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Artificial intelligence (AI) competencies for organizational performance: A B2B marketing capabilities perspective

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A R T I C L E I N F O

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A B S T R A C T

The deployment of Artificial Intelligence (AI) has been accelerating in several fields over the past few years, with much focus placed on its potential in Business-to-Business (B2B) marketing. Early reports highlight promising benefits of AI in B2B marketing such as offering important insights into customer behaviors, identifying critical market insight, and streamlining operational inefficiencies. Nevertheless, there is a lack of understanding concerning how organizations should structure their AI competencies for B2B marketing, and how these ultimately influence organizational performance. Drawing on AI competencies and B2B marketing literature, this study develops a conceptual research model that explores the effect that AI competencies have on B2B marketing capabilities, and in turn on organizational performance. The proposed research model is tested using 155 survey responses from European companies and analyzed using partial least squares structural equation modeling. The results highlight the mechanisms through which AI competencies influence B2B marketing capabilities, as well as how the later impact organizational performance.

1. Introduction

The deluge of data combine with the availability of processing power and storage on digital devices has created a renewed interest in artificial intelligence (AI) in multiple fields over the past years (Enholm et al., 2021). Intense competition among organizations all over the world has also accelerated the need to deploy AI in order to gain an edge over rivals (Ransbotham et al., 2018). AI is not perceived by most C-level executives as a core competence that organizations must foster to remain competitive in the long-run (Kietzmann & Pitt, 2020). One key area of AI use within organizational operations has been B2B marketing (Mikalef et al., 2021). Intelligent solutions to augment B2B marketing capabilities are necessary in a complex business environment, as B2B operations often deal with massive informational complexity and the requirement to make quick decisions. In this regard, AI has the potential to revolutionize how conventional activities are performed due to the ability to process ever-increasing volumes of data, and provide rich insights on key business partners and customers (Bag et al., 2021). Furthermore, AI applications have been suggested to enable automation of many manual processes which can help alleviate bottlenecks and increase operational efficiency in B2B operations (Paschen et al., 2020). In fact, a recent survey on business executives conducted by Garner indicated that the majority believe that AI is likely to be a key development in their business within the next years (Shin & Kang, 2022).

Despite the promise of AI in enhancing B2B marketing activities, a large proportion of organizations are still struggling to leverage their AI investments in a way that adds value (Fountaine et al., 2019). A developing consensus in literature argues that this is due to the fact that AI investments require careful leveraging and development in alignment with organizational operations (Collins et al., 2021; Raisch & Krakowski, 2021). In other words, it is important that AI is perceived as a core competence within organizational boundaries and that key operations are either enabled or enhanced by appropriate AI applications (Borges et al., 2020). While prior literature has investigated challenges associated with adoption of AI (Mikalef et al., 2021), there is to date a limited understanding on how organizations should plan to develop AI

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into a strategic asset that can be leveraged to gain a competitive advantage. This issue is particularly pronounced in the area of B2B marketing, where we still know very little about what effect AI has and what are the potential mechanisms of value-generation from such technologies (Huang et al., 2019). Shedding light on to the value of AI in the B2B to context and how that can be attained is important in order to reduce the number of failed initiatives within organizations as well as to accelerate the deployment of AI within these types of operations. Similarly, recent surveys done with industry experts showcase that there are still some important bottlenecks hindering AI adoption and use in organizations that go beyond technical challenges. In addition, for many managers the value of adopting AI is still now clear, which further hinders the deployment in key organizational operations (Bhalerao et al., 2022). A recent study conducted by McKinsey highlighted that the most popular use cases for AI in organizations relate to service optimization and B2B marketing processes, and that is where respondents identified the greatest value. Nevertheless, there were still several challenges associated with realizing such value from AI investments, and specifically on creating an AI competence that could consistently support business requirements (McKinsey, 2022).

To address this gap, this study builds on core competency theory (Prahalad, 1993) and develops a conceptualization of AI use in organizations boundaries following the key tenets of the theory. Specifically, we propose the notion of AI competence as a core competency of organizations that highlights the need for creative and harmonious deployment of AI. Our theorizing suggests that organizations that are able to develop an AI competency will be those that are able to realize a competitive edge over their rivals. This is due to the fact that AI deployments are idiosyncratic in nature and require a holistic effort from different organizational entities to produce hard-to-imitate and value-generating AI applications. Based on this concept, we develop a research model and corresponding hypotheses and argue that an AI competency can enhance B2B marketing capabilities. Specifically, we distinguish between B2B information management, planning, and implementation capabilities, and argue that that AI competencies have an indirect effect on organization performance mediated through the aforementioned capabilities. Building on a sample of 155 responses received by senior IT executives in the Nordic countries we perform a partial least squares (PLS) analysis to explore the hypothesized effects. Our study therefore attempts to answer the following research questions:

RQ1. What effect do AI competencies have on organizational performance?

and.

RQ2. Through what mechanisms are the effects of AI competencies on organizational performance realized?

The rest of the paper is structured as follows. In the next section we overview some key developments in the domain of B2B marketing, followed by the presentation of the AI competence concept and its theoretical underpinnings. Next, we develop a research model in section 3 and a set of hypotheses. In section 4 we describe the method used to collect data, followed by the analysis and results in section 5. Finally, in section 6 we discuss the research implications of our findings, as well as what they mean for practice, concluding with some important limitations of this work and ways that future research can overcome them.

2. Background

2.1. B2B marketing

Organizations operating in B2B businesses need to develop trustworthy relationships with customer organizations. Thus, B2B marketing focuses on networks and interactions among organizations (Gummesson, 2014). B2C marketing focuses on mass communication and brand development (Reed et al., 2004), whereas B2B marketing is characterized by complex transactions that require trust and higher reliability between buyers and sellers (Kolis & Jirinova, 2013; Saini et al., 2010). Customers are generally handled individually in B2B context, whereas consumer marketing targets for large number of customers that may not need to be handled individually. However, in both contexts marketing capabilities are critical for gaining business success. Marketing capabilities (MCs) are defined as the organizational abilities to conduct a set of tasks utilizing the available organizational resources to achieve a desired performance outcome (Herhausen et al., 2020). According to Guo et al. (2018), marketing capabilities enhance an organization's ability to effectively configure and deploy resources to build sustainable competitive advantage. Thus, MCs are a complex combination of organizational abilities and resources, unique to an organization, and very difficult to imitate by competitors (Mariadoss et al., 2011).

