepted or rejected, the reliability and validity of the underlying measurement model must be ensured. The choice of PLS-SEM is justified by the exploratory nature of the research, the complexity of the structural model involving multiple constructs, indicators, and model relationships, and the focus on testing a theoretical framework from a predictive standpoint (Hair et al., 2017).

The analysis proceeds in three stages:

1. Developing the path model equation
2. Evaluating the measurement model
3. Assessing the structural model

AI implementation was conceptualized as a second-order formative construct and evaluated using a repeated indicator approach.

4.1. Structural model assessment

The hypotheses of the PLS-SEM model were analyzed in two steps: initial PLS analysis of item-construct relationships, followed by structural model testing with bootstrap resampling (Anderson & Gerbing, 1988). The findings support the proper definition of the first-order reflective constructs and confirm the adequacy of each construct's items as indicators of the latent constructs (Appendix D).

Following the assessment of the measurement instrument's quality, the proposed model was estimated using a repeated indicator approach (Ringle et al., 2024). See Figure 3 for the model specification. It was found that all dimensions of Artificial Intelligence implementation demonstrated significant loadings ($p<0.001$) on their respective constructs.

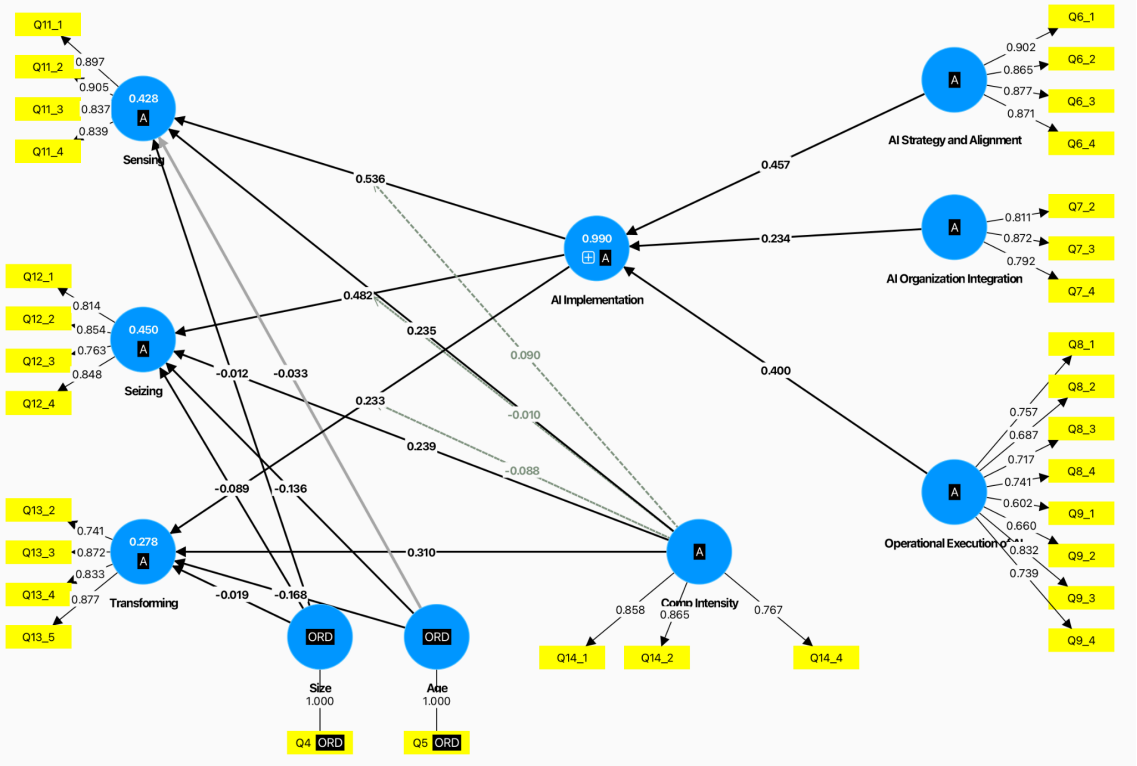


Figure 3: Full structural model specification

The PLS-SEM algorithm quantified the model relationships through path coefficients, indicating the hypothesized relationships between the constructs. These coefficients, significant at levels exceeding zero, suggest positive relationships with the details and levels of significance (t-values or p-values) displayed. The results confirm that all research hypotheses are positively significant. The total effect values are 0.482 for SES ($p<0.001$), 0.536 for SEZ ($p>0.001$), and 0.233 for TRA ($p<0.01$), demonstrating significant influences across these constructs, as seen in Table 6 and the full details in Appendix E.

Hypothesis	β	T statistics (|O/STDEV|)	P values
AII -> SEN	0.536***	7.572	0
AII -> SEZ	0.482***	5.63	0
AII -> TRA	0.233**	2.62	0.004

*Note: ***p<0.001, **p<0.01,*p< 0.05*

Table 6: Hypothesis testing results

The Coefficient of Determination (R^2) measures how much of the variance in endogenous constructs is explained by exogenous variables. Unlike the standard R^2, the Adjusted R^2 compensates for the number of explanatory constructs and the sample size, providing a more nuanced understanding of the model's explanatory power without the bias of model complexity. In this study, the R^2 values indicate the following explanatory powers: SEZ at 45%, SEN at 42.8%, and TRA at 27.8%. The Adjusted R^2 values are slightly lower, reflecting adjustments for the model's complexity (Table 7).

Variable	R-square	R-square adjusted
Sensing (SEN)	42.80%	40.10%
Seizing (SEZ)	45.00%	42.40%
Transforming (TRA)	27.80%	24.40%

Table 7: Coefficient of Determination

4.2. Hypothesis testing

H1: AI implementation enhances sensing capabilities

AI implementation significantly increases sensing capabilities, evidenced by a beta coefficient of 0.536, a T statistic of 7.572 and a P value of 0.000. Thus, H2 is accepted.

