Harkamaljit Singh

Artificial Intelligence in strategic marketing: Value generation and mechanisms of action

Master's thesis in Computer Science
Supervisor: Patrick Mikalef
June 2022

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NTNU
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Kunnskap for en bedre verden

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Preface

Thank you Patrick Mikalef, my supervisor, for giving me his superb guiding for both the specialization project and this thesis. And thank you to all who have directly or indirectly helped me.

Abstract

Use of Artificial Intelligence (AI) has skyrocketed in multiple fields, and the need to deploy AI has never been higher before. One such field to deploy AI in is marketing as it is expected to benefit the exchanging relationship between buyers and sellers. The literature highlights promising benefits of AI in marketing such as offering important insights into customer behaviors, market happenings, and even make a marketer's day-to-day work less repetitive and more effective. However, organizations' lack of understanding about the institutional pressures prompting them to adopt AI for marketing, and how that further augments their marketing capabilities, necessitates a more holistic approach. Hence, drawing on the institutional theory, AI capabilities and marketing literature, this study develops and tests a model that describes relationship between institutional pressures, AI capabilities, marketing capabilities, and organizational performances. The proposed research model is tested using 155 surveys and using partial least squares structural equation modeling results show that coercive and mimetic pressures are strong motivators for organizations to adopt AI for marketing, and that adopting AI indeed augments marketing capabilities which in turn has a positive effect on organizational performances.

Keywords: *Artificial intelligence (AI), AI capabilities, marketing capabilities, adoption of AI for marketing*

Sammendrag

Bruk av kunstig intelligens has økt kraftig i flere industrier i det siste, og en slik industri å ta i bruk kunstig intelligens i er markedsføring siden det er forventet å være til fordel for relasjon mellom en kjøper og en selger. Tidligere studier viser til lovende fordeler av AI for markedsføring som hjelp med å samle viktig innsikt i brukeroppførsel, markedshendelser, og til og med forenkle og effektivisere repeterende daglig arbeid en markedsfører har. Det viser seg at organisasjoner mangler en forståelse for institusjonelle omgivelser som påvirker dem til å adoptere AI for markedsføring, og hvordan det videre forsterker deres markedsføringskapabiliteter. Derfor, med utgangspunkt i institusjonell teori, AI kapabiliteter og markedsføringskapabiliteter litteratur, utvikler og tester dette studiet en forskningsmodell som nettopp prøver å forklare denne koblingen mellom institusjonelle omgivelser, AI kapabiliteter, markedsføringskapabiliteter, og organisatoriske prestasjoner. Denne foreslåtte forskningsmodellen er testet med 155 undersøkelser, og ved å bruke partial least sqaures structural equation modellering viser resultatene at tvangspress og mimetiskpress er sterke motivatorer for bedrifter å ta i bruk kunstig intelligens for markedsføring, og at det faktisk augmenterer markedsføringskapabiliteter som videre har en positiv effekt på organisatoriske prestasjoner.

Abbreviations

AI Artificial intelligence
ML Machine learning
ANN Artificial neural networks
DL Deep learning
NLP Natural language processing
SEO Search Engine Optimizing
CRM Customer relationship management
RBV Resource based view
B2B Business-to-business
B2C Business-to-consumer
MC Marketing capability
PLS-SEM Partial least squares-based structural equation modelling
CR Composite reliability
CA Cronbach's alpha
AVE Average variance extracted
HTMT Heterotrait-Monotrait ratio

Construct variables
AICAP AI capabilities
COERPR Coercive pressures
MIMETPR Mimetic pressures
NORMPR Normative pressures
MARINFMAN Marketing information management
MARIMPL Marketing implementation
MARPLAN Marketing planning
ORGPR Organizational performances

Construct measures (items)
AIBUSINE AI business spanning capability
AIINFR AI infrastructure capability
AIPROACT AI (IT) proactive stance
COER Coercive pressures
MIMET Mimetic pressures
NORM Normative pressures

MARKETINF Marketing information management
MARKETIMPL Marketing implementation
MARKETPLA Marketing planning
PERFOP Operational performance
PERFFINA Financial performance
PERFMARK Market performance

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Chapter 1

Introduction

With abundance of data in various formats, the use of artificial intelligence (AI) has skyrocketed in multiple fields [1]. The intense competition among organizations all over the world has increased the need to deploy AI as never before. The AI is nowadays seen as a must, and 84% of C-suite executives fear the end of a business if AI is not utilized properly within the next five years. It has become important to increase a company's own competitive advantage leading to exploration of AI for marketing as that is expected to benefit the exchanging relationships between companies and consumers [2]. The applicability of AI-based solutions within B2B context has been well acknowledged and discussed in prior literature [3]. Intelligent solutions to augment marketing capabilities are needed in a complex B2B business environment, as B2B operations often have vast customer data available and collected from multiple customer touchpoints [3]. AI promises with revolutionizing opportunities for structuring, analyzing, and processing the ever-increasing volume of data to provide valuable customer insights in a complex business environment [3, 4] benefiting the exchanging relationships between companies and customers [2], and thus helping companies to gain the competitive advantage.