Prior research divided MCs into three categories, namely inside-out, outside-in, and spanning. The inside-out capabilities originate internally from an organization and correspond to different functional activities (Day, 2011; Santos-Vijande et al., 2012), whereas the outside-in ones originate from the market and help organizations understand their customers and competitors (Santos-Vijande et al., 2012). Finally, the spanning ones integrate both the internal and external processes of an organization through knowledge of both the market and the company's internal functioning (Chahal & Kaur, 2014; Santos-Vijande et al., 2012). Thus, spanning marketing capabilities combine both inside-out and outside-in capabilities. Santos-Vijande et al. (2012) notes that "if [a firm] affirms to have spanning capabilities, it can be assumed that they have previously developed inside-out and outside-in capabilities". These capabilities include developing and executing market strategies, policies, and programmes (Chahal & Kaur, 2014).

The adoption and use of AI based marketing is driven by both internal and external processes. Thus, we conceptualize B2B marketing capabilities using spanning capabilities in this study. In particular, the chosen spanning capabilities for this study are marketing information management, marketing planning, and marketing implementation. Marketing information management is the organizational ability to acquire and analyze relevant information about different stakeholders for developing effective marketing programmes (Cavazos-Arroyo & Puente-Diaz, 2019). Marketing planning ability is about anticipating and strategically responding to changes in the market environment, further helping in achieving the organizational goals (Chahal & Kaur, 2014; Liu et al., 2015; Santos-Vijande et al., 2012). Lastly, the marketing implementation ability is about executing, controlling, and evaluating the marketing strategies (Chahal and Kaur, 2014).

Within the past few years there has been a growing discussion of how AI is changing the B2B marketing activities of organizations (Mikalef et al., 2021). According to an emerging stream of research, AI is quickly becoming an integral part of organizations that engage in B2B marketing operations but either automating or augmenting key processes (Rusthollkarhu et al., 2022). This stream of research, as well as prominent examples from industry show that AI can enable improved customer insight generation, greater personalization and planning precision, as well as an enhanced customer experience (Dwivedi & Wang, 2022). As such, there is extensive anecdotal claims concerning the potential applications of AI for B2B marketing activities which rely on a diverse set of technologies. To this end, it is highlighted that was is important for organizations is that they develop AI competencies in order to be able to accommodate such diverse uses of AI (Lundin & Kindström, 2023; Pattinson et al., 2022). Adding to the above, claims from practitioners suggest that the use of AI within B2B marketing can also enable organizations to reach a broader and wider set of customers through targeted applications, which not only improved the performance of existing operations but opens avenues for new ways of conducting operations (Raghupathi et al., 2023).

2.2. Artificial intelligence (AI) competencies

Artificial Intelligence is a sub-field with a long history if the field of computer science. While historically AI has been restricted to a largely theoretical domain, recent advancements in data generation, and computing have allowed AI to move from theory to practice (Haenlein & Kaplan, 2019). The technologies that comprise the notion of AI have been described in different ways, and mainly revolve tools for solving complex and time-consuming problems and secondly as a human intelligence and cognitive process mimicking system (Enholm et al., 2021), or in other words, computational agents that act intelligently (Paschen et al., 2019). A kay pillar of AI technologies is that they are designed and developed to act based of pre-defined requirements building on existing data and information (Paschen et al., 2020). This requirement places an emphasis on the ability of AI technologies to be able to learn from previous experiences and draw inferences through analyzing data. A specific sub-field, and perhaps the most prominent one within the field of AI, is that of machine learning (Ongsulee, 2017). AI technologies which build on machine learning are able to modify their processing based on newly acquired information (Gómez-Pérez et al., 2009). Thus, a key difference with other prior technologies for decision-making or aiding is that there is an inherent adaptability of such algorithms, as they dynamically change based on new input.

Nevertheless, while AI technologies have evolved significantly over the past few years, many organizations are struggling to leverage them in a way that generates value to them (Collins et al., 2021). A growing stream of research has focused on this challenge, highlighting that many of the challenges associated with effectively harnessing the potential of AI stem from the organizational context (Chernov & Chernova, 2019). In juxtaposition, several notable examples of organizations have been successful in leveraging AI into operations and finding ways by which such technologies can be a source of business value (Makarius et al., 2020). Such cases have demonstrated how AI orchestration can be developed into a core competency of the organization, conferring significant organizational value (Batko & Szopa, 2016). The notion of an AI competence therefore extends the conventional thinking of simply developing AI technologies and incorporates its design and deployment in the organizational setting in a way that facilitates value generation. Hence, an AI competency follows a long history of academic research which differentiates between core technologies (AI technologies) and core competencies (AI competencies). Therefore, an AI competency is not merely the technology used to support it, or the technical ability to leverage it effectively, but the creative bundling of such technologies, organizational knowledge, and institutions as a harmonious whole (Prahalad, 1993).

Recent surveys and studies among leading organizations on their use of AI, highlight that their ability to derive value from such technologies stem from precisely such an ability to creative bundle AI into new or revamped processes (Fountaine et al., 2019). As a result, creative orchestration and bundling of AI technologies in a way that adds business value requires the presence of an AI competence. Building on prior literature in the information systems (IS) domain, we define the notion of an AI competence in accordance with prior studies in the domain (Ravichandran, 2018). In line with the conceptualization of competencies by Prahalad (1993) in his seminal work, we argue that an AI competence must include three key features. First, it must address the technical ability to effectively orchestrate the technology in an effective manner and have the potential for competitive differentiation. Second, it must transcend a single business unit and cover a range of operations and processes. Third, it must hard for competitors to imitate, which requires a focus on continuous experimentation and proactiveness. These three aspects in conjunction facilitate the creation of an AI competence.

3. Research model and hypotheses

Based on the above discussion and theoretical grounding, we argue that AI competencies are important for organizations in realizing performance gains. The three underlying pillars that jointly comprise AI competencies include an organization's infrastructure, business spanning ability, and proactive stance. The combination of these enhances B2B marketing capabilities which are important in realizing organizational performance gains. Thus, we argue that the effect of AI competencies of organizational performance is an indirect one. In Fig. 1, we summarize the main hypotheses and direction of associations of our research model.