H2: AI implementation enhances seizing capabilities

AI implementation has a statistically significant positive effect on seizing capabilities with a beta coefficient of 0.482, a T statistic of 5.63 and a P value of 0.000. Thus, H1 is accepted.

H2: AI implementation enhances transforming capabilities

AI implementation positively impacts transforming capabilities, with a beta coefficient of 0.233, a T statistic of 2.62 and a P value of 0.004, indicating statistical significance. Thus, H3 is accepted.

The conclusion of the hypothesis testing is summarized in Table 8.

Relationship	Hypothesis	Results
H1: AII -> SEN	AI implementation enhances sensing capabilities	Supported
H2: AII -> SEZ	AI implementation enhances seizing capabilities	Supported
H3: AII -> TRA	AI implementation enhances transforming capabilities.	Supported

Table 8: Conclusion of hypothesis testing

5. Discussion and conclusion

Microfoundations have been described as “reliable causal mechanisms to explain DC and their consequences” (Salvato & Vassolo, 2017).

This study explored how artificial intelligence (AI) might be shown to influence the DC of Swedish SMEs to examine whether AI implementation could be considered to be a microfoundation to the DC sensing, seizing, and transforming, as described by Teece et al. (1997). To this end, AI implementation was further disaggregated into the AI variables strategy and alignment, organizational integration, and operational excellence. Furthermore, the exploratory moderator of competitive intensity was included to measure the nature of the effect of a foundational concept in the DC literature on our hypothesized relationship.

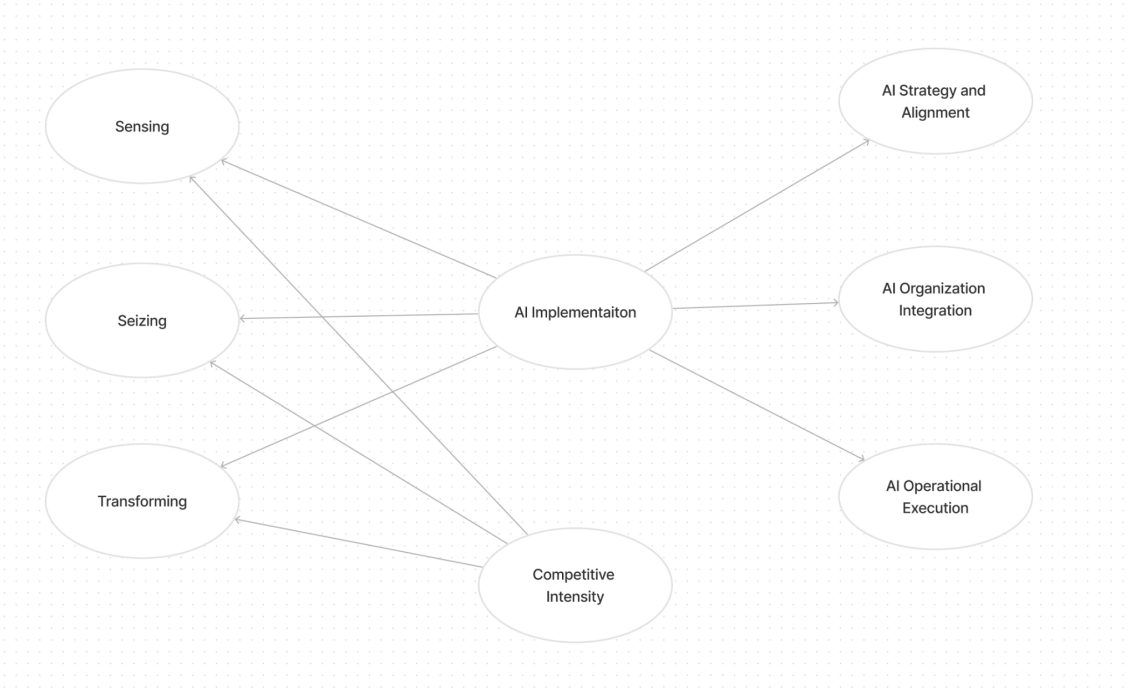


Figure 4: Revised conceptual measurement model

The main findings of the study will first be presented. The research question posed - *does AI implementation affect dynamic capabilities in Swedish firms?* - was evaluated based on the formulated hypotheses. The findings of this study, indeed, show that DC is influenced by a firm’s AI implementation. This was confirmed as all three hypotheses were accepted.

5.1. AI implementation's impact on sensing capabilities

Hypothesis 1 - *AI implementation has a positive effect on sensing capabilities* - was accepted. Thus, this study's findings demonstrate that the degree to which a firm can develop the DC of sensing is impacted by their AI implementation, as indicated by the model's robust statistical results, which show a positive impact ($\beta=0.536$, $p<0.001$). These results are consistent when one bridges Teece's conception of DC with the present understanding of AI implementation at first. Machine learning algorithms and advanced data analysis, can allow firms to quickly receive information about changes in the environment through these technologies' capacity to discover the emergence of patterns long before humans or ordinary organizational capabilities, like simpler data aggregation technologies (Steininger et al., 2021).

5.2. AI implementation's impact on seizing capabilities

Similarly, hypothesis 2 - *AI implementation has a positive effect on seizing capabilities* - was accepted. The results were almost equally as robust as those for hypothesis 1 ($\beta=0.482$, $p<0.001$). From this, one may conclude that the model explains that AI implementation can aid firms in acting on the opportunities identified during the sensing phase. This finding can be understood through the findings on AI-driven insights that can lead to modifications in business strategies, operational processes, and even organizational structures, aligning them more closely with current market demands and future projections.

5.3. AI implementation's impact on transforming capabilities

Similarly, hypothesis 3 - *AI implementation has a positive effect on transforming capabilities* - was accepted. Although the effects are positive and significant ($\beta=0.233$, $p=0.004$), they are of a somewhat weaker magnitude. This might be explained by the novel nature of AI adoption that has yet to allow for transformation capabilities to properly manifest to the same extent as sensing and seizing capabilities. As there is less empirical research on the digital microfoundations of transforming, like with the previous two DC, the smaller magnitude of the effect is not understood. Nevertheless, the positive effect is salient to researchers who are interested in microfoundations.

