Industrial Marketing Management 98 (2021) 80–92

Contents lists available at ScienceDirect

Industrial Marketing Management

journal homepage: www.elsevier.com/locate/indmarman

Artificial intelligence as an enabler of B2B marketing: A dynamic capabilities micro-foundations approach

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ARTICLE INFO

Keywords:
Artificial intelligence
Dynamic capabilities
Business value
B2B marketing
micro-foundations

ABSTRACT

Over the past few decades research has predominantly focused on the technical aspects and theoretical challenges of Artificial Intelligence (AI). With the deluge of data and the increase in processing power, businesses are now facing the challenge of how to deploy AI that generates business value. In this direction, there is still nascent research on how AI can be leveraged in for B2B operations, and particularly marketing. To address this gap, this study draws on the dynamic capabilities view of the firm and specifically on the micro-foundations approach and builds on three selected case studies of large organizations in Norway that use AI for B2B marketing purposes. The study identifies a number of AI-specific micro-foundations of dynamic capabilities, essentially highlighting how organizations can use AI to manage B2B marketing operations in dynamic and uncertain environments. This study also identified several key cross-cutting elements emerging from the data, demonstrating how some key concepts are inter-related and how they affect overall business value.

1. Introduction

The value of Artificial Intelligence (AI) in augmenting organizational operations has started to attract the interest of practitioners over the past few years (Davenport & Ronanki, 2018). A growing number of firms have begun deploying AI initiatives with the aim of automating or augmenting key business processes, with the ultimate goal of gaining a competitive edge (Duan, Edwards, & Dwivedi, 2019). Some practitioners and researchers have associated AI with the next frontier for competition and productivity (Dwivedi et al., 2021), while others have even claimed that it is a revolution that will radically transform how business is conducted (Ågerfalk, 2020). Following the deluge of data, significant developments have been documented in terms of techniques and technologies for data storage and processing (Ransbotham, Kiron, Gerbert, & Reeves, 2017). Yet, empirical research on the value of AI is still at a rudimentary state with a general lack of understanding concerning the mechanisms through which such investments can generate business value (Duan et al., 2019). This fact is rather surprising when taking into account the surge of companies venturing in the area of AI (Ransbotham, Gerbert, Reeves, Kiron, & Spira, 2018). In addition, there is scarce research on how organizations should proceed to embed AI into the organizational fabric, and little knowledge towards the strengthening of which organizational capabilities they should leverage their investments (Mikalef, Fjørtoft, & Torvatn, 2019). There is, as a result, limited understanding on how firms should approach their AI initiatives, and inadequate empirical support to back the claim that these investments result in any measurable business value (Dwivedi, Hughes, Ismagilova, et al., 2021).

According to a recent report by the MIT Sloan Management Review, application area with heightened interest in regards to AI use is that of B2B marketing (Ransbotham et al., 2017). As organizations become increasingly more engaged with the AI paradigm, so will there marketing becoming more and more infused with different types of AI applications (Chui, 2017). Nevertheless, while a large proportion of applications have been placed in the area of B2C marketing, we still know very little about how companies utilize AI to support their B2B marketing activities (Dwivedi et al., 2021). Such B2B marketing activities are becoming increasingly more important for contemporary firms, particularly since a large number of core processes are turning digital (Dwivedi, Ismagilova, Rana, & Raman, 2021). Even more, there is a lack of knowledge about what are the key success factors during the process of doing so (Brynjolfsson & Mcafee, 2017). Understanding the potential of AI in B2B marketing and uncovering the mechanisms and key success factors through which business value is realized has important

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https://doi.org/10.1016/j.indmarman.2021.08.003
Received 31 January 2021; Received in revised form 6 August 2021; Accepted 7 August 2021
Available online 13 August 2021

theoretical and practical implications (Grover, Kar, & Dwivedi, 2020; Nishant, Kennedy, & Corbett, 2020).

From a theoretical perspective, there is still limited understanding regarding how the broad set of technologies that comprise AI can generate business value (Dwivedi, Hughes, Ismagilova, et al., 2021). From a practical point of view, there is a need to highlight the challenges in implementing AI to support B2B marketing operations, as well as to clearly define what outcomes can be expected from such investments. Gaining a deeper understanding of the role of AI in B2B operations is also of increased significance in uncertain conditions, where AI is argued to play a central role in the attainment of competitive performance gains (Hu, Lu, Pan, Gong, & Yang, 2021). High paced and frequently changing conditions have heightened the importance of AI in replacing or augmenting internally- and externally focused processes (Pillai et al., 2021; Zhang, Pee, & Cui, 2021). Understanding how AI technologies can be leveraging for B2B settings is also a matter with high practical relevance, as a growing number of practitioners aim to gain a competitive edge over their rivals by deploying innovative digital solutions (Dubey et al., 2021; Ransbotham et al., 2018).

To explore these questions, the present study builds on a multiple case research approach and attempts to answer two closely related questions:

(i) *How do firms leverage artificial intelligence technology to support B2B marketing activities in dynamic and uncertain environments?*
(ii) *What are the key success factors in generating business value from AI-enabled dynamic capabilities in B2B marketing?*

We build on the emergent literature of micro-foundation of dynamic capabilities to explore the underlying processes through which AI investments are leveraged to support B2B operations, as well as the factors that help shape them into value-adding solutions. Drawing on three case studies conducted in leading Norwegian firms, we examine how they utilize AI in order to support the processes that underpin their dynamic capabilities: sensing, seizing, and transforming. Through the analysis we show some common challenges faced by the three firms, as well as some distinct differences based on the AI applications that they are utilizing and the contextual intricacies of the corresponding processes they are supporting.

The rest of the paper is structured as follows. First, we introduce the theory of dynamic capabilities and describe the key processes that underpin the notion as well as the micro-foundations from which they emerge. In sequence we survey literature on the value of AI in order to understand the ways in which such technological innovation have been used in other contexts. Next, in Section 3 we describe our research approach, followed in Section 4 by our findings. We conclude by drawing on the theoretical and practical implications and highlighting the key limitations that characterize our approach and ways in which future research could expand on these findings.

2. Theoretical background

The role of AI in facilitating effective B2B marketing operations is central to this study, and more specifically, in examining how AI can dynamic capabilities that help exert such effects. This sequence of associations if represented by the conceptual framework adopted in this study (Fig. 1). The logic that this study follows is that AI can enable or enhance the underlying processes that comprise a firm's dynamic capabilities. In turn, having formidable dynamic capabilities allows firms to revamp their B2B marketing operations. The conceptualization of AI and dynamic capabilities, as well as the extant literature is discussed in the subsequent sections.

2.1. Artificial intelligence in B2B marketing

Artificial Intelligence has received a rekindled interest as being the next frontier of productivity and innovation (Syam & Sharma, 2018). The vast majority of studies to date have explored the potential business value that can be delivered from AI application within organizational boundaries with some early research empirically demonstrating such effects (Paschen, Wilson, & Ferreira, 2020). In the broader domain of IT-business value research, and the emerging IT-enabled organizational capabilities perspective, there is a growing consensus that IT enables firms to generate performance gains through intermediate organizational capabilities (Benitez, Castillo, Llorens, & Braojos, 2018; Schryen, 2013). The main premise of this view is that leveraging novel IT applications is central for organizations since it helps develop complementary effects with intermediate organizational capabilities that ultimately lead to competitive advantage. Currently, there is still a limited understanding regarding the mechanisms through which AI-based applications deliver competitive performance gains (Duan et al., 2019). The main argument in our study is that depending on the context of use, organizations can realize different types of benefits for each of the underlying processes that comprise their dynamic capabilities.