3.1. The effect of AI competencies of B2B marketing capabilities

The efficiency of marketing activities is highly dependent on how well market research has been conducted by the organization. The organization must consider industry trends, customers, competitors, and other relevant stakeholders when conducting the market research. Data can be gathered from diverse sources (e.g., internal, and external reports, social media, etc.) for conducting the market research. Analyzing these diverse data and identifying intelligence from such data require AI competencies. Using AI techniques for market research and supporting marketing decision making can help organizations to make better decisions (Pietronudo et al., 2022). For example, AI technologies such as natural language processing (NLP) allows marketers to understand customers' personality and behavior by analyzing texts (Sharma et al., 2022). This allows marketers target customers with personalized content. It also helps understanding of the customers' needs and design products and services that would meet the customers' needs. In this study, we suggest that AI competencies can impact marketing information management capability. For example, organizations can use its AI competencies to analyze different types of market data and create visualizations to aid executives make decisions (Farrokhi et al., 2020). Prior research studies also indirectly support this relationship. For example, Singh (2022) suggest that AI can increase the speed of decision making and thus can help experimenting with multiple marketing strategies. Consequently, we propose the following hypothesis.

H1: There is a positive relationship between AI competencies and B2B information management capabilities.

Next, we propose a positive relationship between AI competencies and B2B planning activities. The planning activities must address the broad organizational goals rather than isolated business issues. Thus, interdisciplinary collaboration in the organization is a pre-requite (Mikalef & Gupta, 2021). Organizations with high level of AI competencies naturally involve business, operational and marketing people to work with analytics expert, and thus transforming siloed work practices into an interdisciplinary collaboration for driving the success of the organization (Fountaine et al., 2019). AI based systems can create and analyze hundreds of millions of options and their possible impacts, and then rank a few optimal options or solutions to the marketing decision makers (Fountaine et al., 2019). Prior IS research indirectly provided some evidence on the possible relationship between AI competencies and B2B planning activities (Saura et al., 2021). For example, Ravichandran (2018) found a positive relationship between IT competencies and organizational agility. Lu and Ramamurthy (2011) also found a positive relationship between IT capability and organization agility. Consequently, we propose the following hypothesis.

H2: There is a positive relationship between AI competencies and B2B planning capabilities.

Finally, we propose a positive relationship between AI competencies and B2B implementation capabilities. Once AI based systems rank different marketing solution strategies, marketing people can use their own expertise to make their final decision that are supported by the AI driven decisions, without the need to get input form their leaders (Fountaine et al., 2019). This greatly enhances the organization's implementation capabilities. Wamba-Taguimdje et al. (2020) points out that "the higher the capacity and ability to derive the informational effects of AI and its technologies, the more effective and quickly the organization can make quality decisions". Several prior studies also noted that organizations that use AI systems for gaining customer, user,

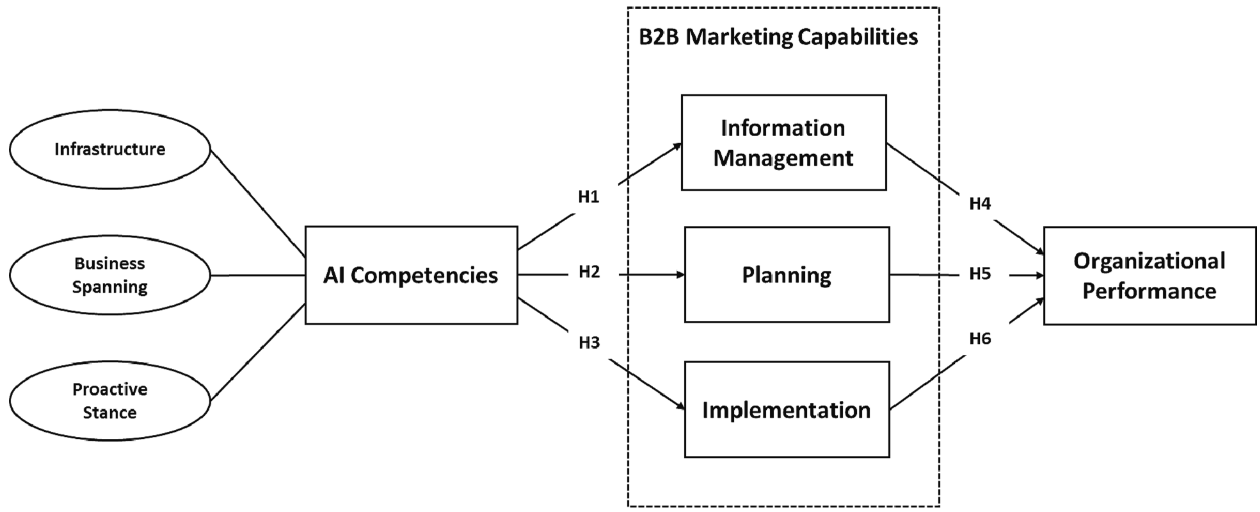

Fig. 1. Research model and hypothesized relationships.

and market knowledge, can three-fold their B2B marketing efficiency (Bag et al., 2021; Rahman et al., 2021; Singh, 2022). Consequently, we propose the following hypothesis.

H3: There is a positive relationship between AI competencies and B2B implementation capabilities.

3.2. *The impact of B2B marketing capabilities on organizational performance*

Prior research studies often linked marketing capabilities with organizational performance. For example, Mariadoss et al. (2011) proposed marketing capabilities to impact both technical and non-technical innovations that in turn impact organization's competitive advantage. In contrast, Morgan et al. (2009) found a direct impact of marketing capabilities on firm's performance. Kamboj and Rahman (2015) noted that when compared to other capabilities, marketing capabilities have strong effect on firm performance. In this paper, we have employed marketing information management, marketing planning, and marketing implementation as the three dimensions to conceptualize marketing capabilities as described earlier. Next, we describe how these three dimensions are related to organizational performance.