If the research on other digital microfoundations were to be extended to AI, this could be explained by the supposition that AI implementation can help firms by recommending how the firm should reconfigure its organizational processes and capabilities in response to industry dynamics (Karna et al., 2016).

5.4. Model specification and explanatory power

The proximity between the R-squared and R-squared adjusted, as described in Table 1, indicates that the model is appropriately specified, which implies that adding additional variables will most likely not improve its explanatory value. Whilst that might entail that this model has been modeled and calibrated correctly based on the existing data, the relatively high R-Square values of sensing and seizing, but to a lesser extent transforming, indicates that the model has some explanatory value. The independent variables indicator's factor loadings are generally above the 0.7 threshold, which means that our variable can be explained by our questions. This reinforces that the chosen variables are well-represented by the corresponding survey questions. This robust alignment suggests that the model's constructs are both relevant and effectively measured, providing foundation for interpreting the impact of the independent variables on the dependent outcome.

5.5. Competitive intensity

This included the exploratory moderating variable of competitive intensity, which was purported to explore how the competitive environment in which firms implement AI technologies and solutions and adopt their organization accordingly affects their DC. The moderating effect was not found; instead, a direct effect was discovered. As the relationship we explore is relatively novel, this is not explained by our model or relevant theory. We hope that this influences future researchers to use other methods to explore this relationship. It should be added that, as is with the nature of exploratory variables, their inclusion has the function of examining an effect without a consistent theoretical basis; it further complicates the model, which violates the model parsimony (Söderlund, 2023; Hair et al., 2017).

5.6. Empirical contributions

The methodological approach of the thesis, utilizing a quantitative survey to measure the impact of AI on DC, provides a robust empirical basis to validate the proposed hypotheses. This approach is reflective of the current trends in DC research, which increasingly rely on empirical data to refine theoretical assertions and expand the understanding of how these capabilities function in different organizational contexts (Schilke et al., 2018). The discussion of these results is enriched by integrating insights from the broader literature on DC and AI. For instance, Steininger et al., 2021 highlight how AI can lead to significant business strategy modifications, which aligns with the observed impacts on transforming capabilities.

5.7. Theoretical implications

DC theory emphasizes the role of organizational and strategic processes in adapting to rapidly changing environments. Researchers have increasingly focused on the concept of microfoundations to understand the individual and group activities that underpin these capabilities. These studies investigate how routine interactions, skills, and decision-making processes at the micro level influence the agility and adaptability of organizations. Mikalef et al. (2023) highlight how these technologies offer new opportunities for exploring microfoundations, suggesting that the integration of digital tools and platforms can provide deeper insights into how individual actions and interactions contribute to the development of DC. This perspective is crucial as academics increasingly focus on the ability of organizations to maintain competitiveness in rapidly changing digital environments.

6. Limitations & future research

This study is not without limitations. The model used in this study - PLS-SEM - while appearing to robustly capture the influence of AI on DC, does not fully account for the variability in AI maturity and technological heterogeneity across different firms. The latent variables that seek to model the underlying constructs of AI implementation do not fully capture the variance in the model, which informs the belief that the model has some distance from reality. This limitation leads to an oversimplification of the

interactions between AI technologies and DC. Furthermore, the results derived from the data are constrained by the sample size and the specific demographic characteristics of the Swedish SMEs surveyed, which limited the generalizability of the findings to other contexts, as well as larger enterprises existing in other countries. The survey's sample size is relatively small. We prioritized the quality of responses over quantity by targeting only those decision-makers directly involved and well-informed enough to thoroughly assess the AI and DC aspects of the firm.

It can be noted that it is possible that a firm's DC has an effect on dynamic capabilities. It is not inconceivable that the level of developed DC in a firm makes them more inclined to implement AI as a consequence of e.g sensing capabilities which pick up on new opportunities offered by newly proliferated AI technologies. This can in turn have a reinforcing effect on a firm's DC. The probable existence of an interplay between DC and its microfoundations is reflective of a type of *chicken or egg* critique which has long been levied at proponents of DC. Whilst understandable as it pertains to the framework's lucidity, it is nevertheless relevant for exploratory studies of this thesis' nature to investigate certain aspects of the bidirectional relationship between AI implementation and DC.

6.1. Heterogeneity

Additionally, the reliance on self-reported measures introduces potential biases in the data, affecting the accuracy and reliability of the findings regarding how firms perceive and report changes in their capabilities. Moreover, it is not only possible but very much the case that this study's conceptual model, as described in Figure 1, does not describe reality to the fullest extent, as shown by the R-squared of the dependent latent variables. Furthermore, the independent reflective-formative higher-order construct does not fully capture the variance of its lower-order constructs, which may very well be due to the unobserved heterogeneity discussed above.

6.2. Sample size

Additionally, the demographic data showing moderately broad industry participation suggests that the findings may have broad applicability across different sectors, reinforcing the relevance of DC in various contexts. The sample size and the demographic distribution of the firms involved in the study could limit the generalizability of the findings. If the sample predominantly includes firms from a specific sector or of a certain size, the results might not be applicable to other contexts or larger, more diverse populations. This limitation is crucial when discussing the sensing capability, as different industries may have varying dynamics and competitive pressures that affect how AI is utilized for environmental scanning (Teece et al., 1997).

6.3. Self-reported measures and cross-sectional design

Furthermore, as mentioned in the research design, the desired method of study is of a qualitative nature. Due to the nature of this study, this was not the case. Therefore, this study lacks qualitative depth. Thus, future studies should seek to further explore this relationship through other designs beyond the quantitative cross-sectional design to longitudinal studies which allow us to explore the evolving impact of AI on DC.