While there is still limited empirical research exploring the mechanisms through which AI leads to business value gains in B2B marketing (Collins, Dennehy, Conboy, & Mikalef, 2021), some papers have offered insight into what AI can deliver (Bag, Pretorius, Gupta, & Dwivedi, 2021). Specifically, there is an ongoing debate about how AI can help organizations automate processes, gain insight from data that was previously unattainable, and improve their engagement with key customers (Davenport & Ronanki, 2018). AI has been shown to allow firms to automatize several different manual processes, including interactions with customers (e.g. through the use of chatbots), or other intensely manual activities (Davenport & Ronanki, 2018). In their recent work, Coombs, Hislop, Taneva, and Barnard (2020) present a conceptual model of business value for Intelligent Automation, a subset of AI technologies. This work demonstrates the synergistic relationship between technological and non-technological investments, and the proposed mechanisms through which business value is realized. Building on the domain of B2B marketing, Bag, Gupta, Kumar, and Sivarajah (2021) provide a theoretical model to explain the impact of AI in B2B marketing by improving rational decision-making. This work shows that the power of AI is not restricted to automating processes but also enhancing knowledge management practices pertinent to B2B marketing activities. Other empirical work also offers insight into how marketing-specific activities such as pricing, consumer behavior can be enhanced by use of AI technologies (Leone, Schiavone, Appio, & Chiao, 2020).

Other work such as that of Wamba-Taguimdje, Wamba, Kamdjoug, and Wanko (2020) also illustrates that AI can enable key stakeholders to uncover insight and hidden patterns in data that can signal trends or hint towards unknown facts. Being able to analyze data and generate insight from vast amounts of data has been argued to be a major contributor to gaining a competitive edge (Mikalef, Boura, Lekakos, & Krogstie, 2019). Finally, AI applications have the potential to provide greater engagement with employees and customers through the use of intelligent

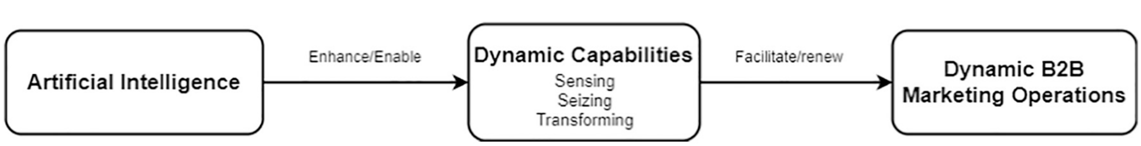

Fig. 1. Conceptual framework.

agents and recommendation systems (Heer, 2019; Syam & Sharma, 2018). In the context of B2B marketing all three types of value delivered by AI are relevant and have the potential to lead to competitive performance gains. Nevertheless, the ways by which AI applications are leveraged for such activities, and particularly in relation to the underlying dynamic capability processes they support has not been examined extensively to date (Martínez-López & Casillas, 2013). Early studies have shown that advanced analytics methods have an impact on a firms dynamic capabilities and overall performance (Gupta, Drave, Dwivedi, Baabdullah, & Ismagilova, 2020; Mikalef, van de Wetering, & Krogstie, 2020; Steininger, Mikalef, Pateli, de Guinea, & Ortiz-De, 2021), however, the process of AI deployment in relation to B2B marketing operations is still at an early stage.

2.2. Dynamic capabilities and micro-foundations

The Dynamic Capabilities View (DCV) has been one of the most influential theoretical perspectives in the study of strategic management over the past decade (Schilke, 2014). Building on a Schumpeterian logic of creative destruction, dynamic capabilities are suggested to allow firms to sense and seize emerging business opportunities, and reconfigure the way they do business in order to adapt to shifting market conditions (Teece, 2007). Although there is some variation in used definitions, there is an increasing convergence on the idea that dynamic capabilities are purposefully developed, and comprise of a set of identifiable and specific processes (Schilke, Hu, & Helfat, 2018). These processes are commonly understood as learned and purposeful, directed towards independent corporate actions (Winter, 2003). A key reason for much research attention on the notion of dynamic capabilities has been their proposed influence on important outcome variables (Schilke et al., 2018). Dynamic capabilities contrast with operational or ordinary capabilities which are directed towards how a firm currently makes a living, and are proposed to confer value by enabling evolutionary fitness (Helfat & Peteraf, 2009). Recent studies have confirmed such claims, with empirical results demonstrating that they effectuate systematic change, by enabling renewal of operational capabilities and increased flexibility in response to market changes (Pezeshkan, Fainshmidt, Nair, Frazier, & Markowski, 2016). These represent key areas in the attainment of a sustained competitive advantage (Teece, 2007).

The literature has disaggregated dynamic capabilities into three underlying processes oriented towards strategic change. These include *sensing* new opportunities and threats, *seizing* new opportunities through business model design and strategic investments, and *transforming* or reconfiguring existing business models and strategies (Helfat & Raubitschek, 2018; Steininger et al., 2021). In his seminal article, Teece (2007) argues that sensing involves analytical systems of scanning, search and exploration activities across markets and technologies. On the other hand, *Seizing* includes the evaluation of existing and emerging capabilities, and possible investments in relevant designs and technologies that are most likely to achieve marketplace acceptance (Wilden, Gudergan, Nielsen, & Lings, 2013). Finally, *transforming* includes continuous alignment and realignment of specific tangible and intangible assets (Katkalo, Pitelis, & Teece, 2010). Past studies have predominantly examined the outcomes of dynamic capabilities (Drnevich & Kriauciunas, 2011; Protogerou, Caloghirou, & Lioukas, 2011), with significantly less research looking into how the underlying processes that comprise dynamic capabilities emerge (Capron & Mitchell, 2009). In this stream of research, studies have examined at antecedents at different levels of analysis, including the organizational (Eisenhardt, Furr, & Bingham, 2010), individual (Hsu & Sabherwal, 2012; Shareef et al., 2021), and environmental levels (Killen, Jugdev, Drouin, & Petit, 2012), to isolate factors that either enable or hinder the formation of dynamic capabilities. Yet, there is, to date there is little research to the best of our knowledge regarding the impact that AI has on enabling the underlying processes that comprise dynamic capabilities (Steininger et al., 2021). In Table 1 depicted below we present the definitions used for each process, as well as the activities which they typically include according to Conboy, Mikalef, Dennehy, and Krogstie (2020). While there is broad discussion on how AI can help organizations become more competitive, there is a lack of understanding on how the unique features that AI introduces may affect the underlying dimensions, and the microfoundations that comprise them (Kouropalatis, Giudici, & Acar, 2019).