First, marketing information management can be viewed as an organization's ability to acquire and analyze relevant information about different stakeholders for developing effective marketing strategies (Cavazos-Arroyo & Puente-Diaz, 2019). Thus, improved marketing information management can provide faster information access to the executives when needed. This can also help executives understand and cater to the customers better, which may lead to increased customer satisfaction, firm revenues, and profitability. When an organization integrates AI based marketing information management tools, it can help them in decision making, thus resulting in higher productivity and a better overall performance. Moreover, the knowledge created by using AI technologies can provide new ideas and hence the organization may discover new business opportunities and create new offerings to markets faster than its competitors. Consequently, we propose the following hypothesis.

H4: There is a positive relationship between B2B information management capabilities and organizational performance.

Marketing planning is the ability to anticipate and strategically respond to changes in the market environment, further helping in achieving the organizational goals (Chahal & Kaur, 2014; Liu et al., 2015; Santos-Vijande et al., 2012). Improved marketing planning allows an organization to integrate its diverse resources and formulate marketing strategies for driving success. Anticipating and strategically responding to the changing market is critical in today's competitive environment. If an organization fails to take necessary actions in due course, it cannot succeed in today's uncertain market. An AI based marketing planning may consider historical data about the markets, competitors, stakeholders, and industry trends, among others to provide different course of actions. Innovative firms experiment and peruse different course of actions to stay competitive in the market and drive business success (Ravichandran, 2018). Consequently, we propose the following hypothesis.

H5: There is a positive relationship between B2B planning capabilities and organizational performance.

Finally, the marketing implementation ability is about executing, controlling, and evaluating the marketing strategies (Chahal and Kaur, 2014). While marketing planning is about preparing for the ever-changing market, marketing implementation is about executing the action and allocating resources (Cavazos-Arroyo and Puente-Diaz, 2019). The competency in evaluating and executing different marketing strategies is needed for continuous adaptation to the market and achieving business success. Implementation of actions when required can increase the operational, financial, and the market performances. With the help of AI technologies, an organization can effectively and quickly make quality decisions than its competitors, which in turn can positively impact organizational performance (Wamba-Taguimdje et al., 2020). Furthermore, firms with higher implementation capabilities can assemble resources together to execute new marketing strategies that align with their business models or even rethink their existing business models based on the received feedback from the marketing activities. Thus, we propose the following hypothesis.

H6: There is a positive relationship between B2B implementation capabilities and organizational performance.

4. Empirical study

4.1. *Survey, administration and data*

To examine the above set of hypotheses we used a questionnaire based method as it facilitates generalization of results, can be easily replicated, and allows for the examination of a large number of constructs (Pinsonneault & Kraemer, 1993). Furthermore, survey-based studies are an established means of capturing general tendencies and in highlighting associations between constructs of interest. According to Straub et al. (2004), survey-based research is an important approach in settings of exploratory studies and in early stage of theory formation. For the purpose of this study, we built on constructs and corresponding survey items that are either previously published in other studies or adapted to fit the context of this research. The constructs that were utilized and their respective items were measured on a 7-point likert scale, which is an accepted approach in subjective concept measurements (Kumar et al., 1993). To ensure that the adapted constructs were reliable and captured the underlying concept that was intended to be measured, we performed a small-cycle study with 22 organizations. These organizations were conveniently selected from a group of affiliated organizations in Norway and were not used in the main study. During this phase, we were also able to establish the face and content validity of constructs and to make sure that the respondents were capable of answering them. Once the first round of pre-testing was completed, respondents were contacted in order to give their feedback and to improve the clarity of any questions that were not easy to answer.

For the main study, a panel service company was contacted to aid with the identification of appropriate respondents and to collect data. Specifically, the target respondents included organizations that operate in the Nordic region as they have high levels of AI adoption and very similar market conditions. The recruitment criteria requested that respondents were high-level IT managers that had a good expertise of both AI-related and business-related matters. The data collection process was performed between March 2022 and April 2022 and resulted in 155 completed responses Table 1. A series of qualifying questions were used in order to ensure that the organizations were indeed utilizing AI applications for B2B marketing purposes and that respondents had the appropriate knowledge to respond. To check for potential bias in our sample we compared those that gave complete responses vs those that were excluded during the qualifying phase. By performing paired tests, we found no significant differences. Furthermore, we checked for late response bias by comparing those that completed the survey within the first week from launch with those that completed it in the last week. Running chi-square tests for firm size, industry, AI experience in years, and respondent position we found no significant differences. As all data was collected in one point in time, we controlled for common method bias based on the recommendations of Chang et al. (2010). Before respondents answered they were provided with an information page that assured them that all data would remain confidential, anonymous, and used for research purposes only. After the data collection was finalized, we also used Harman's one factor test which showed that there was no single construct that could account for the largest part of variance (Fuller et al., 2016). To further ensure that common method bias was not an issue within our model, we built on the latest guidelines by Kock (2017) and examine the collinearity of the inner model of the PLS-SEM analysis. By examining the variance inflation factors (VIF) for the constructs used in the study, we found that no value was greater than the threshold of 3.3. In fact, the highest VIF was 2.79 which is well below the set threshold, which is a good indicator that common method bias is not a concern in this study.

Table 1
Descriptive statistics of the sample and respondents.

Factors	Percentage (%)
Industry	
Bank & Financials	5.8%
Consumer Goods	9.2%
Oil & Gas	5.2%
Industrials (Construction & Industrial goods)	9.2%
ICT and Telecommunications	18.3%
Technology	9.7%
Media	9.2%
Transport	2.7%
Other (Shipping, Basic Materials, Consumer Services etc.)	30.7%
Firm size (Number of employees)	
1 – 9	10.4%
10 – 49	24.7%
50 – 249	34.6%
250+	30.3%
Total years using AI	
< 1 year	8.8%
1 – 2 years	21.7%
2 – 3 years	28.0%
3 – 4 years	23.4%
4 + years	18.1%
Respondent's position	
CEO/President	10.1%
CIO	73.0%
Head of Digital Strategy	6.3%
Senior Vice President	3.8%
Director	3.4%
Manager	3.4%

The responses that were obtained came from companies in different industries. Most of them were from the ICT and telecommunications domain, technology, industrials, media, and consumer goods. The size-class of companies were also predominantly from medium-sized and large organizations. In addition, most of the firms had some experience with AI in their operations, with the majority having at least 2 years of prior experience, whereas a significant proportion of the sample had worked with AI for more than 4 years in their respective organizations. Finally, the respondents were a good match to the questions we posed as the vast majority were C-level IT executives that were knowledgeable of both the IT and business aspects of their organizations. In terms of sample size, the 155 responses satisfy the of: (1) ten times the number of formative indicators used to measure one construct, and (2) ten times the largest number of structural paths directed at a particular latent construct in the structural model (Hair et al., 2019). In addition we performed a g* power analysis given the parameters of our research model. The results confirmed that the sample size greatly exceeds the lower threshold required to provide a valid analysis.