Various areas of marketing could benefit from the wide-ranging applications of AI. The AI promises to offer important insights for B2B businesses helping them build effective marketing strategies regarding e.g., company branding, customer relationship, and development of new products and services [5]. Furthermore, combining the AI technologies with big data is expected to three-fold B2B marketing efficiency [6]. Automation, achieved with help of AI, replacing the manual marketing activities is expected to simplify a marketer's day-to-day work by e.g., automating customer interactions and engagement activities using chatbots, or AI for supporting content creation and curation. The overall business decision making often become difficult when the business environment turns more turbulent, which has been occurring more frequently and rapidly than before [7]. The business decision makings often include decisions about segmentation and targeting of customers, understanding their needs, and proper investment in marketing activities and customer relationship management [5]. Previous literature has concluded that AI can indeed help with these decision makings in an efficient and cost-effective ways which further enhances organizations' value-creating abilities in a competitive market [8–10].

Institutional theory, a commonly used theory to explain organizational behavior, points out that the organizations want to inherently achieve social legitimacy. Their behavior, strategies, and decision-makings are thus influenced by external institutional pressures [11]. This legitimacy further provides with access to important and scarce resources leading to increase in their competitive advantages [12–14]. Previous literature has used the theory in IS research to identify antecedents and inhibitors affecting the implementations and adoptions of any new technology in firms [3, 15], such as adopting big data analytics in B2B organizations [10] and utilizing big data and predictive analytics for improving cost and operational performance [16]. Furthermore, the institutional theory has also been used in the marketing field to examine various impact it has on areas such as innovation [12, 14], the affect business intelligence has on strategical decision-making in turbulent times [17], and how and why social media is leveraged to improve marketing performance [18]. To avoid failing to meet the expected performance levels and consistently being influenced by external pressures, companies are pushed to take necessary actions to adopt relevant solutions [6, 11, 12, 14, 18–21].

Most of the prior research has till date been focusing on adoption and use of AI in B2B context, or on the AI and its implications for market knowledge that augments B2B marketing rational decision-making. However, to be able to take full advantage of the AI potential in marketing, organizations need to understand the pressures prompting them to adopt AI for B2B marketing context and how that further augments their marketing capabilities. Although some studies have, as mentioned earlier, focused on specific parts of this research gap, further holistic understanding and examination of AI adoption for B2B marketing, its implications for marketing capabilities, and examining types of pressures and practices companies have, is required. Hence, this research attempts to address the literature gap by grounding the study on institutional theory and exploring the key institutional pressures leading to adoption of AI and augmentations of marketing capabilities, and the effect it has on business performances. Following two research questions are addressed in this study:

1. **RQ1.** What kind of pressures prompt organizations to develop AI capabilities for B2B marketing?

2. **RQ2.** What is the effect of AI capabilities on marketing capabilities in a B2B marketing context?

The research questions are answered by analyzing data collected from a sample of 155 organizations using the factor-based PLS-SEM. The institutional theory is integrated to theoretically substantiate the empirical results as it can explain the institutional pressures influencing organizations to adopt AI capabilities for B2B marketing. Next, necessary argumentations regarding AI capabilities' influence on marketing capabilities, and effects marketing capabilities have on organizational performances are presented as well.

The paper is organized as follows. In the next section, background is presented, and theoretical foundations are established followed by hypotheses development. Section 3 describes the research methodology including construct operationalization, sampling design and data collection process. The subsequent sections consecutively discuss data analysis and results and provide discussion about implications for theory and practice. Finally, the study is concluded with limitations and directions for future research.

Chapter 2

Background

2.1 B2B marketing

The term marketing can be defined in several different ways, as seen in Table 2.1, however a common notion is that marketing is a way of satisfying customer demands and to manage profitable customer relationships while promoting the company brand. In 1964, E. Jerome McCarthy introduced the 4Ps (product, price, place, and promotion), also known as the marketing mix, "as a means of translating marketing planning into practice" [2]. Pride and Ferrell mentions that creating and maintaining the right mix of the 4Ps is often the prime goal of marketing managers [2]. However, the marketing mix has been heavily criticized to have weakness, leading to alternative frameworks such as 4Cs (customers, competitors, capabilities, and company) and 5Vs (value, viability, variety, volume, and virtue). Nonetheless, the 4Ps have been "extremely influential in forming the development of both marketing theory and practice" [2], and thus is still relevant today.

B2B marketing is a subset of the marketing field characterized as having extra focus on relationships, networks, and interactions [22]. B2B organizations have a greater focus on relationship development because they generally have large number of customers that must be handled quite individually; an area where consumer marketing differs from. Consumer marketing is often for large number of customers that don't need to be handled individually, making the mass communication and brand development one of the main activities in consumer marketing [23].

When it comes to the overall B2B marketing, it is usually characterized by big numbers of complex transactions consisting of several steps and people involved [24]. Furthermore, it is pointed out by Saini and Johnson that customer loyalty is higher in B2B relationships compared to in B2C relationships [25], which is explained by Kolis et al. [24] as to be a need of higher reliability between the B2B buyer and seller.

Table 2.1: Sample definitions of marketing. Whole table is taken from Singh [2]

Reference	Definition
What is marketing? 2021	Marketing is the activity, set of institutions, and processes for creating, communicating, delivering, and exchanging offerings that have value for customers, clients, partners, and society at large.
7Ps 2021	Marketing is the management process responsible for identifying, anticipating and satisfying customer requirements profitably.
Pride and Ferrell, 2021	Marketing is a buyer-seller interaction where satisfying exchanges are developed that both benefit customers and marketers.
Grönroos, 2006	Marketing is a customer focus that permeates organizational functions and processes and is geared towards making promises through value proposition, enabling the fulfilment of individual expectations created by such promises and fulfilling such expectations through support to customers' value-generating processes, thereby supporting value creation in the firm's as well as its customers' and other stakeholders' processes.
Armstrong, 2009	Marketing is managing profitable customer relationships. The twofold goal of marketing is to attract new customers by promising superior value and to keep and grow current customers by delivering satisfactions.