3. Research approach

3.1. Research sites and data collection

Since empirical research on the value of AI and its diffusion into strategic development, particularly in business-to-business contexts, is at an early stage of maturity, we adopted an exploratory case study method (Benbasat, Goldstein, & Mead, 1987). The choice of a case study research method was based on the fact that it allows for the collection of a rich description of phenomena and a detailed explanation of developments that are not well understood in literature from the perspective of multiple key actors (Yin, 2017). In our study design we opted for a choice of a multi-case study design since it allows a replication logic, through which a set of cases are treated as a series of experiments, each serving to confirm or disconfirm a set of observations (Yin, 2009).

We conducted our research in high-tech firms, as these types of firms have been shown to be within the forerunners of AI implementation (Ransbotham et al., 2018). Furthermore, the types of projects initiated

Table 1
Dynamic capabilities and underlying processes (Source: Conboy et al. (2020)).

	Sensing	Seizing	Transforming	Reference
Definition	*Sensing* is defined as the identification and assessment of opportunities	*Seizing* is defined as the mobilisation of resources to address an opportunity and to capture value from doing so	*Transforming* is defined as the continued renewal of the organization	(Teece, 2007)
Underlying activities	• Gathering marketing intelligence • Spotting opportunities • Identifying target market segments • Spotting changing customer needs and customer innovation • Interpreting changes and uncertainties • Conceptualising new customer needs/business models	• Building competencies • Choosing decision-making practices • Selecting partners and distribution channels • Committing to R&D • Mobilising resources to address opportunities • Forming alliances and joint ventures	• Achieving recombination's • *Re*-engineering processes • Reconfiguring capabilities • Managing knowledge • Asset co-specialisation • Dynamic alignment of tangible and intangible assets	Jantunen, Tarkiainen, Chari, & Oghazi, 2018; Katkalo et al., 2010; Teece, 2007; Wilden et al., 2013)
Value creation	• Positioning for first mover advantage • Determining entry timing	• Leveraging complementary assets	• Managing threats • Changing the business model • Continued renewal	(Katkalo et al., 2010; Teece, 2007)

by companies in this sector tend to be more sophisticated and tend to be to a greater extent a core part of the firms competitive strategies (Mikalef, Pappas, Krogstie, & Giannakos, 2018). The hype of the last few years has prompted a large number of firms to invest in AI pilot projects (Dwivedi, Hughes, Ismagilova, et al., 2021). Firms are now realizing that AI is not merely a means to gain a competitive advantage but a necessity in order to remain on competitive par. The three cases that were selected for the purpose of this study had all implemented AI solutions at least 2 years ago. In addition, the firms initiated their implementations at almost the same time rendering their maturity levels similar. In their respective industries, each firm is within the top performers on national level, in terms of revenues, profits, market share, and number of employees. All firms also have significant international presence with a large proportion of their revenues being a result of activities performed outside of their national borders. Nevertheless, while sought firms with similarities to be able to compare them and replicate findings, we also deemed it necessary that they had a sufficient degree of heterogeneity to help assess potential generalizability. In Table 2 we provide relevant details and the three selected firms of this study.

The research was conducted by using a semi-structured interview method with a total of 10 employees who were directly (e.g. marketing director, data scientist) or indirectly (e.g. project manager, IT manager) involved in the deployment and use of the AI solutions. The experience of all participating respondents related to the years they had worked in the specific industry as well as the time working for the focal firm as presented in Table 3. Interviews were conducted from January 2020 to March 2020 and lasted approximately between 65 and 85 min each. All interviews were recorded and transcribed with permission of respondents. In addition, all respondents were asked to fill out a consent form which also informed them about the purpose of the study and how collected data would be used. In the data collection process, we also used additional material for comparison and saturation purposes, including company reports and presentations, observations, material from common projects with university students, industry reports, news publications, as well as other public information.

3.2. Data analysis

For the data analysis, we followed the guidelines of Miles, Huberman, and Saldana (2013) and opted for a thematic analysis in exploring the data. Through a systematic and iterative procedure, in which data comparisons, emerging themes, and latest literature was used to facilitate the process. As a first step we developed separate case studies for each firm. We looked at patterns within the answers of respondents and any differentiating aspects in their descriptions of how AI was utilized to support B2B marketing operations. To do so we used a combination of pre-defined codes based on the definitions presented in Table 1, as well as an open-coding schema to uncover complementary aspects. In addition, we examined the underlying mechanisms and core conditions that linked such solutions to improvements in B2B marketing activities. To establish reliability of the generated codes, the coding of answers was performed independently by the two co-authors, and themes were compared until an inter-coder reliability of above 90% was achieved (Boudreau, Gefen, & Straub, 2001). Inter-coder reliability was applied in order to improve the systematicity, communicability, and transparency of the coding process, and to promote reflexivity and dialogue within the research team (O'Connor & Joffe, 2020).

Table 3
Respondent profiles.

Firm	Respondent	Duration (Minutes)	Years in the industry	Years in the firm
Firm A	A1. Vice President of Next Generation Services	75	12	9
	A2. Senior Research Scientist	68	14	8
	A3. Senior Data Scientist	77	7	7
	A4. Regional Marketing Manager	65	18	12
Firm B	B1. Online Presence Manager	84	17	14
	B2. Technical Support Manager	66	13	7
	B3. Data Scientist	74	8	8
Firm C	C1. Chief Information Officer	79	21	13
	C2. Vice President of Digital Strategy	77	18	16
	C3. IT Manager	83	10	8

Following this process, we linked related concepts within each case. As a part of this phase, we looked at the conclusions that had been drawn during the initial coding and established links between our selected categories and emergent themes. While we had a set of theoretically-driven concepts to partially guide the identification of key notions, we allowed for other concepts and patterns to emerge based on the collected primary data. To improve the generalizability of findings and to deepen the understanding and explanation of these concepts, we performed a comparative analysis between each category and between same categories in different cases. The purpose of doing this was to be able to compare and contrast how operations had changed in each of the three firms with the introduction of AI applications, how the process of doing so had been performed, as well as what challenged they had faced. All differences between coders were resolved through discussion. Furthermore, once we had reached a first version of conclusions, we shared these with the key informants in order to assess their plausibility and point out to any aspects we had not comprehended correctly or missed out on.

During the last phase, we connected emergent themes and concepts with the theoretical concepts in literature. We therefore performed an iterative approach moving back and forth between emerging themes and the extant literature to explore broadly possible explanations for our findings and to develop an explanation of findings (Yin, 2017). In the section that follows we discuss the findings that the three case studies yielded. First, we discuss how the introduction of AI has changed the way these firms perform B2B marketing activities. Second, we explore the mechanisms and key components that link these investments to improvements in B2B marketing.

Table 2
Overview of the case firms.

Firm	Year founded	Industry	Primary operation	Number of employees	Annual revenue	Year when AI was implemented
Firm A	1970	Telecommunications	Fixed and mobile telephony	35.121	13,749.1 million €	2016
Firm B	1983	Semiconductors	Production of wireless semiconductor components and integrated circuits	566	209.9 million €	2017
Firm C	1985	Technology provider	Provision of IT services and cognitive solutions	361	102.3 million €	2017

4. Findings

4.1. Utilization of AI to enable dynamic capabilities for B2B marketing

In line with our research question, we first investigated how the introduction and utilization of AI has transformed the functions of B2B marketing within the three case studies. We found that the use of AI led to improvements in insights, faster reaction times, the development of new marketing approaches, and the generation of new sources of revenue. Below we discuss the performance gains in more detail. In the three cases examined, the use of AI was geared towards supporting a broad range of performance aspects in relation to marketing (e.g. generation of new insights, targeted information dissemination), new business models (e.g. creation of new services based on analytics), customer care (e.g. faster response time to customers, increased satisfaction from customer queries), as well as quality assurance (e.g. ensure product quality, respond to defects). Table 4 presents the types of AI technologies deployed by each firm as well as the impact it had on their B2B marketing operations.