Furthermore, researchers should strive to develop approaches that leverage the potential of digital technologies to provide richer, more granular data to adequately capture the dynamic nature of the capabilities being studied. Such methodologies could provide insights into the interactions and adaptations within organizations that drive the evolution of DC; this could serve to develop the field by providing tools to scholars to confront criticisms on how DC are measured. Additionally, interdisciplinary approaches that draw from fields such as information systems, cognitive science, and organizational behavior could enrich our understanding of how micro-level factors influence macro-level capabilities. By embracing these methodological advancements, the field of DC can provide more relevant and actionable insights, helping organizations navigate the complexities of the digital age more effectively.

7. Conclusion

This study examined the impact of AI on the DC of Swedish SMEs using a quantitative analysis of survey data from 455 executives. It found that AI significantly enhances sensing, seizing, and transforming capabilities, indicating that AI deployment can improve firms' ability to identify, adapt to, and act on market opportunities and challenges. This research highlights AI's role as a microfoundation in DC, providing insights into how strategy, organizational integration, and operational excellence influence AI's effectiveness. Despite limitations such as its focus on Swedish SMEs and using cross-sectional data, the findings offer exciting perspectives for managers on leveraging AI to enhance competitiveness. Future studies could expand on this by exploring AI's impact in different contexts and over time, using both quantitative and qualitative methods to capture the evolving influence of AI on business strategy and performance.

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Appendices

Appendix A: Demographic data

Variable (Category)	Number (n)	Percentage (%)
Duration in Current Position		
1-3 years	172	38.7%
4-6 years	111	24.9%
More than 10 years	61	13.7%
Less than 1 year	58	13.0%
7-9 years	43	9.7%
Industry Type		
J Information and Communication	83	18.7%
M Professional, Scientific and Technical Activities	58	13.0%
C Manufacturing	49	11.0%
K Financial and Insurance Activities	47	10.6%
S Other Service Activities	41	9.2%
G Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles	19	4.3%
R Arts, Entertainment and Recreation	18	4.0%
L Real Estate Activities	18	4.0%
Q Human Health and Social Work Activities	18	4.0%
P Education	17	3.8%
H Transportation and Storage	13	2.9%
D Electricity, Gas, Steam and Air Conditioning Supply	12	2.7%
F Construction	10	2.2%
I Accommodation and Food Service Activities	5	1.1%

E Water Supply; Sewerage, Waste Management and Remediation Activities	5	1.1%
An Agriculture, Forestry, and Fishing	4	0.9%
N Administrative and Support Service Activities	3	0.7%
T Activities of Households as Employers; Undifferentiated Goods and Services Producing Activities of Households for Own Use	3	0.7%
O Public Administration and Defence; Compulsory Social Security	3	0.7%
B Mining and Quarrying	2	0.4%
U Activities of Extraterritorial Organisations and Bodies	1	0.2%
Number of Employees		
250+	153	34.4%
10-49	134	30.1%
50-249	85	19.1%
0-9	73	16.4%
Duration of Operation		
More than 20 years	205	46.1%
11-20 years	84	18.9%
1-5 years	78	17.5%
6-10 years	77	17.3%
Less than 1 year	1	0.2%
AI Technologies Used		
Generative AI	271	60.9%
Machine learning	196	44.0%
Natural language processing (NLP)	178	40.0%
Intelligent planning and scheduling	89	20.0%
Robotics	77	17.3%

Deep learning	52	11.7%
Computer vision	46	10.3%

Appendix B: Measures used in this study

Measures	Items	Measurement items
ASA	Q6_1	Our AI strategy includes clear goals and objectives.
	Q6_2	Our AI strategy includes KPIs to measure success.
	Q6_3	Our AI strategy is aligned with our overall business strategy.
	Q6_4	Our AI strategy is regularly reviewed and updated.
AOI	Q7_1	Cross-departmental collaboration is encouraged in our organization.
	Q7_2	The benefits of AI are communicated to employees.
	Q7_3	Ethical considerations of AI are effectively communicated to employees.
	Q7_4	Our approach to AI includes systematic risk mitigation.
AOE	Q8_1	AI is integrated into our core business processes.
	Q8_2	We have data governance policies in place for AI projects.
	Q8_3	We prioritize AI technologies that automate decision-making processes.
	Q8_4	We prioritize AI technologies that improve operational efficiency.
	Q9_1	We use cloud-hosted AI platforms and services.
	Q9_2	We have a robust data infrastructure to support AI initiatives.
	Q9_3	Feedback from AI applications is used for continuous improvement.
	Q9_4	We have guidelines for AI development and deployment.
SEN	Q11_1	Our company knows the best practices in the market.
	Q11_2	Our company is up-to-date on the current market situation.
	Q11_3	Our company systematically searches for information on the current market situation.
	Q11_4	As a company, we know how to access new information.
	Q11_5	Our company always has an eye on our competitors' activities.
SEZ	Q12_1	Our company can quickly relate to new knowledge from the outside.

	Q12_2	We recognize what new information can be utilized in our company.
	Q12_3	Our company is capable of turning new technological knowledge into process and product innovation.
	Q12_4	Current information leads to the development of new products or services.
TRA	Q13_1	By defining clear responsibilities, we successfully implement plans for changes in our company.
	Q13_2	Even when unforeseen interruptions occur, change projects are seen through consistently in our company.
	Q13_3	Decisions on planned changes are pursued consistently in our company.
	Q13_4	In the past, we have demonstrated our strengths in implementing changes.
	Q13_1	In our company, change projects can be put into practice alongside the daily business.
CI	Q14_2	Competition in our industry is cutthroat.
	Q14_3	There are many ’promotion wars’ in our industry.
	Q14_4	Price competition is a hallmark of our industry.
	Q14_5	One hears of a new competitive move almost every day.