2.2 AI in B2B marketing

Abundance of data combined with new technologies in the last decade has sky-rocketed the use of artificial intelligence in multiple fields. Today's competition among companies has increased the need to deploy the AI, as nowadays it has almost been seen as a must to run a profitable business. 84% of C-suite executives agree that the risk of going out of business entirely in the next five years will increase if AI is not being utilized properly [2]. One area to deploy AI into to gain competitive advantage is marketing, which is believed to benefit the exchanging relationships between companies and consumers [2].

2.2.1 AI and machine learning

Artificial Intelligence is a sub-field of computer science which can be defined in two ways. Firstly, AI can be seen as a tool for solving complex and time-consuming problems and secondly as a human intelligence and cognitive process mimicking system [26], or in other words, computational agents that act intelligently [27]. One of the main foundations of AI is to act rationally based on existing data and information [27, 28], which requires the AI to be able to learn from previous experiences. This ability is the essence of machine learning. Machine learning's (ML) objective is to modify its processing based on newly acquired information [29]. Furthermore, the ML is an inductive approach which uses algorithms and data to learn and make informed decisions [7, 26].

Machine learning algorithms are often categorized into supervised, unsupervised, semi-supervised and reinforcement learning. Supervised learning uses labelled training data to learn patterns and develop rules for future instances of the same problem [27]. Some possible marketing applications of the supervised technique are customer churn prediction, since past examples can help identify common characteristics of customers leaving, and sentiment analysis of reviews. On the other hand, for the unsupervised learning no structured or labelled data is provided and the ML must identify patterns and infer rules on its own. One example of unsupervised learning marketing application is customer and market segmentation as there can be a lot of unlabeled segmentations that the ML can help us identify. When it comes to the semi-supervised learning, as the name suggests, it is a combination of supervised and unsupervised where both labeled and unlabeled data is used, however the amount of labeled data is usually smaller than unlabeled one.

Compared to the supervised, unsupervised, and semi-supervised learning, the reinforcement learning has a psychological perspective of human behavior [5]. This technique tries to teach the system to learn from feedbacks received through interactions with the system's own external environment. A reward policy is set by a human agent, and the AI agent tries to maximize its rewards by finding and performing the optimal actions and tactics [26]. Possible use cases of reinforcement learning are using it to find an optimal policy for a marketing campaign, and personalizing suggestions to increase user satisfaction [29, 30].

Lastly, the machine learning can further be categorized into two subfields as a shallow or as a deep machine learning, and all the four techniques defined above apply to both the shallow and the deep machine learning [26]. Shallow ML is the most traditional one where the ML uses labeled and predefined structures, while the deep ML uses artificial neural networks (ANNs) that mimics human neurons. Deep machine learning, also known as deep learning (DL), creates an ANN by structuring algorithms in network layers, a sequence of computational stages, that allow the AI to learn and make intelligent decisions on its own [26, 27]. When the data available is huge the DL outperforms shallow ML, and for the opposite, when only a small amount of data is available the shallow ML is more accurate [31].

Recent abundance of data, an increase in computational power, versatility of and ability to produce remarkably accurate results in various domains has increased the popularity of deep learning.

2.2.2 Value of AI in B2B marketing

Two very broad categories of AI usage are AI for automation and AI for augmentation [26]. When it comes to B2B marketing, both broad categories of AI apply. More specifically we can divide the possible usage of AI in marketing into AI marketing automation combined with the following four main areas for AI mediated augmentation: market research and market orientation, customer and user knowledge, positioning and branding, and promotion [2]. The foundation of all marketing activities is often market research and market orientation, which artificial intelligence promises to help with. For instance, using the different AI and ML classification algorithms, profiles of current and new customers can be created and further used to improve, among other things, customer relationship, products, and services. More specifically, AI technologies such as NLP (Natural Language Processing), speech recognition, emotion recognition and AI automation, adopted to marketing specific activities, can be used to improve the overall competitive advantage. Reddy and Jaidev [32] and Borges et al. [1] showed that NLP for sentiment analysis can be well utilized for designing marketing and business strategies, referred to as knowledge-based marketing by Paschen et al. [27]. Some examples indicating potential of AI automation that will simplify a marketer's day-to-day work are automation of customer interactions and engagement using e.g., chatbots or recommendation systems. Other possible marketing activities that would also benefit from AI automation are email marketing, content creation and curation, and AI automated advertisements. For promotion specific activities, NLP and ML clustering algorithms can be used to make SEO perform better. This increases a company's organic reach and help to grow the business [33]. Lastly, for the branding and positioning aspects of marketing, Gustafson and Pomirleanu [34], points out that brand legitimacy positively benefits brand reputation, awareness, and credibility. AI textual analysis and classification for evaluation of current branding investments can help with useful branding improvement suggestions, and thus helps in achieving brand legitimacy. According to Keegan et al. [35], firms are attracted to AI by two primary drivers: technological capabilities and cost reduction. Automating manual marketing activities, as described above, can naturally reduce costs. However, in general the value creation of AI in B2B marketing includes faster decision-making and knowledge-based marketing. AI is also able to categorize (big) data in meaningful ways and help with identifying general market trends. Furthermore, it also aids in understanding rapidly changing and ever-evolving customers' needs and demands [36]. Combining the big data with AI technologies can according to Bag et al. three-fold B2B marketing efficiency [5]. This rapid speed and effective assistance combined with the overall cost reduction possibilities with AI, can augment marketers' and managers' rational decision making and assist in quickly exploring multiple positionings, marketing strategies and tactics, and thus have a positive effect on a company's organizational performances.