The respondents across the three cases argued that the diffusion of AI provided them with additional insights into aspects related to B2B marketing and allowed them to develop better informed response strategies and new business models to consolidate their competitive position (see Table 5 for a more detailed description). In particular, respondents highlighted three main themes of activities in which AI solutions provided improvements to their firms, corresponding to the underlying dimensions of dynamic capabilities.

First, all three argued that the adoption of AI had allowed them to understand their customers' needs and key issues in much greater detail, since they were in place to make sense of vast amounts of information and categorize them in meaningful ways. In fact, they noted that in cases where there was great complexity and an overload of information, AI applications facilitated the generation of comprehensive and accurate insight. In addition, they were able to uncover more insights from large amounts of data relating to market conditions or general trends. Second, they noted that the forms of interactions with their customers had changed significantly. After the adoption of AI solutions, they were in place to provide more accurate information to their customers, much faster, while being able to reduce costs. Furthermore, AI enabled the organizations to orchestrate their resources more effectively and significantly alter how internal processes are handled. Third, respondents talked about the potential that AI had on developing new services and solutions for their customers, providing new avenues for revenue creation. Additionally, respondents reported that through AI they were able to improve their product and service offerings through the insight they developed. The insight they were able to aggregate helped develop more accurate responses to customer needs, and reduced the time needed to implement these changes. Such evidence leads to the following proposition:

Proposition 1. Leveraging AI to support B2B marketing operations can lead to performance improvements through enabled or enhanced dynamic capabilities.

Table 4
AI technologies used and their impact on B2B marketing operations.

Firm	AI technology(−ies) used	Impact on B2B marketing operations
Firm A	Machine learning Intelligent agents	• Identification of customer needs • Insight generation and commercialization • New service development
Firm B	Natural language processing (NLP) Support vector machines	• Thematic clustering of customer issues • More accurate and early identification of emergent issues with products • Clustering of customer portfolios • Automatic replies to known problems
Firm C	Machine learning	• Customer analytics • New service development

We now scrutinize each of the sub-components of dynamic capabilities (sensing, seizing and transforming), to ascertain evidence for sub-propositions.

When examining each of the three types of processes described in the dynamic capabilities view, we observe some commonalities and some differences in terms of the activities they leverage AI solutions. Specifically, respondent A1 in Firm A noted:

> We have developed a number of services to better monitor what our customers need and to discover emerging opportunities or threats based on machine learning. Our approach is to be proactive by not only monitoring in real-time the needs and wants of our customers but also trying to predict what they might require in the near future.

Another respondent from Firm B (B3) explained how they use data to sense the external environment:

> Our customers, which are mainly other firms, usually have a lot of interaction with us by various means. We recently launched an online virtual agent platform in which they can find information and we can correspond with them at any time. We can now identify themes of topics that we are frequently asked about or identify problems that are products may have. We have also applied cognitive computing solutions to learn from our past responses and to help formulate recommendation to our customers. This has led to a massive reduction in the need of human effort to go through all information and respond appropriately. We can now utilize these human hours in more productive tasks.

In Firm C there were significant advancements in the use of AI in interacting with other businesses that were customers. Firm C used such technologies in several areas to monitor customer preferences, competition, as well as the overall market. A quote from respondent C1 is indicative of this focus:

> We collect a lot of data from our customers and have developed many channels to receive this data. While in the past we would create pools and only use data once we had a specific even to analyze, now we utilize it on the fly. We still collect data but now we rely much more on real-time feedback. It is the orientation of the company to offer top level services to our customers, so we have to be attuned to their requirements. We also use occurrences in one client as an opportunity to prevent these in others. Nevertheless, we constantly look out for new ways of reaching more companies and providing solutions. In this respect we take the suggestions provided by our clients very seriously and try to be ahead in the game.

Based on this evidence regarding sensing, where the firms have been able to monitor their customer preferences more closely, their distinct needs, as well as the various clusters of profiles within them, this leads to the following proposition:

Proposition 1. (*a*): *Leveraging AI to support B2B marketing operations can lead to performance improvements through enabled or enhanced sensing.*

While for all three cases sensing their customers' needs and identifying emerging opportunities and threats in the marketplace was a top priority, they did not only rely on AI-generated insight as a source of action-taking. In other words, while much effort was placed in sensing opportunities and threats using AI, when it came to making decisions and seizing new evolving circumstances complementary information was taken into account. There was, however, a tendency for all three firms to base decision-making increasingly more on data-driven insight in order to seize opportunities. In all three cases insight derived from AI was utilized to change the specific processes within key area of marketing were performed. For instance, Firm B monitored in real time sentiments through natural language processing (NLP) and used this

Table 5
Assessing firms processes and performance outcomes from AI solutions.

Underlying processes	Indicator information	Value from AI	Performance benefits	Firm A	Firm B	Firm C
Sensing						
Customer need identification	Extent to which a firm can understand the requirements of its customer base	Better identification of thematic areas; faster or real-time sensing of core needs; use of more diverse information sources	Customer satisfaction; customer retention; increased profitability	✓	✓	✓
Identifying target markets	Extent to which a firm can detect new profitable market segments	Identification of themes in unlabeled data; trend spotting and forecasting	Increased market share; higher-profit margins; first-mover advantage	✓		✓
Quality monitoring	Extend to which a firm can monitor the quality of its products and services	Aggregation of sentiment from customers; isolation of defective features	Reduction of operating expenses; customer satisfaction; reduced liability and risk	✓	✓	✓
Seizing						
Process adaptation	Extent to which a firm can incorporate feedback and adjust production and marketing processes	Provide aggregated information in the form of evidence to make decisions; prioritization of key areas based on knowledge visualization	Improved agility; reduction of operating expenses	✓	✓	✓
Resource orchestration	Extent to which a firm can dynamically allocate resources in necessary areas	Proactive arrangement of resources; investment in areas forecasted to be important; proactive fault detection	Reduced fault occurrence; reduced operating expenses; limitation of slack resources	✓		
Reconfiguring						
New business models	Extent to which a firm can formulate new ways of doing business and generating revenues	Developing new services based on data-generated insight; using knowledge for consulting; commercializing insight	Innovation; Increased market share; market disruption; profitability; sustainability	✓		✓
Reconfiguration of capabilities	Extent to which a firm can change the way it performs core activities	Adjustment of organizational capabilities based on data-based indicators; selection of empirically grounded best practices	Reduced production time; Increased profitability	✓	✓	

input in combination with prior knowledge to formulate marketing approaches with its customers. This feedback was then used to develop alternative approaches and test their efficacy, indicating that data-driven approaches and their effectiveness were gauged in order to promote further seizing. Through a process of continuous improvements, the firm developed different profiles of client businesses and formulated a series of different ways to promote new products and services to each. The respondent B1 of Firm B stated the following:

> Our clients are companies with different needs that operate under a completely different set of conditions. Also, the people behind their activities have different personalities so it is important that you understand them and develop optimal way to engage them and fulfil their requirements. AI has helped identify such clusters and fine-tune out approaches towards them. We now not only know our customers much better but have insight with regards to what approaches work best to satisfy their needs.