Appendix C: Outer loadings

	Original sample (O)	T statistics (|O/STDEV|)	P-values
Q11_1 <- Sensing	0.897	34.395	0
Q11_2 <- Sensing	0.905	44.34	0
Q11_3 <- Sensing	0.837	22.46	0
Q11_4 <- Sensing	0.839	19.899	0
Q12_1 <- Seizing	0.814	21.304	0
Q12_2 <- Seizing	0.854	22.661	0
Q12_3 <- Seizing	0.763	13.658	0
Q12_4 <- Seizing	0.848	28.589	0
Q13_2 <- Transforming	0.741	11.485	0
Q13_3 <- Transforming	0.872	34.913	0

Q13_4 <- Transforming	0.833	22.905	0
Q13_5 <- Transforming	0.877	29.746	0
Q14_1 <- Competitive intensity	0.858	25.585	0
Q14_2 <- Competitive intensity	0.865	23.4	0
Q14_4 <- Competitive intensity	0.767	11.659	0
Q6_1 <- AI strategy and alignment	0.902	41.471	0
Q6_1 -> AI implementation	0.847	24.801	0
Q6_2 <- AI strategy and alignment	0.865	32.579	0
Q6_2 -> AI implementation	0.807	23.366	0
Q6_3 <- AI strategy and alignment	0.877	38.133	0
Q6_3 -> AI implementation	0.835	30.66	0
Q6_4 -> AI implementation	0.798	18.484	0
Q6_4 <- AI strategy and alignment	0.871	31.881	0
Q7_2 <- AI organizational integration	0.811	22.789	0
Q7_2 -> AI implementation	0.727	15.091	0
Q7_3 -> AI implementation	0.674	11.076	0
Q7_3 <- AI organizational integration	0.872	30.795	0
Q7_4 <- AI organizational integration	0.792	16.76	0
Q7_4 -> AI implementation	0.647	9.726	0
Q8_1 -> AI implementation	0.747	18.421	0
Q8_1 <- AI operational execution	0.757	20.819	0
Q8_2 -> AI implementation	0.656	9.92	0
Q8_2 <- AI operational execution	0.687	10.073	0
Q8_3 -> AI implementation	0.643	12.043	0
Q8_3 <- AI operational execution	0.717	15.431	0
Q8_4 -> AI implementation	0.709	13.084	0
Q8_4 <- AI operational execution	0.741	16.919	0
Q9_1 <- AI operational execution	0.602	7.356	0
Q9_2 <- AI operational execution	0.66	11.131	0
Q9_3 <- AI operational execution	0.832	22.925	0
Q9_3 -> AI implementation	0.779	18.946	0

Q9_4 <- AI operational execution	0.739	15.248	0

Appendix D: Results of hypothesis test

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P-values
AI implementation -> Seizing	0.482	0.484	0.086	5.63	0
AI implementation -> Sensing	0.536	0.537	0.071	7.572	0
AI implementation -> Transforming	0.233	0.238	0.089	2.62	0.004
AI operational execution -> AI implementation	0.4	0.4	0.021	18.91	0
AI organizational integration -> AI implementation	0.234	0.233	0.023	10.256	0
AI strategy and alignment -> AI implementation	0.457	0.456	0.024	18.948	0
Age -> Seizing	-0.136	-0.141	0.087	1.568	0.058
Age -> Sensing	-0.033	-0.032	0.086	0.388	0.349
Age -> Transforming	-0.168	-0.178	0.093	1.807	0.035
Competitive intensity -> Seizing	0.239	0.24	0.088	2.729	0.003
Competitive intensity -> Sensing	0.235	0.242	0.093	2.536	0.006

Competitive intensity -> Transforming	0.31	0.306	0.101	3.067	0.001
Size -> Seizing	-0.089	-0.085	0.089	0.993	0.16
Size -> Sensing	-0.012	-0.011	0.097	0.123	0.451
Size -> Transforming	-0.019	-0.011	0.106	0.178	0.429
Competitive intensity x AI implementation -> Seizing	-0.01	-0.009	0.073	0.138	0.445
Competitive intensity x AI implementation -> Sensing	0.09	0.084	0.1	0.9	0.184
Competitive intensity x AI implementation -> Transforming	-0.088	-0.086	0.097	0.904	0.183

Appendix E: Model total effects

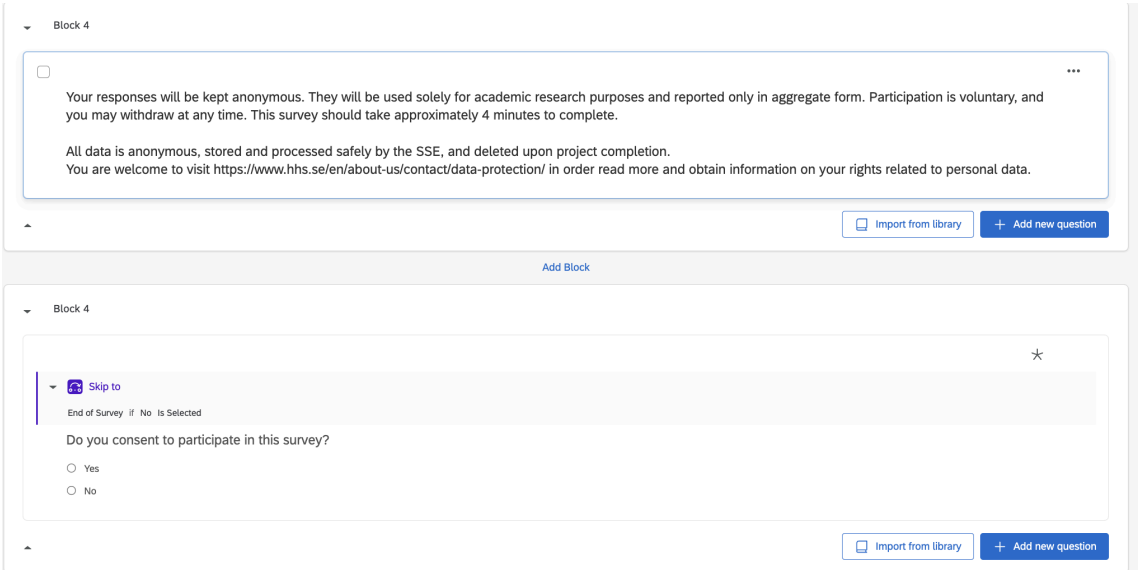
	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI implementation -> Seizing	0.482	0.484	0.086	5.63	0
AI implementation -> Sensing	0.536	0.537	0.071	7.572	0
AI implementation -> Transforming	0.233	0.238	0.089	2.62	0.004
AI operational execution -> AI implementation	0.4	0.4	0.021	18.91	0
AI operational execution -> Seizing	0.193	0.194	0.038	5.043	0