2.3 Theoretical underpinnings

2.3.1 Institutional theory

The institutional theory helps explaining how organizational behavior and strategies are influenced by external institutional forces that in turn influence organizations' decision-making [11]. Firms are interested in achieving social legitimacy, but are influenced by external and established rules, norms, values, and traditions. The legitimacy is obtained, enhanced, or protected by actions that conform to social and institutional expectations and norms [12, 14]. Managers often strive to gain legitimacy or acceptance within society all while maintaining required efficiency within a firm. Obtaining legitimacy may further provide access to importance and scarce resources which in turn can enhance the organization's status in social networks even more, and eventually increases the organization's competitive advantage [12–14].

According to the theory, a firm's decision-making is influenced by three forms of institutional pressures: coercive, normative, and mimetic [3, 6, 12–14]. Under these pressures, the firms are forced to adopt proactive strategies aimed at coping with the pressures, and to maintain or gain competitive advantage. These pressures "exert significant effects on organizational behaviour, structure, strategy, governance and process" [13]. Jiao et al. [14] points out some possible sources of institutional pressures: "regulators, key purchasers, media, peers or competitors, non-government organizations, environmental experts, industry associations, major business partners, fund providers, local communities, the public, special interest groups and other stakeholders".

When it comes to B2B context, Wallin and Fuglsang [37] point out that institutional theory is perceived to be "the best fit for interpreting issues of implementation of new technology when the different organizations function to improve their B2B relationships". The theory has been used in IS research to help identifying antecedents affecting the implementations and adoptions of any new technology in firms [15].

Prior research utilizing institutional theory points out possible antecedents of AI adoption in B2B marketing field. Organization's need to perform activities that are perceived as being legitimate to maintain efficiency and satisfy stakeholder's expectations, make them adopt innovative technologies such as predictive analytics with AI for B2B marketing purposes [7, 16]. Furthermore, they may also feel pressure to be more data-driven in nature due to more managers having a combination of technology and management background [16]. Other literature also indicates that competitors within same industry that have adopted AI in B2B context can create pressure among relevant companies to increase AI investments, as that increases the overall competitive advantage. In addition, regulatory pressures from statutory bodies, and customer and supplier pressure make organizations more likely to invest in required AI infrastructure and technologies [5]. Companies are also facing external pressures e.g., from governments, customers, and competitors for upgrading employee skills to stay relevant. Upgrading the employee skills is highlighted by Bag et al. [5] as being positively associated with adoption of AI in organizations. Similar views are also presented by Chatterjee et al. [3], although they focused on AI customer relationship management (AI CRM) adoption in the B2B context. Chatterjee 2021 highlighted that in addition to performance being an antecedent for adopting AI in B2B, successful implementation of AI CRM need focus on employee skills, technological capabilities, and active support of the top management [3].

Jiwat et al. [10] also pointed out possible organizational needs for adopting AI in B2B organizations. The main organizational need was to adopt AI because of operational efficiencies. Organizations want to increase their productivity, reduce costs, remain competitive, increase customer satisfaction and retention, need to innovate their product or services, and perform a digital transformation of the business [3]. In term of organization's B2B marketing specific needs, companies' internal needs such as need of qualifying and nurturing leads, discovering new patterns and segments, and reaching out to the relevant customer segments work as antecedents of AI adoption for B2B marketing [2]. Lastly, Jiwat et al. [10] also pointed out two external driven needs of organization for adopting AI. The first one being the data driven competition among competitors, and the second one being the fast-growing maturity of the AI technology combined with access to big data. These external organizations' needs combined with other external institutional pressures make them adopt innovative AI technologies in B2B marketing, and as mentioned earlier, failing to respond effectively to these relevant needs or pressures may reduce their performance levels.

2.3.2 AI capabilities

AI capability is an organizational capability of using and leveraging AI in a beneficial way to realize value for the organization itself [36]. Organizational capabilities often rely on skills, accumulated tacit knowledge and interdependent actions of stakeholders involved making the capabilities intangible and complex resources [36, 38]. These complex and intangible resources can be hard to imitate, making them useful for increasing and maintaining competitive advantage [38]. In line with Enholm et al. [26] and Mikalef et al. [36] used notion of AI capability, this study's notion of AI capability closely aligns with the concept of organizational readiness to deploy AI solutions. However, the three dimensions used to measure AI capabilities in this study are adapted from Herhausen et al. [39], and are AI infrastructure, AI business spanning capability, and IT proactive stance. Adopting AI capabilities is necessary compared to solely adopting third-party AI products, because these capabilities help organizations to orchestrate and leverage all the

AI resources thus serving their ambitions, help with achieving innovation and organizational performances [36, 38].