Similar remarks were made by the respondents of Firm C. The company uses direct feedback mechanisms for its customers in order to continuously re-align their service offerings with requirements, while also using this input as a basis to target similar companies that are non-clients. Respondent C2 noted the following:

> I believe that one of things we have managed to learn and codify is what needs companies have under different circumstances. We have, for instance, clients that are in the retail sector, so we have learned from them and their experiences. They provide us with a set of requirements and then there is a process of exchanging information and making improvements to the services we provide. Through this journey we prepare ourselves for similar cases in the future and we can also target new customers by showing that we know their needs better than competition.

Therefore, on the basis of these findings we formulate the following proposition:

Proposition 1. (*b*): *Leveraging AI to support B2B marketing operations can lead to performance improvements through enabled or enhanced seizing.*

Finally, with regards to transformation capabilities, the utilization of AI also enabled Firms A and C to develop radically new products based on derived insight, and also led to operational transformation in the ways in capabilities are operated. For instance, Firm A utilized mobility data from its customers and combined it with other data sources such as weather, events on social media and indicated attendance, news about strikes or disruptions in transportation to provide services to third parties by means of AI applications. Respondent A2 from Firm A stated the following in relation to this:

> We used the opportunity to exploit the data we had and combine it with other data that is freely available. Our goal was to create services and insight that we could then sell to other interested companies. We were quite successful in doing that as we have data that if harnessed appropriately can be of high value.

On a different level, Firm B was able to analyze the data posted on its online portal to capture defects with its products that had not been identified during testing. When a critical number of similar issues were identified, and a trend was detected, technical teams operated so as to identify the source of problems and adjust production processes accordingly. Respondent B2 provided the following comments about this activity:

> While we try to do as much testing as possible there are always errors that only show up after you have shipped a product and it has reached its destination. Sometimes it is an issue of hardware while most of the times firmware needs modifications. We are now faster to detect these issues and do something about them. Before we were just drowning in a sea of information, so it was not so easy to identify these issues before it was too late….[]The introduction of natural language processing has enabled us to leverage this data and actually make use of it to transform our customer support operations.

In all the cases the introduction of AI created new opportunities of leveraging and coalescing data sources, that facilitated the transformation of activities or the creation of radically new ones. We therefore describe the following proposition:

Proposition 1. (*c*): *Leveraging AI to support B2B marketing operations can lead to performance improvements through enabled or enhanced transforming.*

4.2. Exploring the factors affecting the micro-foundations and mechanisms of value creation of AI

The previous section illustrated that AI can be used to enable and enhance dynamic capabilities in B2B marketing operations. The series of processes in which AI applications can have an impact demonstrate that such investments can indirectly and under circumstances lead to performance gains. Nevertheless, our findings point out that there are multiple complementary factors at different levels that play a role in realizing such value, and that value differs based on the type of process it is oriented towards enhancing. The overview of these factors is presented in Table 6.

Building on the literature that argues that realizing value from AI requires firms to leverage other complementary organizational resources (Borges, Laurindo, Spínola, Gonçalves, & Mattos, 2020; Demlehner, Schoemer, & Laumer, 2021; Mikalef & Gupta, 2021), we investigated the micro-foundations and mechanisms through which such elements exert an effect. Recent literature advocates that in order to realize value from AI investments, firms must also invest in maturing other complementary resources which jointly comprise a firms AI capability (Mikalef, Fjørtoft, & Torvatn, 2019). Nevertheless, one of the limitations of such approaches is that they do not differentiate between the different levels of analysis and how notions in each level interact and lead to emergent phenomena of higher levels. In line with suggestions of Wilden, Devinney, and Dowling (2016) we differentiate between corporate, business, and individual level to examine how AI applications are diffused in the enterprise fabric to lead to performance gains. One of the main tenets we build upon is that there may exist heterogeneity is the ways these core resources are structured. In addition, there is likely diversity how mechanisms are executed for leveraging these resources, and how the processes they are targeted to strengthen diffuse and lead to performance gains.

Proposition 2. *There are various factors that influence how AI affects the micro-foundations and mechanisms of value creation.*

Table 6
Factors affecting the value from AI-enabled dynamic capabilities.

	Firm A	Firm B	Firm C
Level 3 - Corporate			
Digital Strategy	While an explicitly formed strategy didn't exist at the early stages of AI projects, it emerged as a necessity to think about how the firm viewed data and what it wanted to achieve.	There was no AI strategy but rather a view to exploit as much data as possible from what was available to the firm.	The whole organizational strategy was oriented around new technologies and specifically around AI.
Top Management Support	There was a strong direction by top management to rely heavily on data-driven decision-making and make data into a core resource.	Top management supported initiatives after they had produced results demonstrating business value.	Top management set a data-driven approach as a top priority and supported actions taken at the business unit and individual levels.
Resource Investment	Heavy investments were made in terms of infrastructure, people, and other financial resources to support this strategy.	Moderate investments were made in hiring data scientists and in acquiring software licenses for AI application software licenses (e.g. Microsoft Azure Machine Learning Studio).	The firm invested heavily in technological infrastructure and data to complement existing sources. It also allocated a large part of financial budget and time resources to experiment with new ideas.
Cross-functional Communication	Communication with each business unit managers was established in order to receive input about how they envision the future of their departments in the age of data.	The lead of AI projects was done by the chief information officer and revolved largely around the IT department.	A steering group for the different departments met once a week to align their initiatives and coordinate efforts.
	Weekly meetings between heads of business units were organized to address common challenges and opportunities by using data.	The technical department had frequent meetings and discussion about ideas on improving insight generation but there rarely included members of other departments.	Bottom-up input was also included in these meetings transferring the ideas and insights from employees to top management.
Incentives	Incentives were provided to managers to explore new ideas about how to harness data to create value.	Managers were self-motivated to discover new ways to address issues with errors faced by clients.	Managers provided incentives to employees to come up with new projects based on ideas they had by allowing them more time to work on them thus promoting more liberty.
Level 2 – Business			
AI Project Governance	A centralized project governance scheme was established so that data from different departments would be accessible to all under specific access rights. Procedures, structures and roles were established as well as procedures for incorporating or sharing data with external parties.	A decentralized project governance scheme was established where decision was made locally and without any central control. Within business units' different approaches regarding data-ownership and rights were established.	AI project governance was defined very concretely with well-established procedures for data management, rights on data ownership and access, procedures for analyzing and interpreting data, as well as processes for incorporating new data sources.
Partnerships	Open innovation was promoted by certain business unit leaders where they included input from academia and other stakeholders as well as partnerships for data sharing.	Technical expertise was sought after externally though the partnership with researchers and academics.	Collaboration was established with lead researchers from academic institutions as well as with other technology companies for shared expertise.
Level 1 - Individual			
Skills	Technical skills in combination with industry-specific skills were placed as a priority.	Technical skills in combination with industry-specific skills.	Technical skills in combination with industry-specific skills.
	Data scientists expertise (statistical or interpretative knowledge) was given increased emphasis.	Data scientists expertise (statistical or interpretative knowledge).	Data scientists expertise (statistical or interpretative knowledge).
	Interpersonal skills and collaborative skills were fostered through training programs.	Knowledge of community about and key issues in past products.	Market-driven managerial approach.
		Good knowledge of sentiment analytics.	Technical expertise with machine learning.
Training and Development	Training was provided to existing employees about new analytical methods.	Online courses were promoted to employees to develop their skills.	Training was provided to employees through participation in workshops and seminars.
Cognitive Processes	Understanding of biases in AI outcomes and decision-making on data scientist and manager level were examined in seminars.		There was an increased focus on understanding cognitive biases and trying to reduce them during analytics initiatives and interpretation of results.