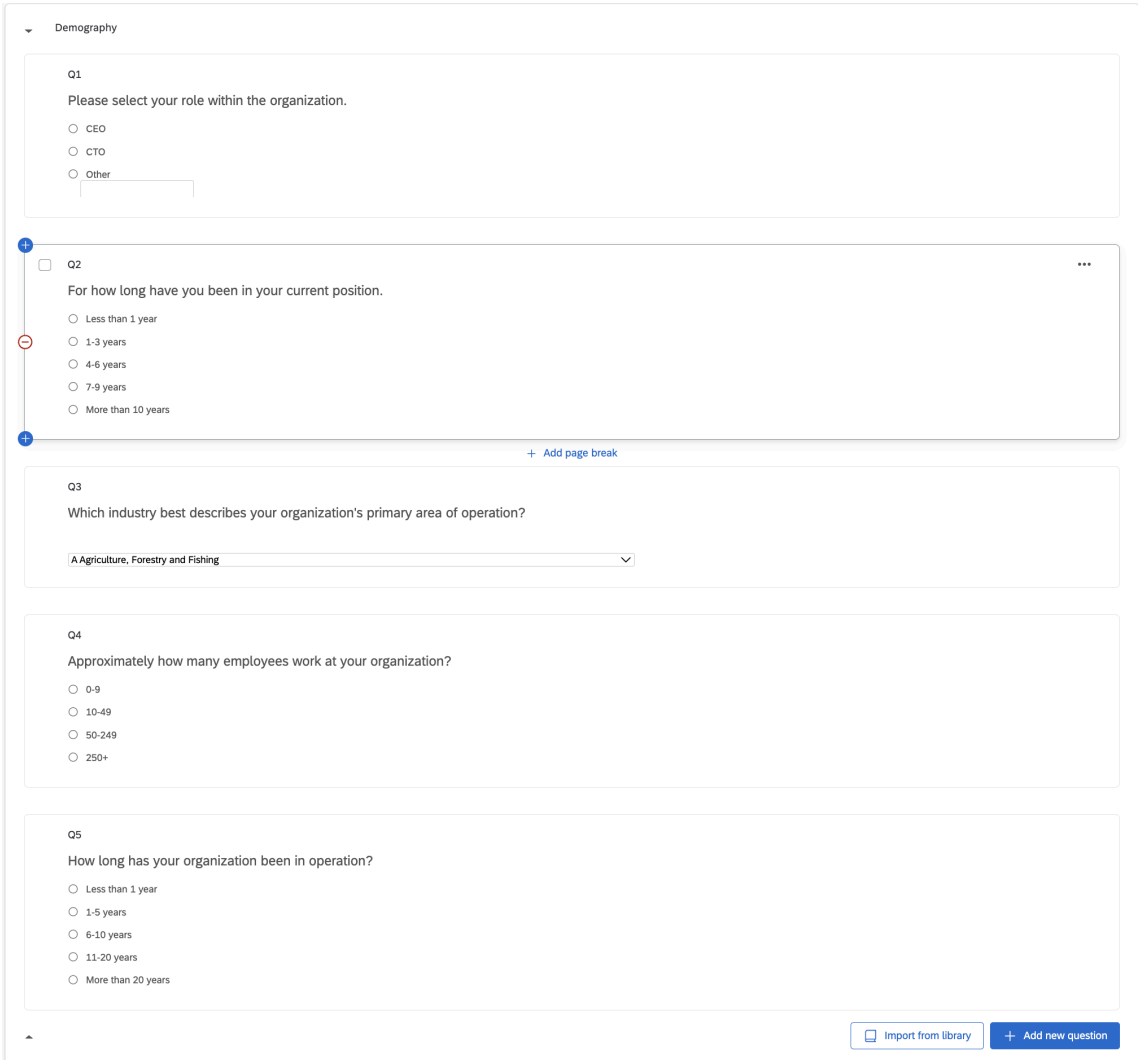
AI operational execution -> Sensing	0.215	0.215	0.03	7.061	0
AI operational execution -> Transforming	0.093	0.096	0.038	2.479	0.007
AI organizational integration -> AI implementation	0.234	0.233	0.023	10.256	0
AI organizational integration -> Seizing	0.113	0.112	0.02	5.656	0
AI organizational integration -> Sensing	0.125	0.125	0.021	6.054	0
AI organizational integration -> Transforming	0.054	0.055	0.02	2.659	0.004
AI strategy and alignment -> AI implementation	0.457	0.456	0.024	18.948	0
AI strategy and alignment -> Seizing	0.22	0.221	0.04	5.481	0
AI strategy and alignment -> Sensing	0.245	0.245	0.034	7.207	0
AI strategy and alignment -> Transforming	0.106	0.109	0.041	2.627	0.004
Age -> Seizing	-0.136	-0.141	0.087	1.568	0.058
Age -> Sensing	-0.033	-0.032	0.086	0.388	0.349
Age -> Transforming	-0.168	-0.178	0.093	1.807	0.035
Competitive intensity -> Seizing	0.239	0.24	0.088	2.729	0.003
Competitive intensity -> Sensing	0.235	0.242	0.093	2.536	0.006