2.3.3 Marketing capabilities

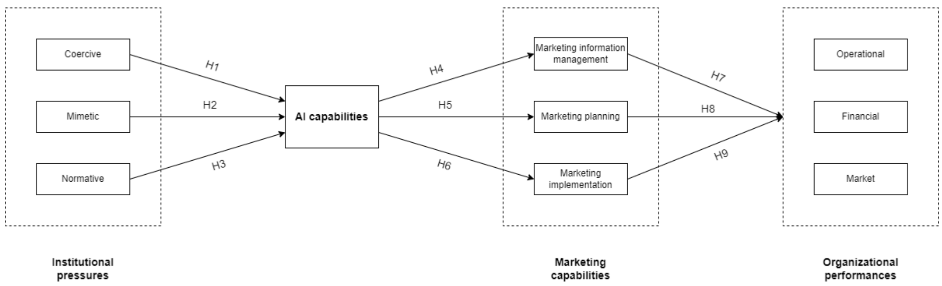
Compared to the artificial intelligence capabilities, the marketing capabilities (MCs) are quite similar in definition but with a focus on marketing instead. They are the organizational abilities of performing a coordinated set of tasks utilizing organizational resources to achieve a specific result or desired performance [39]. The MCs are also distinct and complex making them difficult to imitate by competitors [40]. Furthermore, in prior research it has been pointed out that the marketing capabilities and market orientation ability works as complementary assets that both contribute to superior firm performance [41]; however, a small difference in their notions is still present. Market orientation is an organizational ability used to learn about the market and utilize the knowledge gained to guide the actions appropriately [42]. Merrilees et al. [43] through their empirical study found that the market orientation ability "act as enabling mechanisms for building marketing capabilities", and as further pointed out by Barrales-Molina et al. [44], the market orientation ability ensures responsiveness and cross-functional coordination of a firm. Guo et al. [45] summarizes the relationship between marketing capabilities and market orientation as the former being a behavioral representation of the later. The marketing capabilities are important for a firm as they "enhance a firm's ability to effectively configure and deploy resources, help build a sustainable competitive advantage" [45], and contribute to the overall business performances [40, 41, 43, 44]. From empirically benchmarking MCs for sustainable competitive advantage Vorhies and Morgan [42] found that market-orientated firms require strong MCs to deliver superior customer satisfaction and business performances.

In general, the MCs can be divided into three categories: inside-out, outside-in, and spanning capabilities. Summarized, the inside-out capabilities begin internally within a firm and thus correspond to different functional activities in the company [46, 47], while the outside-in ones start with the market and help organizations understand their customers and competitors [47]. Lastly, the spanning capabilities are those that integrate both the internal and external processes of a company through knowledge of both the market and the company's internal functioning [47, 48]. Since the objectives of this study are focused on institutional pressures affecting adoption of AI (capabilities) and how those effect marketing capabilities, the marketing capabilities chosen were the spanning marketing capabilities as they are both based on the inside-out and the outside-in capabilities. And as Santos-Vijande et al. [47] argues, "if [a firm] affirms to have spanning capabilities, it can be assumed that they have previously developed inside-out and outside-in capabilities". These spanning capabilities include activities such as "developing and responding to marketing strategies, plans, policies and programmes which represent the features of these capabilities" [48]. The spanning capabilities chosen in this study are marketing information management, marketing planning, and marketing implementation. The former one is the organizational ability to acquire relevant information about key market stakeholders and further analyze it to develop effective marketing programs [49, 50]. Marketing planning is the ability to anticipate and strategically respond to changes in the market environment, further helping in achieving the organizational goals [47, 48, 50]. Lastly, the marketing implementation ability is the ability to execute, control and evaluate the marketing strategies [48]. Drawing on institutional theory and AI capabilities and marketing capabilities literature, this study proposes the research model shown in Figure 1.

Chapter 3

Hypothesis development

Figure 3.1: Research model and hypotheses



3.1 Institutional pressures' impact on AI capabilities in B2B context

Organizations after having carefully considered the institutional pressures, need to take necessary actions to continue being a competitive competitor. As mentioned earlier, there are three main types of institutional pressures: coercive-, normative-, and mimetic pressures. Coercive pressures are pressures that are put in place by those in power such as different government agencies or other statutory bodies [6, 12]. Regulatory policies, also known as regulatory pressure – a type of coercive pressure, exerted by government agencies may influence a firm's actions [12]. Use of regulatory pressures, often combined with penalties, supervision, or incentives, are common practices to control the overall industry performances [12]. The pressures work as intended and companies feel pressure to behave a certain way and follow the regulations to gain legitimacy and avoid unnecessary penalties.

Possible sources of coercive pressures when investing in AI capabilities are governments, regulations and policies, standards, and industry associations that are in place to protect data for safe usage [6]. To maintain legitimacy, competitive advantage, and avoid being punished, firms will most likely conform to social, regulatory, and institutional expectations. Furthermore, everchanging customer and user demands, and their increased privacy concerns are also likely to affect a firm's activities when utilizing AI for marketing purposes. Lastly, other stakeholders such as board members and investors may also want companies to exploit available data to improve strategic decision making and efficiency, and that too within the boundaries of privacy norms.