To control for the existence of bias within our sample we built on the suggestions of related methodological studies (Podsakoff et al., 2003). Once data were collected, we run a series Harmon one-factor tests on the main constructs of our study. The outcomes of these analysis did not signify any issues of common method bias as the maximum variance explained by any one factor was below 45% for all constructs. We also followed the suggestions of Tenenhaus et al. (2005) and examined the goodness-of-fit in our model. As argued by Wetzels et al. (2009), the value of 0.39 exceed the lower limit so we stablished that there was sufficient goodness-of-fit.

4.2. Measurements

To capture the variables used in this study, we relied on scales for that were either adopted from prior literature or have been adapted to fit the context of examination. We provide a description of each in this subsection, as well as a more detailed listing of the specific items in Appendix A, where a summary of the exact questions asked to respondents is located.

AI Competence (AIC) was developed as a latent construct conceptualized in three dimensions: infrastructure, business spanning, and proactive stance. An AI competence is defined as the ability of a firm to harmoniously combine its AI-based technologies, skills, knowledge, and other complementary resources in a way that builds a defining strength among competition. The dimensions of the latent construct are in coherence with prior studies on IT competence (Lu & Ramamurthy, 2011), and the underlying measures are adapted and tested for AI-specific infrastructure and processes. The infrastructure (INFR) dimension captures the ability of a firm to effectively manage its data assets in a secure way, as well as the overarching infrastructure needed to convert raw data into meaningful AI applications or insight. The business spanning (BUSP) dimension refers to the capacity of management to exploit AI in a way that enhances business objectives from ideation to realization. Finally, a proactive stance (PROS) concerns the ability to strive for new ways to utilize novel and emerging approaches related to AI and to constantly seek ways of leveraging them. The construct of AI competence was developed a Type 2 construct (reflective-formative second-order construct) which comprised of 13 indicators in total. All items were measured on a 7-point likert scale and pre-tested for their statistical properties prior to launching the main study. Prior to launching the construct in this study, a small cycle study was performed in order to confirm the reliability and statistical properties of the items. During the first cycle a group of eight academics were asked to assess the clarity of the items and respective dimensions in relation to AI. At a second stage, a small-scale study was performed with a sample of 22 organizations. By examining the statistical properties of the construct we established that there were no concerns over the reliability and validity.

In measuring a firms B2B marketing capabilities we utilized the three constructs that captured complementary facets that are important in such activities. Specifically, we built on the work of Vorhies and Morgan (2005) that distinguish between three key capabilities of B2B marketing, information management, planning, and implementation. Information management (INFM) refers to the process by which firms learning about their markets and use that market knowledge. Planning (PLANN) rerefers to a firm's ability to conceive marketing strategies that optimize the match between the firms' resources and its marketplace. Finally, implementation (IMPL) concerns the process by which an envisioned B2B marketing strategy is transformed into realized resource deployments. A total of nine items were used to measure the three constructs, each measured on a 7-point likert scale.

Organizational performance (ORGP) was measured as a first order reflective construct based on the items proposed by Lee and Choi (2003). The construct captures the relative performance of the focal firm in relation to the main competitors in the market in terms of different key performance indicators. Respondents were asked to evaluate the performances on a seven-point Likert scale on five different items.

5. Analysis

To examine the validity and reliability of our proposed research model, we built on a partial least square based structural equation modeling (PLS-SEM) analysis. We used SmartPLS 4 as the software to run analyses (Ringle et al., 2015). For the type of analysis we conduct PLS-SEM is deemed as an appropriate technique as it allows the examination of the relationships between dependent, independent, and mediating variables (Hair et al., 2011). As PLS-SEM is a variance-based approach, it allows for (i) flexibility concerning normality, (ii) use of reflective and formative constructs, (iii) analysis of models with smaller samples, and (iv) the potential of theory building (Nair et al., 2017). Over the past years, PLS-SEM has widely been used for the analysis of models with complex relationships between constructs in several subject areas (Ahammad et al., 2017; West et al., 2016). Furthermore, PLS-SEM enables the identification of indirect and total effects, which makes it making it possible to not only simultaneously assess the relationships between multi-item constructs, but also to reduce the overall error associated with the model (Astrachan et al., 2014). The sample of 155 responses of this study surpasses both the requirements of: (1) ten times the largest number of formative indicators used to measure one construct, and (2) ten times the largest number of structural paths directed at a particular latent construct in the structural model (Hair et al., 2011). Furthermore, as the research model we examine builds on exploratory theory building instead of confirming, we consider that PLS-SEM is the best alternative.

5.1. Measurement model

As our proposed research model and operationalization of constructs contains only reflective constructs, we conducted reliability, convergent validity, and discriminant validity tests. Reliability was established at both the item and construct level. At the item level reliability was assessed by determining if construct-to-item loadings were above the lower limit of 0.70. At the construct level we examined the Composite Reliability (CR), and Cronbach Alpha (CA) values, to ensure they surprised the threshold of 0.70 (Nunnally, 1978). Convergent validity was examined looking if AVE values were greater than the threshold of 0.50, with the lowest observed value being 0.61. Discriminant validity was gauged by two approaches. First, we examined if each indicators outer loading was greater that its cross-loadings with other constructs (Farrell, 2010). Second, we examined the heterotrait-monotrait ratio (HTMT) to ensure that values for constructs were below 0.85. rough the above tests we established that first-order reflective measures are valid to work with and support the appropriateness of all items as good indicators for their respective constructs Table 2.