Competitive intensity -> Transforming	0.31	0.306	0.101	3.067	0.001
Size -> Seizing	-0.089	-0.085	0.089	0.993	0.16
Size -> Sensing	-0.012	-0.011	0.097	0.123	0.451
Size -> Transforming	-0.019	-0.011	0.106	0.178	0.429
Competitive intensity x AI implementation -> Seizing	-0.01	-0.009	0.073	0.138	0.445
Competitive intensity x AI implementation -> Sensing	0.09	0.084	0.1	0.9	0.184
Competitive intensity x AI implementation -> Transforming	-0.088	-0.086	0.097	0.904	0.183

Appendix F: The complete survey




Block 4
Your responses will be kept anonymous. They will be used solely for academic research purposes and reported only in aggregate form. Participation is voluntary, and you may withdraw at any time. This survey should take approximately 4 minutes to complete.
All data is anonymous, stored and processed safely by the SSE, and deleted upon project completion.
You are welcome to visit https://www.hhs.se/en/about-us/contact/data-protection/ in order read more and obtain information on your rights related to personal data.
Import from library
Add new question
Add Block
Block 4
Skip to
End of Survey if No Is Selected
Do you consent to participate in this survey?
Yes
No
Import from library
Add new question

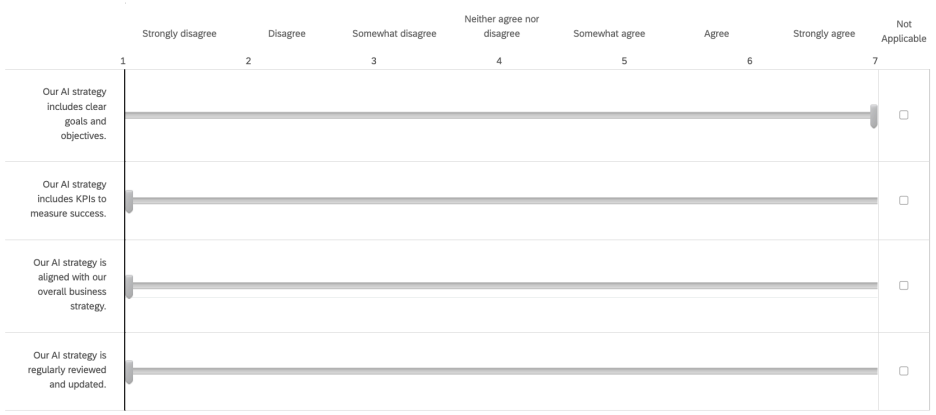

Demography
Q1
Please select your role within the organization.
CEO
CTO
Other
Q2
For how long have you been in your current position.
Less than 1 year
1-3 years
4-6 years
7-9 years
More than 10 years
Add page break
Q3
Which industry best describes your organization's primary area of operation?
A Agriculture, Forestry and Fishing
Q4
Approximately how many employees work at your organization?
0-9
10-49
50-249
250+
Q5
How long has your organization been in operation?
Less than 1 year
1-5 years
6-10 years
11-20 years
More than 20 years
Import from library
Add new question

AI Implementation Block

This section includes questions regarding AI implementation in your organization.

Q6

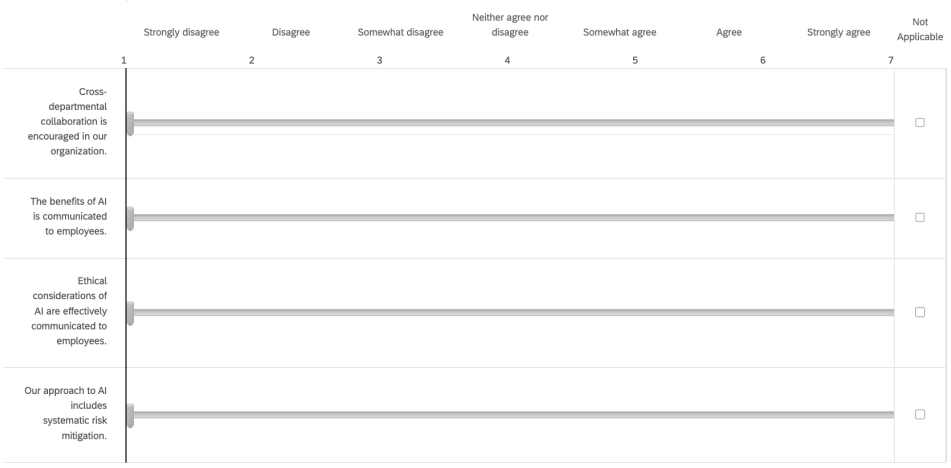
Please rate the following statements on a scale from 1 to 7.



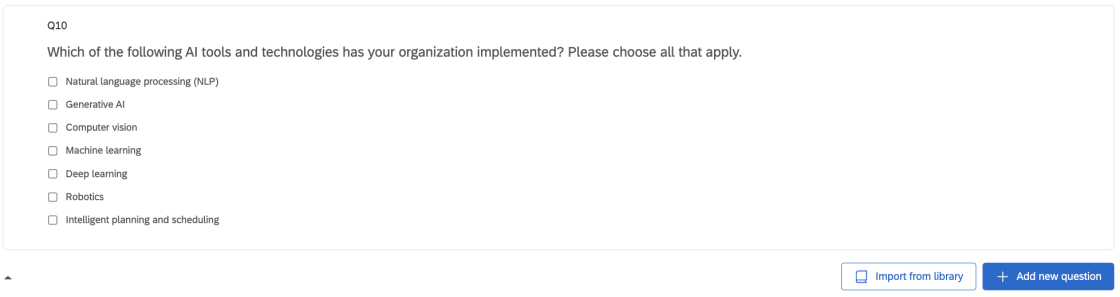
Add page break

Q7

Please rate the following statements on a scale from 1 to 7.