All the above-mentioned coercive pressures might make companies have a more proactive stance in terms of using AI for dealing with the different pressures such as managing and utilizing ever-increasing customer data. IT proactive stance is an organizational ability to acquire and exploit the knowledge and innovations made possible by new technology, in this case, the artificial intelligence [51]. Connecting parallels to IT proactive stance, having positive attitudes towards artificial intelligence might make companies experiment more with the AI infrastructure, tools, and techniques for including data management services, architectures, and security. Consequently, new AI innovations regarding better ways for conducting market research, increasing customer satisfaction, or effectively responding to changing market demands, can be made [19, 20]. Other stakeholders such as board members and investors can pressurize managers to apply AI resources to support business goals, requiring ability to conduct AI planning process, and develop and integrate a robust AI planning with strategic business planning [19, 20]. Therefore, following hypothesis is formulated:

> **H1:** There is a positive relationship between coercive pressures and AI capabilities

Normative pressures are pressures that make sure companies perform organizational activities that are perceived as being legitimate, or in other words, according to the expectations, common responsibilities and standards established to perform the right actions [11, 14]. The values and standards of conduct may originate from suppliers, vendors, customers, trade unions and other industry associations [12, 14, 21]. Normative pressures go together with the firm's need to be recognized and increase their legitimacy and visibility [18]. Investing in emerging and disruptive technology projects, such as AI for marketing, is typically viewed as innovative. Furthermore, since both digital transformation and AI is a hot topic in most industries, companies might act according to expectations of becoming e.g., a data driven company that utilizes AI for various tasks. This will naturally pressurize managers to integrate AI planning with the overall business strategic planning. Doing so may lead to an image of being an innovator and thus help gaining further visibility, credibility, and access to valuable resources such as industry professionals that contribute to the overall business value [18, 21]. Therefore,

> **H2:** There is a positive relationship between normative pressures and AI capabilities

When companies replicate their competitors' organizational activities, usually to gain similar results, then they are often under the influence of mimetic pressures. Mimetic pressures often arise from a state of uncertainty, hesitancy, indecision, or lack of experience combined with competitors' success being a consequence of their own organizational activities. These competitors are often the most authoritative and advantaged organizations in the industry [14]. Managers dealing with new pressures are often uncertain of effective initiatives to maintain legitimacy, leading to justification of imitating the successful competitors [14].

Competitors' success with adopting AI for their organizational activities, may create industry wide pressures to invest in adoption of AI. These leading competitors make behavior of other companies through imitation converge to the most effective industry standards and practices [14]. Bai et al. [21] points out that mimetic pressures are powerful as both forces for change and as avenues for learning. Possible AI capabilities imitations involve state-of-the-art AI technologies including cloud services, data management services, infrastructures, and architectures for AI. In addition to imitating the technology, companies may also try to replicate the work environments of their successful competitors. This may lead to increased investments in AI experimentations leading to gradual enhancements of AI usage, and not to mention, creating a supportive climate for the employees. To summarize, imitating competitors can increase the IT proactive stance, investment in AI infrastructure, and force companies to develop more clear vision regarding AI contributions and not to mention more effective AI planning. Therefore, following hypothesis is formulated:

> **H3:** There is a positive relationship between mimetic pressures and AI capabilities

3.2 AI capabilities augmenting marketing capabilities

Marketing activities' efficiency is often dependent on how well the market research has been performed. It is common to gather information and conduct market research about customers, users, and the overall external market. Rational decisions based on market research is important for making effective marketing campaigns, increasing ROI and to gain competitive advantage [2, 5, 52]. User and customer knowledge is useful for decisions related to new product development and service offerings [5]. External market knowledge is important for getting informed about the latest happenings in the market [5]. In other words, tracking market happenings and performing market research is necessary for companies to cater to natural changing requirements, and to maintain and improve their competitive advantage.

Adopting AI data processing, automation, and marketing analytics capabilities, or in other words automated business intelligence with ML techniques and algorithms, for market research and supporting marketing decision-making can increase a company's business value. By utilizing both structured and un-structured data, AI can help collect, store, process and disseminate customer, user, and external market information within a firm [53]. Increased speed of rational decision making with AI makes it possible to experiment with multiple marketing strategies [2]. Using AI technologies such as NLP makes it possible to identify psychographic characteristics, sentiments, values and attitudes of customers and users, which not only allow for greater personalization when catering to customers and users, but it also increases the overall innovation in products and services [52, 54]. B2B marketing analytic-driven firms utilizing AI applications for gaining customer, user, and market knowledge, can three-fold their B2B marketing efficiency [2, 5, 54]. Lastly, Wamba-Taguimdje et al. [53] also 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 [...]", which leads to increased financial and market performances. Therefore, following hypotheses are formulated:

> **H4:** There is a positive relationship between AI capabilities and marketing information management

> **H5:** There is a positive relationship between AI capabilities and marketing planning

Considering the everchanging customers' and users' requirements, and new happenings in the market in general, a huge part of marketers' work is often to continuously perform market research, retarget and reposition to achieve the marketing aims; making the marketing activities labor-intensive and repetitive [55]. As described earlier, artificial intelligence enhances marketers' efficiency by augmenting their marketing capabilities. When it comes to customers and users, they usually have a long customer journey consisting of different phases. Utilizing artificial intelligence for engaging with them through their journey helps increasing the efficiency of marketing resources [2]. For instance, artificial intelligence can help with automating routine tasks such as content creation and curation for advertisements and social media posts, execution of campaigns, social media targeting, retargeting, positioning and repositioning [2]. Furthermore, artificial intelligence can also be used for dynamic pricing purposes, and thus assist in customer retention activities. Artificial chatbots are also great for providing customer centric support, creating good customer experiences, and improving their overall satisfaction all while increasing the efficiency and reducing support costs [56, 57]. In conclusion, artificial intelligence, as proposed by Chen et al. [7], has the potential to "enhance a firm's marketing performance through improved dynamic selling capability, dynamic pricing capability, dynamic new product development capability, dynamic advertisement capability, and dynamic customer relationship management capability". Therefore, following hypothesis is formulated:

> **H6:** There is a positive relationship between AI capabilities and marketing implementation

3.3 Marketing capabilities and organizational performances

Prior research has concluded that marketing capabilities generally have a significant positive effect on business performances such as market share and profitability, and in addition help build a sustainable competitive advantage [40, 41, 43, 45, 58]. These MCs help firms to provide superior added value to the market and help better adapt to the changing market conditions [47]. For this study, following marketing capabilities were chosen as the constructs: marketing information management, marketing planning, and marketing implementation.