To establish the validity and reliability of the higher-order construct of AI competencies, we first examined the weights of the formative lower-order constructs on their higher-order constructs (three first-order constructs). All weights were significant and positive on the assigned higher-order construct. The next step involved examining if the first-order constructs presented multicollinearity. To explore this, we calculated the Variance Inflation Factor (VIF) values, and set 3.3 as the cut-off threshold (Petter et al., 2007). All values of first-order constructs were below this threshold indicating that multicollinearity was not a concern within our sample Table 3.

5.2. Structural model

After confirming the measurement model properties, we performed a PLS analysis in order to obtain the path weights and explained variance. Specifically, the results of the analysis are summarized in Fig. 2. In the figure, there are visually represented the standardized path coefficients (β) along with the t-value and significance levels, as well as the explained variance of endogenous variables (R^2). The structural model is verified by examining coefficient of determination (R^2) values, effect size of predictor variables (f^2), predictive relevance (Stone-Geisser Q^2), and the effect size of path coefficients. To obtain the significance of estimates (t-value), a bootstrap analysis was run using 5000 resamples. Through the analysis we find that AI competencies exert a significant and positive on all three B2B marketing capabilities. Specifically, we find that AI competencies have a stronger and more pronounced effect on information management ($\beta = 0.413$, $t = 9.234$, $p < 0.001$). Similarly, AI competencies had a positive and significant effect on planning ($\beta = 0.335$, $t = 6.934$, $p < 0.001$), and a slightly lesser effect on implementation ($\beta = 0.256$, $t = 4.575$, $p < 0.01$). In turn, we find that information management influences organizational performance in a positive and significant way ($\beta = 0.246$, $t = 6.942$, $p < 0.001$), as well as planning ($\beta = 0.277$, $t = 7.460$, $p < 0.001$), and implementation ($\beta = 0.378$, $t = 8.421$, $p < 0.001$). The structural model explains 31.5% of variance for information management ($R^2 = 0.315$), 27.4% for planning ($R^2 = 0.274$), and 19.8% for implementation ($R^2 = 0.198$). Organizational performance presented an explained variance of 39.4% ($R^2 = 0.394$). Apart from examining the R^2, the model is assessed by examining the effect size f^2 which allows an identification of an exogenous constructs contribution to an endogenous latent variables R^2. and since all direct values are either above the thresholds of 0.15 and 0.35, we can conclude that the have moderate to high effect sizes.

5.3. Test for mediation

To examine if the effect of AI competencies on organizational performance is mediated through the B2B marketing capabilities, we performed a bootstrapping approach (Hair Jr et al., 2016; Preacher & Hayes, 2008). Following the guidelines of of Hair Jr et al. (2016), at a first stage we confirmed that the mediated paths (AIC → INFM → ORGP, AIC → PLANN → ORGP, and AIC → IMPL → ORGP) are significant. As these were found to be significant, we then included the direct path from

Table 2
Assessment of reliability, convergent and discriminant validity of reflective constructs.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Infrastructure	**0.91**						
(2) Business spanning	0.403	**0.92**					
(3) Proactive stance	0.465	0.436	**0.91**				
(4) Information management	0.475	0.389	0.370	**0.89**			
(5) Planning	0.388	0.399	0.307	0.475	**0.88**		
(6) Implementation	0.430	0.378	0.222	0.335	0.464	**0.90**	
(7) Organizational performance	0.399	0.420	0.384	0.476	0.473	0.424	**0.89**
Mean	4.26	4.33	4.08	4.34	4.28	4.40	4.48
Standard Deviation	1.39	1.41	1.35	1.47	1.51	1.49	1.37
AVE	0.83	0.84	0.83	0.80	0.79	0.81	0.80
Cronbach's Alpha	0.84	0.87	0.85	0.89	0.88	0.91	0.87
Composite Reliability	0.86	0.88	0.89	0.90	0.89	0.88	0.87

Table 3
Higher-order construct validation.

Construct	Measures	Weight	Significance	VIF
AI Competencies	Infrastructure	0.376	$p < 0.001$	2.053
	Business spanning	0.357	$p < 0.001$	1.985
	Proactive stance	0.315	$p < 0.001$	2.173

AIC → ORGP in the model and find that there is a positive and significant effect ($\beta = 0.215$, $t = 3.935$, $p < 0.01$). To test for the type of mediation, we used the parameter estimates from the bootstrapping procedure in PLS, based on a resampling of 5000 subsamples. Then we calculated the standard error of each mediation effect and at a later stage computer the t-statistic for each mediation path by dividing the effect of the indirect path (i.e. the product of each indirect path), by the standard error of mediation effects. By building on this method the there is the advantage of not imposing any distributional assumptions of the indirect effects. Furthermore, this approach allows for the calculation of the entire indirect effect simultaneously in the presence of multiple mediating effects as we have in this model. With the inclusion of the direct effect, the remaining paths retained their significance, albeit to a lesser level which indicates that there is partial mediation Table 4.

6. Discussion

In this study we have sought to understand if AI can enable organizations to realize performance gains in B2B activities, and if so through what means. Specifically, we build on the core competencies theory to develop a conceptualization of AI competencies which goes beyond solely the technical facets of AI. Through this conceptualization, we argue that organizations that are able to foster AI competencies will realize organizational performance gains through their B2B operations. Specifically, we argue that AI competencies allow organizations to

Table 4
Summary table of hypotheses and findings.

Hypothesis	Structural path	Effect	t-value [a]	Conclusion
H1	AIC → INFM	0.413	9.234***	Supported
H2	AIC → PLANN	0.355	6.934***	Supported
H3	AIC → IMPL	0.256	4.575***	Supported
H4	INFM → ORGP	0.246	6.942***	Supported
H5	PLANN → ORGP	0.277	7.460***	Supported
H6	IMPL → ORGP	0.378	8.421***	Supported