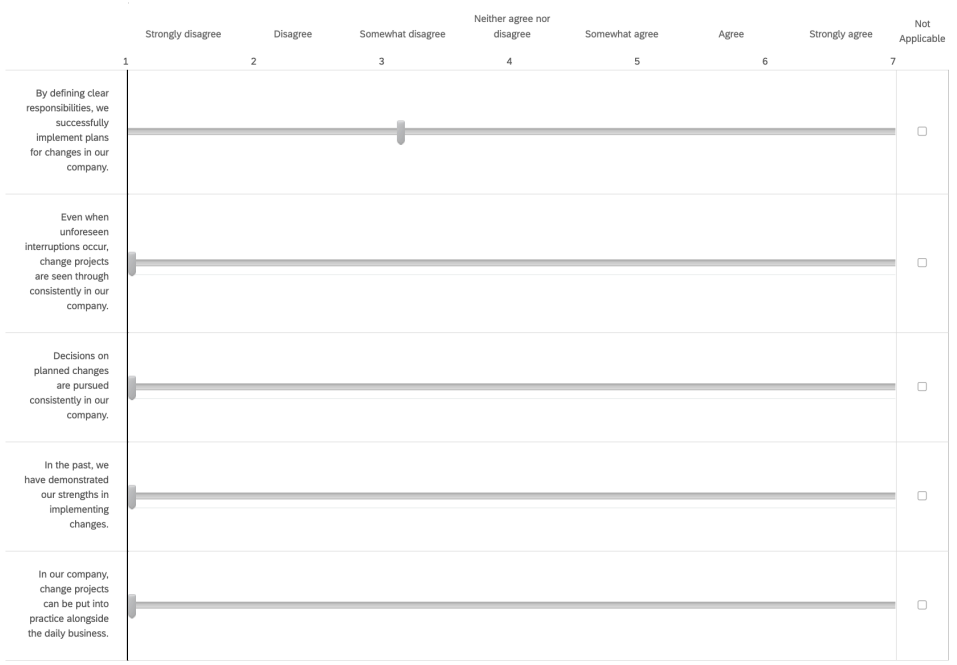

Q8
Please rate the following statements on a scale from 1 to 7.
Strongly disagree
Disagree
Somewhat disagree
Neither agree nor disagree
Somewhat agree
Agree
Strongly agree
Not Applicable
1
2
3
4
5
6
7
AI is integrated into our core business processes.
We have data governance policies in place for AI projects.
We prioritize AI technologies that automate decision-making processes.
We prioritize AI technologies that improve operational efficiency.


Q10
Which of the following AI tools and technologies has your organization implemented? Please choose all that apply.
Natural language processing (NLP)
Generative AI
Computer vision
Machine learning
Deep learning
Robotics
Intelligent planning and scheduling
Import from library
Add new question


Q9
Please rate the following statements on a scale from 1 to 7.
Strongly disagree
Disagree
Somewhat disagree
Neither agree nor disagree
Somewhat agree
Agree
Strongly agree
Not applicable
1
2
3
4
5
6
7
We use cloud-hosted AI platforms and services.
We have a robust data infrastructure to support AI initiatives.
Feedback from AI applications is used for continuous improvement.
We have guidelines for AI development and deployment.

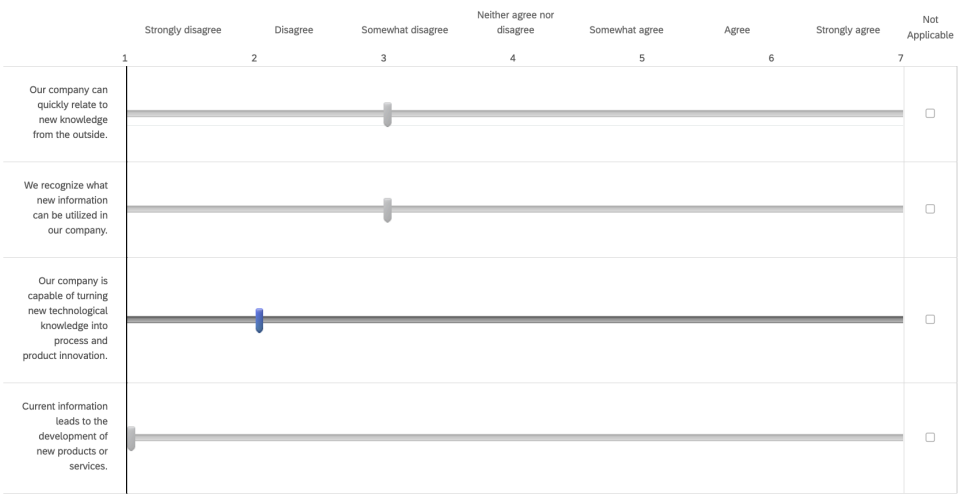
Q13

Please rate the following statements on a scale from 1 to 7.



Q12

Please rate the following statements on a scale from 1 to 7.



+ Add page break

Appendix G: Data collection

The data required for the study was fetched through the Cognism platform, a tool usually used for sales intelligence thanks to its extensive database of companies and people. Cognism meets the highest security standards, and everyone who chooses to opt out of email campaigns is automatically excluded.

Appendix H: AI usage

We have leveraged the power of several AI tools to augment our thesis writing process, primarily through code-generation AIs like Github Copilot, ChatGPT, and Sana AI. These tools have significantly expedited our data analysis process, allowing us to focus on more complex aspects of our research.

The main risks with utilizing AI tools are hallucinations, which can become severe problems if one takes them for ground truth without examining the validity of the responses. To mitigate this risk, we have used grounding by providing relevant assets to ChatGPT and Sana AI to ensure that the AI only uses relevant content from the research papers and references the assets used. It is far from perfect and requires much trial and error. However, it can be a helpful tool if one knows how to utilize it as effectively through prompt engineering and utilizing grounding (providing more context to the chatbot. It was especially helpful in allowing us to go through the PLS-SEM model steps.