Improving marketing information management can make firms understand and cater to their customers better, which may lead to increased customer satisfactions, revenues, and profitability; however, assuming the firms perform the required actions needed to follow the effective marketing programs developed. The same goes for the marketing planning capability, as anticipating and strategically responding to the ever-changing market is a valuable ability to have in today's competitive context [47]. Taking required actions at right time can increase the operational, financial, and the market performances. One may also argue that the competence of executing, controlling, and evaluating the marketing strategies is a must for continuous adaptations to the market environment and thus achieve desired business performances. Therefore, based on arguments presented above, following hypotheses are hypothesized:

> **H7:** There is a positive relationship between marketing information management and organizational performances

> **H8:** There is a positive relationship between marketing planning and organizational performances

> **H9:** There is a positive relationship between marketing implementation and organizational performances

Chapter 4

Method

4.1 Sample and data collection

Data collection was targeted at IT and business managers who were associated with or involved in their firm's AI and marketing projects. These participants were chosen as they often possess necessary knowledge, are familiar with the strategic issues of a project and have access to their firm's performance metrics. The firms are from different industries, different firm size and experience with using AI; see Figure 4.1 for the descriptive statistics of the sample and respondents. A survey panel vendor was contacted and hired to perform the data collection. The panel made sure to collect high quality data with an appropriate incentive scheme. Lastly, since the data were collected from only one respondent at a single point in time within a firm, the study may be subject to bias. By sampling multiple respondents and taking measurements at different intervals, the above-mentioned bias can be mitigated in future studies.

4.2 Measurements

Scales of the ten constructs used in the proposed research model were adopted from previous research studies. The scales used and their source(s) are provided in Appendix A.

The measurement of institutional pressures, coercive pressures (three items), normative pressures (three items), and mimetic pressures (three items), were based on the scale of study by Dubey et al. [16] which has been empirically confirmed as reliable by other studies [6]. Respondents were asked to evaluate their organizational behavior as a result of the institutional pressures through a total of nine items on a seven-point Likert scale.

AI capability of a firm represent their organizational capacity to employ AI technology to convert inputs into outputs and utilize AI in a resourceful manner to perform human-like tasks [59]. The items used to measure AI capability include AI infrastructure capability, AI business spanning capability, and IT proac-

Figure 4.1: Descriptive statistics of the sample and respondents

Factors	Percentage (%)
Industry	
Bank & Financials	5.8%
Consumer Goods	9.7%
Oil & Gas	5.8%
Industrials (Construction & Industrial goods)	9.4%
ICT and Telecommunications	20.0%
Technology	11.1%
Media	9.4%
Transport	2.7%
Other (Shipping, Basic Materials, Consumer Services etc.)	30.8%
Firm size (Number of employees)	
1 – 9	10.4%
10 – 49	27.0%
50 – 249	33.2%
250+	23.2%
Total year using AI	
< 1 year	8.8%
1 – 2 years	21.7%
2 – 3 years	28.0%
3 – 4 years	25.4%
4+ years	16.0%
Respondent’s position	
CEO/President	10.1%
CIO	73.0%
Head of Digital Strategy	5.7%
Senior Vice President	3.4%
Director	3.4%
Manager	4.0%

tive stance. The AI infrastructure capability and AI business spanning capability items measure how well a firm is capable of strategically developing and deploying an AI system while IT proactive stance items measure a firm's capability to keep up with new AI innovations. Respondents were asked to evaluate their effectiveness in multiple aspects related to their organization's AI capability, and that through thirteen items on a seven-point Likert scale.

The measurement of Marketing information management, Marketing planning, and Marketing implementation are adopted from Vorhies and Morgan study measuring marketing capabilities and performance [42]. The items measure effectiveness of a firm's marketing capabilities pertaining to information management, planning, and implementation compared to their major competitors. Respondents were asked to evaluate the effectiveness through a total of fifteen items on a seven-point Likert scale.

Operational performance items (four), financial performance items (four), and market performance items (five) were respectively adopted, adapted and based on prior empirical study conducted by respectively Wang et al. [20], Kim et al. [60], and Dangelico, R. M. [61]. The operational performance items measure respondents' firm's operational performance compared to their competitors. The financial performance items and the market performance items measure general financial and market performance over the past year. Respondents were asked to evaluate the performances on a seven-point Likert scale. Lastly, to solve the collinearity issues with the model, item number three of financial performances was removed from the survey. Therefore, the final survey included only three financial performance items.

Chapter 5

Data analysis and result

The proposed research model was empirically tested using the partial least squares-based structural equation modelling (PLS-SEM) analysis, together with the software SmartPLS3. PLS-SEM is a soft modeling technique and is variance-based making it suitable for this study as the sample size is relatively small (N = 155), and the research model is a relatively complex one [12, 62]. Factor loadings and path coefficients were estimated using a PLS algorithm with path weighting scheme, and the significance of the factor loadings and path coefficients were examined using bootstrapping with 5000 resamples [12].