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

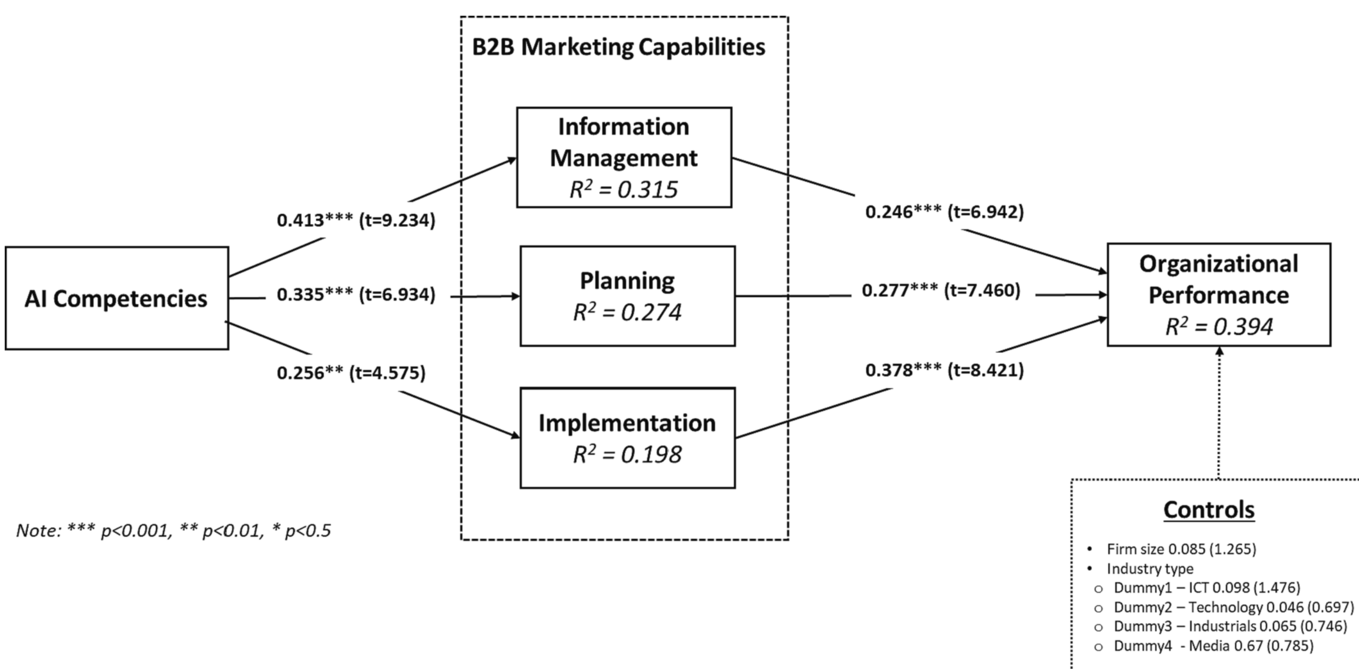

Fig. 2. Estimated relationships of structural model.

develop three channels of B2B marketing capabilities, information management, planning, and implementation. Through a sample of 155 responses from senior IT executives in the Nordic countries, we explore the hypothesized relationships by using a PLS-SEM approach. Below, we discuss the research and practical implications of our findings, as well as some important limitations and ways future research can overcome them.

6.1. Implications for research

Building on the body of research that examines the value of AI, one of the objectives of this study was to try to understand if and under what conditions AI can lead to organizational value for firms. To answer this question, we have grounded our conceptualization of the AI artifact based on the core competencies theory (Prahalad, 1993). We therefore consider AI competencies from the standpoint of a key organizational capability that has the potential to confer a competitive advantage to organizations. Thus, AI competencies are not perceived simply from a technical standpoint but encompass the ability of management to creatively envision applications that are value-adding for the organization and involves the ability to experiment and test new ways of using AI. Building on this approach also considers an AI competency as a core competency that organizations should strive to foster, rather than being just an auxiliary class of capabilities that can support certain operations. The implications of conceptualizing AI competencies in this way are that it places weight on the idiosyncratic ways in which such AI competencies are developed and maintained in organizations. The implications of such an approach are that each organization must find its unique way of constructing such AI competencies based on several different aspects such as the industry it operates in, the organizational history, organizational cultural elements, as well as those that characterize the environment in which firms operate.

A second important finding from this study concerns the nature through which AI competencies confer value to organizations. Our results indicate that they affect organizational performance in an indirect manner by enhancing B2B marketing capabilities. This finding highlights the fact that AI competencies are malleable and can be directed towards different types of organizational operations which can be enabled or enhanced through the application of different AI methods. In our study, we have specifically shown the value that can be realized in B2B marketing activities which constitute an important part of organizational operations. By enhancing such processes through the targeted use of AI applications organizations can attain an edge over their competitors. The activities of B2B marketing provide ample opportunities for use of AI since they entail large complexity and rapidly changing circumstances in which AI can quickly analyze data and provide appropriate insight. In addition, many tasks associated with B2B marketing activities can be automated through use of AI or enhanced though human-AI collaboration (Mikalef et al., 2021). Nevertheless, an interesting finding from the empirical analysis is that the impact of AI competencies on the different types of B2B marketing capabilities is not equal. We find that when it comes to implementation capabilities, the extent is lesser compared to information management. This can be explained by the fact that information management capabilities in B2B contexts are easier to infuse with AI compared to implementation capabilities. Thus, there is an increased level of complexity in introducing AI in certain operations, which though could provide organizations with a competitive edge.

Our results also highlight this, as organizations that can foster strong B2B marketing implementation capabilities also present higher levels of organizational performance. This finding confirms the key tenets of core competency theory which argues that organizations that are able to develop a distinct and hard to imitate capability will be able to realize a competitive edge. Furthermore, the outcomes indicate that although AI can deliver value through the three aforementioned B2B marketing capabilities, these are not the only channels of value generation. Since the effect of AI competencies on organizational performance is partially mediated through the three aforementioned capabilities, this entails that there are alternative forms of value-generation from AI that were not included in this study. Nevertheless, the extent to which B2B marketing capabilities influence performance outcomes is quite significant, which highlights the importance that such activities have for future research. While this study highlights the magnitude of and mechanisms of AI through prompting changes in B2B marketing capabilities, it also encourages further research on the different ways in which such effects and translated into practical applications. Thus, while this study is an important first step in identifying the way in which AI need to be organized within companies and the mechanisms of value generation, there needs to be further research on the specific types AI applications and the challenges in deploying them.