4.3. Organizational factors

In terms of the organizational level, our results show that the firms demonstrated very different ways of designing their approaches to AI. One of the differences in the way the firms were structured can be attributed to their strategic orientation, with Firms A and C being more oriented towards data-generated insight as a key asset, whereas Firm B had as the main product semiconductors and other electronic components, making insight a secondary or supportive process. For example, respondent A4 from Firm A stated the following:

> We are now in the phase that we realize that our business is built on the data we have, and what we do with it. This has created a new wave of making strategic decision based on what data we are missing, how we can obtain it, and how this will make us better than competition.

The differences that stem from strategic orientation were also observable in the business unit and organizational level of analysis, where routines, structures and priorities presented some heterogeneity (Wilden, Gudergan, & Lings, 2019). Top management support for AI projects resulted in different structures and processes to support them. For instance, in Firm C that was more reliant AI for operations, there was a greater emphasis on structural ambidexterity where different competencies, systems, incentive, processes and cultures were fussed together. This contrasted Firm B where departments were more siloed and less heterogeneous in terms of skills, cultures and worldviews. Respondent C2 from Firm C noted the following:

> There has been a push from top management to re-organize the entire company to address our big challenges. This has meant that we work in a more fluid way, and we have meetings and discussions with departments that we knew very little about before. Of course, we keep to our own core competence, but we now have several joint sessions and working hours where we collaborate with our colleagues from other departments.

The different approaches of these firms were also evident from the incentives set by top management, where more freedom was provided employees to experiment with their own ideas and realize a sense of ownerships on projects they undertook. Both Firm A and Firm C were given more liberty to work with research projects that were of their own interest, and there was an incentive scheme setup at the organizational level including prizes for most innovative use of AI to solve business problems. Respondent A1 from Firm A noted the following:

> I think we are realizing now that the problems we face required us to explore new knowledge. In the organization there is a new strategy now of providing us some free time to experiment with new ideas and approaches, and there is a dedicated budget for further training. There is a very strong move from the board to incentivize us to pursue more projects that make use of AI.

Therefore, our first sub-proposition is as follows:

Proposition 2. (*a*): *The organizational structure and associated factors influence how AI results in performance gains.*

4.4. Business factors

The significance of AI to overall business strategy was also associated with the level of sophistication of the governance for such operations, as has also been noted in prior studies (Hunt & Madhavaram, 2019). While all three cases had established project governance procedures to some extent, only Firms A and C had defined processes and rules for running projects and connecting business outcomes to specific methods and activities. These processes according to the respondents had played a critical role in facilitating better utilization of AI and in measuring business value. They had also positively contributed towards keeping projects within timeframes and identifying areas that needed to be matured. One of the respondents from Firm A also noted that in deciding which projects to pursue, having a clearly defined method of calculating expected returns of investments was very useful. According to him many companies struggle in quantifying value from AI and the reasons why they do not invest sufficiently is because they do not have such process to connect investment to expected outcome. Specifically, respondent A3 from Firm A noted:

> We realized early on that we need to define certain processes and expected outcomes for our AI projects. Without these we ended up having difference expectations about what AI is meant to do, and how to work. After some early attempts we scaled up the use of AI an established an inter-departmental working group. Through this we were able to decide who is responsible for what and where the accountability lies. This has enabled us to work much more efficiently and to have AI that is actually useful.

One important component is being able to execute projects effectively was by establishing partnerships with external entities. For instance, Firm B developed such partnerships with academic institutions in order to acquire know-how about sophisticated methods for machine learning, and specifically convolutional neural networks, while Firm A used the opportunity to expand the network of partners in order to acquire complementary data. Specifically, respondent B2 from Firm B noted the following about external partnerships:

> At some point we understood that we were going into too deep waters, and many of us had no experience with the technologies and how some techniques should be applied. It is then that we decided to seek knowledge through the university and establish projects with students that could help transfer this know-how to us. The knowledge we were able to gain from these projects helped us to expand into more applications using AI and to achieve better results.

Based on the above points we post the following proposition relating to the influence of business factors and AI for B2B marketing activities:

Proposition 2. (*b*): *The business model and associated factors influence how AI results in performance gains.*

4.5. Individual factors

Finally, at the individual level, perhaps the most noted concern of respondents was that of skills. The skills that were noted were mostly of a technical nature that revolved around specific technologies or methods. Furthermore, respondents noted the importance of business and domain skills as critical for project success since they ensured that targets were met, and the projects were geared towards outcomes that had meaning for the overall business strategy. They also noted that it was critical that employees in managerial positions had strong technical expertise in order to be able to understand how problems can be tackled and to form corresponding teams to undertake them. The issue of requiring new skills or extending existing ones was one that was noted by all interviewees. Specifically, respondent C1 from Firm C noted the following:

> I believe a lot has changed in the last years over what type of competencies our new hires need to have. Knowledge and skills appear to be much more specialized now and harder to find. To compensate for this, we have established a series of training workshops for our new and older employees. We used different resources to perform training, such as online videos, workshops, and best practices through communication with experts.

Finally, the issue of biases was brought up with Firms A and C noting that such constraints exist at different stages of projects. These firms had realized the significance that biases may have at different stages of analytics and had therefore taken action to try to reduce them through training and talks from managers (Cao, Duan, Edwards, & Dwivedi, 2021). Respondent A3 from Firm A noted the following on this issue:

> What quickly became obvious when we were looking for patterns in the data, is that we had very different interpretations about what were seeing. Effectively what we realized is that there is not only bias in what data we used in the analysis, but also how we perceive the outcomes. This has changed the processes through which we take actions based on data-driven insight.

The importance of the individual and the interaction with AI is one that has not only been shown through our cases, but also has been noted in recent empirical studies (Balakrishnan & Dwivedi, 2021; Pillai, Sivathanu, & Dwivedi, 2020). From the previous points related to how individual factors influence AI use for B2B marketing operations we put forth the following proposition:

Proposition 2. (*c*): *Factors at the individual level influence how AI results in performance gains.*

4.6. Cross-case analysis

Our analysis did reveal though that the benefits from the use of AI in B2B marketing operations was greater for Firm A and Firm C than for Firm B. By looking at the areas where each firm directs its efforts, we can identify that there exist differences between the firms in terms of level of use. These differences can be attributed to the importance that each place on data as a core resource, as well as on the types of markets they operate in. For instance, Firm A and Firm C operate in a market where the product is more intangible compared to that of Firm B where the product is a physical object. This difference means that Firm A is more attuned to viewing intangible resources such as data as an opportunity to create and capture value. Therefore, it is expected that AI deployments will be to a greater extend an important part of operations for Firm A and others that operate in similar industries. The quotes from the respondents A3 of Firm A and B3 of Firm B respectively illustrate this difference in the type of value that is realized from AI-enabled dynamic capabilities:

> For us using AI and applying all sorts of techniques to data has not only enabled us to create new insights, but has opened up a completely new market. We can now position ourselves as a data company, and we provide insights and services that are a large part of our revenues.