6.2. Implications for practice

From a practical perspective the findings of the study provide practitioners several important key insights which they can use when deploying AI for B2B marketing purposes. First, our conceptualization of the AI competencies concept underscores the importance for fostering an environment that allows experimentation. In addition, managers should be aware of the possibilities offered by AI in order to creatively suggest ways in which AI applications can be used to support operations. This can be done by providing training to existing managers on important developments in the domain during the past years and illustrating successful use cases. Furthermore, from the organizational side it is important that top management does not only allocate appropriate financial resources for AI projects to develop, but also allow enough liberty and time for free experimentation. A key element of the AI competencies notion is the proactive stance dimension, which places a focus on employees being allowed to experiment freely with new ideas, techniques, and approaches. Furthermore, the business spanning dimension highlights the need for concurrent direction from the top management towards value-generating applications of AI and flexibility for experimentation. Balancing this tension may prove challenging for many managers and will likely depend on the idiosyncrasies of the organization and team.

The outcomes of the study also highlight several key areas in which AI can enhance efficiency, and in particular for B2B marketing activities. Developing an internal AI competency can have ripple effects on several key organizational capabilities, such an information management, planning, and implementation. Enhancing such B2B marketing capabilities may require different types of AI applications and different technologies to support them. So, it is important rather that adopting a narrow perspective on enhancing one particularly activity through a targeted AI application, that managers foster a logic of turning AI into a core competency of the organization. In this way, they will be able to enhance the key underlying capabilities that support B2B marketing activities. Furthermore, the outcomes showcase the value that AI can have for the three underlying capabilities. As markets become increasingly distributed, fast-paced, and evolving, it is important that organizations enhance their operations through AI applications in order to deal with the complexity and speed that is required. Thus, managers can utilize these findings empirical evidence of the effectiveness of such technologies as a mean to attain a competitive edge over rivals. As AI competencies require time to develop, it is more probable that those organizations that invest early and continuously that will realize distinct competencies that can help them outperform competition.

As a whole, the outcome of this study provide some insight into how contemporary organizations should approach the emerging phenomenon of AI within the B2B marketing context. Specifically, the need for experimentation combined with the large diversity of potential areas of use underscore the need to develop a more external orientation and to quickly identify new emerging use areas and tools. Doing so requires from management a larger openness to participating in seminars, workshops, and industry-led events concerning new AI applications. In addition it highlights that unlike other types of information systems that have been in the spotlight in the past, AI applications have a broader area of application and thus necessitate a more diverse set of skills. As shown in the results, an AI competence can influence different activities pertinent to B2B marketing activities so it is important that managers are aware of the potential for use. Doing so places weight on the necessary knowledge that must be kept up to date as different types of techniques and applications are constantly emerging.

6.3. Limitations and future research

While our study has attempted to highlight the value of AI competencies towards the enhancement of B2B marketing capabilities and ultimately organizational performance, it does not come without certain limitations. First, while we have attempted to capture the mechanisms through which AI competencies enhance B2B marketing capabilities, the choice of method only allows us to infer causality and assume that there isa significant effect. Nevertheless, due to the diversity of organizations included in our sample it is likely that they have developed radically different approaches in leveraging their AI competencies to enhance B2B marketing capabilities. A qualitative approach with a smaller sample and in a specific industry can yield interesting results concerning the types of AI applications that are developed and the process of doing so. Such findings could also highlight the challenges in each industry or for specific types of AI applications. Second, while we have tried to be inclusive in terms of the organizations we maintained in our sample, the responses did come from organizations that operate in the Nordics. As such, it is likely that organizations within this sample have sufficient financial resources to invest in AI and appropriate conditions to foster deployment. This might not be the case in other countries that are developing or face other types of hindrances in relation not technology deployment. Hence, the effects that we find may be less pronounced in different countries. Finally, we have opted for a survey-based study that has the limitation of collecting data in a snapshot in time. As such the effects that AI competencies have on B2B marketing capabilities may be miscalibrated due to lag effects. In order to more accurately capture the influence of AI competencies on organizational phenomena, future studies can opt for a lagged approach in capturing performance data, or alternatively use objective performance indicators.

CRediT authorship contribution statement

Patrick Mikalef: Conceptualization, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing. **Najmul Islam:** Conceptualization, Data curation, Formal analysis, Methodology, Writing- original draft. **Vinit Parida:** Supervision, Resources, Project administration, Writing - original draft, Writing - review & editing. **Harkamaljit Singh:** Conceptualization, Investigation, Writing - review & editing. **Najwa Altwaijry:** Supervision, Resources, Project administration

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. . Questionnaire

Construct	Items
AI Competencies	
Infrastructure	1. Data management services and architectures for AI. 2. Network communication services and cloud services3. AI application portfolio and services (e.g. Microsoft Cognitive Services, Google Cloud Vision)4. AI facilities' operations/services (e.g., servers, large-scale processors, performance monitors) . 5. AI infrastructure to ensure that data is secured from to end to end with state-of-the-art technology
Business Spanning	1. Developing a clear vision regarding how AI contributes to business value. 2. Integrating business strategic planning and AI planning. 3. Enabling functional area and general management's ability to understand value of AI investments. 4. Establishing an effective and flexible AI planning process and developing a robust AI plan.
Proactive stance	1. We are capable of and continue to experiment with new AI tools and techniques as necessary. 2. We have a climate that is supportive of trying out new ways of using AI. 3. We constantly seek new ways to enhance the effectiveness of AI use. 4. We constantly keep current with new AI innovations.
B2B Marketing Capabilities	
Marketing information management	1. Gathering information about customers and competitors Using market research skills to develop effective marketing programs Tracking customer wants and needs Making full use of marketing research information Analyzing our market information
Marketing planning	1. Marketing planning skills Ability to effectively segment and target market Marketing management skills and processes Developing creative marketing strategies Thoroughness of marketing planning processes
Marketing implementation	1. Allocating marketing resources effectively Organizing to deliver marketing programs effectively Translating marketing strategies into action

(continued on next page)

(*continued*)

Construct	Items
	Executing marketing strategies quickly
	Monitoring marketing performance
Organizational Performance	1. Compared to our key competitors our organization is more successful.
	Compared to our key competitors our organization has a greater market share.
	Compared to our key competitors our organization is growing faster.
	Compared to our key competitors our organization is more profitable.
	Compared to our key competitors our organization is more innovative

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