> Using AI has helped speed up the process of detecting faults in our firmware, and sending updates before they create any major issues. It has been very useful for our business but I see it as becoming a commodity in our industry. We compete on the hardware we sell and on how sophisticated and affordable it is.

Furthermore, the outcomes showed that the type of AI applications and the support types of dynamic capabilities they are oriented in strengthening have different types of effects on B2B marketing operations. For example, in Firm B, AI was used to identify issues with customers that did not comprise the most profitable segment. The application of an online intelligent agent was only useful in facilitating a certain service-level agreement. For the customers that were conglomerates and comprised the most profitable customer segment, Firm B had dedicated employees ready to provide assistance. It was therefore perceived by the company that AI can only provide a certain part of operational improvement for B2B marketing activities. Similarly, Firm C adopted a similar approach and used its AI solution for customer support for the largest proportion, but not most profitable segment. Respondent C2 from Firm C noted the following:

> For us maintaining an excellent quality of service to our largest customers is critical. While we can use AI to improve certain processes, there is a need for human intelligence and agency in many circumstances where it would be hard to be replaced by a computer. Lets just put it this way – AI can help us automate large volumes of structured tasks – at least for now.

We therefore see that while AI applications are used to automate part of activities related to B2B marketing operations, in some cases they are not as effective as other approaches. This findings reflect a tension about what humans can do better than AI, and how they human-machine symbiosis can be optimized (Coombs et al., 2021). We therefore develop the following proposition:

Proposition 3. Generally accepted AI-enabled capabilities may not be effective in a B2B marketing context.

Adding to the above, Firm B and Firm C noted that security and privacy issues were important concerns from their most important customers. This meant that a lot of the information that was required to feed the AI algorithms for their deployed solutions could not be applied for this important segment. Therefore, while AI applications could be deployed for a large part of their customers, data confidentiality and black-box procedures in AI algorithms created a form of distrust from the larger most important customers. According to the respondent from Firm B, their largest customers did not feel safe disclosing log files and other important information over channels which they had little control over, as it made it difficult to identify where security breaches may exist making corporate responsibility fuzzy in case of data leaks to competitors. The issue that emerged in this case concerned lack of clear accountability frameworks and fear for security breaches I the exchange of sensitive data that might jeopardize client relationships. We therefore develop the following proposition based on the previous points. Respondent B2 from Firm B noted the following:

> For our smaller clients we typically use the community boards where they can seek out help and documentation, and upload information to help them with the problems they are facing. Our large clients however are a different story. For them providing data and information about the use of our products may mean that they are disclosing too sensitive information and have refrained from using our platform for communication. There we use dedicate human agents and secure lines of communication.

Our findings indicate that there are some important aspects unique to AI that heighten the importance of security concerns around the data artifact (Trocin, Mikalef, Papamitsiou, & Conboy, 2021). First, AI applications and their subsequent value is based on the availability of large amounts of data that are in appropriate level of granularity. This imposes certain requirements on the richness of data that needs to be exchanged (Kumar, Dwivedi, & Anand, 2021), especially in inter-organizational settings such as those in B2B marketing activities. Second, the availability of data, such that it allows useful and timely insight places a unique set of requirements on it can be transferred, cleansed, and analyzed in a secure and efficient manner. Finally, since many datasets contain sensitive or personal information, there is a need to establish procedures where it is not possible to trace back specific instances in the data, and that allow for sufficient flexibility to dynamically update datasets that are used for training and prediction.

Proposition 4. Security concerns over the data artifact have an important influence on if AI-enabled capabilities can be utilized for B2B marketing operations.

5. Discussion

While AI solutions are becoming an increasingly more important part of B2B marketing operations, there is still very limited understanding of how such technologies can deliver value and under what conditions. The purpose of this research was to empirically examine this process by theoretically building on the dynamic capabilities view of the firm and conducting a in depth analysis of three firms that utilize such technologies to support their operations. Our multiple case study approach building on responses from several key respondents within these firms enabled us to understand the main processes through which such technologies lead to value creation, as well as to explore the underlying conditions and mechanisms that are required for value to be derived.

5.1. Theoretical implications

Consistent with our theoretical stance in understanding AI diffusion in B2B marketing operations, our study makes two main theoretical contributions. First, we show that the utilizations of such technologies in B2B marketing activities can enhance overall business value. Specifically, we highlight that such effects can be discernible in the processes that comprise dynamic capabilities and describe the ways in which such processes are enabled by virtue of AI applications. Such effects then demonstrate that the value of AI can be identified through a series of different performance measurements and at different levels in the firm. As a result, firms directing their efforts towards more digitized B2B marketing capabilities through AI can realize performance gains in terms of increased market share, higher-profit margins, first-mover advantage, customer satisfaction and customer retention amongst others. These findings complement a growing body of research that attempts to explore in which ways AI can generate business value, and through what mechanisms and organizational processes such value is realized (Bag, Gupta, et al., 2021; Coombs et al., 2020; Leone et al., 2020). While there is a lot of anecdotal evidence regarding the proposed value that firms can realize through AI, the theoretical insights of AI-driven business value still remain largely underexplored. Our study shows that AI can influence through several ways the underlying dimensions of a firm's dynamic capabilities. These are essential capabilities in enabling organizations to maintain their competitiveness in shifting business environments. The results also indicate that AI can generate value in these processes by specifically addressing issues of accuracy, timeliness, and dealing with informational complexity.

Second, drawing on the emergent literature on the micro-foundations of dynamic capabilities, we explore the mechanisms and differences in design through which the three firm realize gains in their marketing capabilities (Steininger et al., 2021). We do so by distinguishing between three levels of analysis, those of corporate, business, and individual. Our analysis reveals a set of factors under each of these levels as well as how they diffuse to the lower ones through different mechanisms. We propose a new emerging propositional model (Fig. 2 below), extending the original conceptual framework at the outset of the study. We show that while there is commonality in terms of the factors that are important in driving business value, the ways in which the firms decide to address them presents significant heterogeneity. This is in accordance with the view proposed by Wilden et al. (2016) of the house of dynamic capabilities. By doing so, we open up the discussion about how technology and its effects on core organizational capabilities needs to be understood and studied at different levels within and throughout an organization (Mikalef et al., 2020). We also demonstrate that there is considerable heterogeneity in how the three firms leverage AI, which is a result of the idiosyncrasies of the focal firm and the environment in which it operates in.

Our findings however offer additional research implications for B2B marketing, and specifically operations in the age of data. We show that firms are increasingly more dependent on the use of AI to support operations and make decisions. The use of AI can offer multiple ways to enhance B2B marketing which are likely to be very different depending on the context in which they are examined. Our results also confirm this since the within the three case studies examined the ways in which they leveraged AI and the activities towards which they utilized them were significantly different. This outcome calls for further work using configurational approaches on quantitative samples. From a theoretical point of view, these outcomes essentially hint to the fact that there is a need to integrate complementary theoretical perspectives when trying to understand the specifics and the resulting business value of AI investments, such as the contingency view (Donaldson, 2001).

We also demonstrate that the general recommendations from the extant dynamic capabilities and AI literature may not always apply in the specific nuanced area of B2B marketing, where for example, the AI functionality may be compromised by too little data from a small number of clients, and an over-dependence on a single contact point to obtain sufficient and sufficiently accurate data. Specifically, there are issues such as transparency and accountability when it comes to the development of AI applications that are used for important clients of B2B marketing operations that may mean that such applications are not able to be deployed. In other words, while AI applications may be readily available and fully functional, there are important cross-organizational aspects that play an important role that may mean that human-centered operations are preferred over AI-based B2B marketing operations. Our findings also open the discussion about what AI governance should include, and at what levels of analysis it should be examined. In cases like B2B marketing where AI is used across firm boundaries, our results indicate that there is a need to examine procedures, structures, and relational mechanisms from the individual to the corporate level. This finding necessitates a more detailed examination of the constituents' components of an AI governance scheme, and how it can be deployed. While recent studies have begun looking into aspects that influence individual interaction with AI systems and how they can be improved (Gursoy, Chi, Lu, & Nunkoo, 2019), there is still limited work explaining how these individual attitudes and beliefs diffuse to the organizational level.

5.2. Practical implications

Our results provide some insight into how AI can result in business value in B2B marketing activities, which can be useful for practitioners

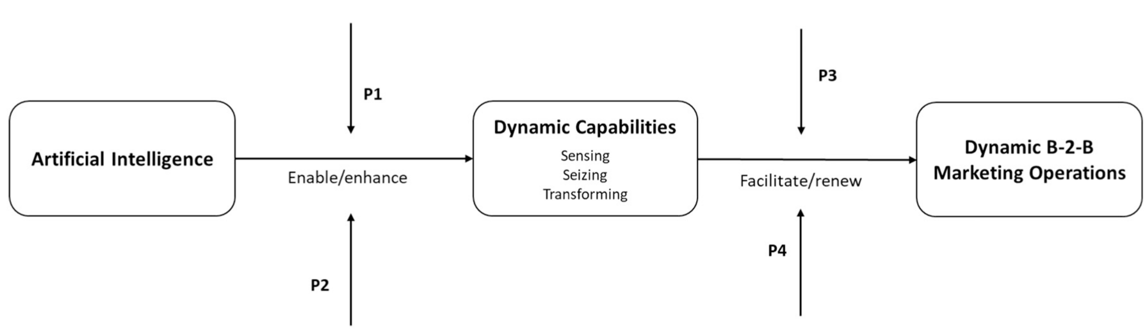

Fig. 2. Emerging propositional model.

in their respective deployments. Specifically, we can derive some useful practical suggestions from the results that can help guide practitioners in their future projects on the areas they need to focus their investments and planning on. The first important practical implication that needs to be considered is how such technologies fit into the overall business strategy and how the strategy is adapted to incorporate such technological innovations. Our examples have showed that all firms adopted a top-down approach in driving their AI initiatives which led to a series of actions been undertaken from the organizational to the business and finally to the individual level. Thus, it is important to view B2B marketing approaches using AI as a strategic initiative. Such a perspective is important in order to guarantee that all required resources are available, and that overall projects success is guaranteed.

Furthermore, the findings from our study can be used as a guideline for practitioners as the distinct processes that comprise dynamic capabilities as well as the ways in which AI solutions can serve to enhance them can provide concrete measures of success and attainable sub-goals. Adding to the abovr, the approaches, structure, and organization of resources that each of the three firms chose for their deployments can be used as an example for similar initiatives. While we do not provide an exhaustive description of different types of companies, our results serve to show that there are different ways that can be followed depending on a number of factors of the internal and external environment.

Our results also add to practical guidance about how to proceed with AI applications revolved around B2B marketing operations. Most research today is focused on AI as stand-alone applications without considering the context of their applications. This study provides specific guidance as to how AI can be used in an uncertain, dynamic, time pressured context. Our illustrative examples through the three cases studied in this research show not only what types of functions AI can be used to enhance, but also some important organizational aspects that need to be taken into account when doing so. In addition, we also draw on some important limitations of AI applications, which help managers balance their decisions on whether or not to adopt AI for certain operations or clients.

Furthermore, our results provide some evidence towards managers that unlike conventional IS applications, AI applications, while well intended, may simply not be suited for particular nuanced of B2B marketing. Such issues can occur due to the lacking quantities or detail of data, a limited range of clients that makes training AI algorithms impossible, or an over-dependence on one 'data' person or team in these partner companies. It is therefore important that before engaging in AI investments, managers are able to weigh the barriers and challenges of implementing AI solutions to enhance B2B marketing operations. Some applications such as omnichannel B2B marketing may be possible for certain types of customers (Hossain, Akter, Kattiyapornpong, & Dwivedi, 2020), but not for the full client base of firms.

5.3. Limitations

There are limitations of this study which should be considered. The study adopted an exploratory, case-based approach. Longitudinal studies would be particularly desirable, given it would be somewhat ironic to study the use of analytics in dynamic changing conditions without, at some point, examining the use of analytics either 'before and after' or during such change events. Such longitudinal research would reduce issues such as recall or recency bias which affect much case study research.

Second, as with any exploratory set of case studies, there are also many contextual factors of this study that must be considered. To maximize the general representation of the study we selected three case organizations that belonged to different industries. However further research is required to generalize the results of the study. Readers of this study may also think about AI-enhanced capabilities in different industries or indeed examining different applications of AI altogether. Given, the diversity of tools, applications and contexts in the AI domain, it is important that researchers consider the specific context and use of such tools. In addition, factors such as the size-class or the internal capability formations, decision-structures, and others factors are likely to have an important impact on the types of AI uses and the resulting business value.

Third, while dynamic capabilities are certainly relevant and often critical to most contemporary organizations, one should not automatically assume that AI applications should be geared to support dynamic capabilities over the routine, static activities of an organization. Before adopting the suggestions of this research, or taking corrective action, it is important to determine (i) to what extent dynamic capabilities take priority over routines, and (ii) to what extent AI plays a role in each. The microfoundations developed in this study will need to be researched or applied with these trade-offs and complementarities in mind.

Fourth, the three case studies that were included in this article were firms operating in the same country which means there was limited diversity in terms of the operating environment. There are likely differences between countries that are based both on the place of operation, as well as other societal and cultural norms. Future studies should delve further into such differences comparing and contrasting the similarities and differences between countries.

6. Conclusions

In this paper we have identified the microfoundations through which AI can enable the processes that comprise dynamic capabilities, i.e., sensing, seizing, and transforming, and examined how they have impacted B2B marketing activities. We also isolate the factors affecting the value from AI-enabled dynamic capabilities on a corporate, business, and individual level. Based on these findings we develop a number of propositions. Our results also point out to the contextual nature of AI use in organizations, where the value of deployed solutions is contingent upon several internal and external factors. Our discussion section builds on these findings and elaborates on how they influence the discourse of future research and theorizing regarding the use of AI in the organizational context, as well as the practical implications that the findings raise.

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