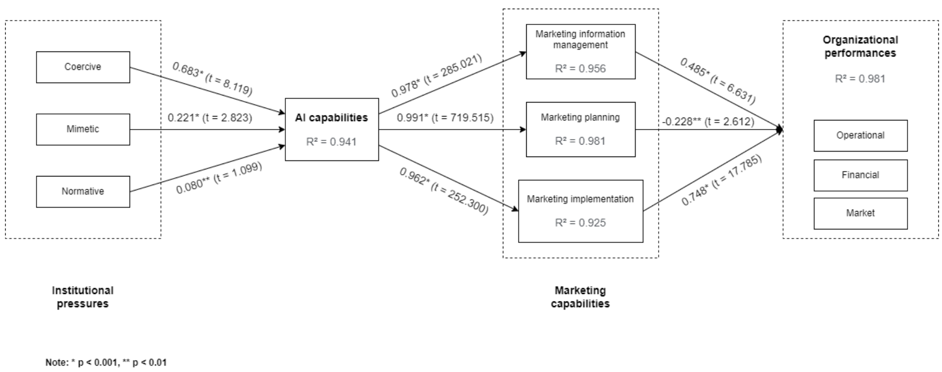
5.1 Measurement model

To assess the research constructs used in the study it was conducted reliability, convergent validity, and discriminant validity tests. For the reliability, at the construct level, Composite Reliability (CR) and Cronbach's Alpha (CA) values were found to be above their threshold of 0.70; CR ranged from 0.977 – 0.993, and CA ranged from 0.970 – 0.990 (see Appendix B). For the indicator reliability, all the construct-to-item loadings were examined and found to be above the threshold of 0.70; see Appendix C. Convergent validity of the constructs was measured by examining the average variance extracted (AVE) values, "a measure of variation explained by the latent variable to random measurement error" [3], which all greatly exceeded the lower limit of 0.50 (range: 0.868 – 0.979); see Appendix B . Lastly, the discriminant validity was tested using the AVE square root of all the constructs by checking if "all the square roots of AVEs are greater than the correlation values for that particular latent variable" and using the Heterotrait-Monotrait ratio (HTMT). Unfortunately, both the values are not acceptable. Only square roots of AVEs for coercive pressures, mimetic pressures, normative pressures, and organizational performances latent variables, are greater than the correlation values (Appendix D), and all HTMT values are above 0.85 threshold ranging from 0.910 – 1.012 (Appendix E) [59]; see limitations for further discussion.

5.2 Structural model

Figure 5.1 presents the structural model from the PLS analysis presenting the variance of endogenous variables (R^2) and the path coefficients (β). The power of the research model is assessed using the β coefficients, their significance levels, and the predictive relevance (Stone-Geisser Q^2) [18, 59]. T-statistics, significance of the parameter estimates, were obtained using bootstrapping analysis with 5000 resamples. The empirical analysis results support most of the hypotheses. Both the coercive pressures ($\beta = 0.683, t = 8.119, p < 0.001$) and mimetic pressures ($\beta = 0.221, t = 2.828, p < 0.001$) have a significant positive effect on AI capabilities, and thus support both H1 and H3 respectively. On the contrary, the normative pressures ($\beta = 0.080, t = 1.090, p < 0.01$) have a non-significant effect on AI capabilities leading to H2 not being supported. AI capabilities were also found to have impact on marketing information management capability ($\beta = 0.978, t = 285.021, p < 0.001$), on marketing planning capability ($\beta = 0.991, t = 719.515, p < 0.001$), and on marketing implementation capability ($\beta = 0.962, t = 252.300, p < 0.001$) leading to respectively supporting H4, H5, and H6.Furthermore, the analysis shows that the marketing information management capability has a significant effect on organizational performances ($\beta = 0.485, t = 6.631, p < 0.001$), making H7 hence supported. Next, marketing planning capability ($\beta = -0.228, t = 2.612, p < 0.01$) exert a negative and significant effect on organizational performances thus not supporting H8. Lastly, the marketing implementation capability ($\beta = 0.748, t = 17.785, p < 0.001$) has a positive and significant effect on organizational performances, hence supporting H9. To summarize, all hypothesis from H1 to H9 except H3 and H8 are supported.

Figure 5.1: Structural model with path coefficients, t-statistics, and R squared values for all the latent variables



The structural model explains 94.1% of variance for AI capabilities (R^2=0.941), 95.6% for marketing management capability (R^2=0.956), 98.1% for marketing planning capability (R^2=0.981), 92.5% for marketing implementation capability (R^2=0.925), and 98.1% for the organizational performances (R^2=0.981). These coefficients help evaluating the model's predicting power, and as they are now, they provide great support for the proposed research model [59]. The model is further evaluated with Cohen's f^2 formula that allows for assessing an exogenous construct's contribution to an endogenous latent variable R^2 [59]. All constructs except three, mimetic pressures, normative pressures, and marketing planning, are above the value of 0.35 and are thus considered high effect sizes. The effect size of mimetic pressures on AI capabilities is 0.070, effect size of normative pressures on AI capabilities is 0.012, and the effect size of marketing planning on organizational pressures is 0.043, which are respectively considered small to medium, less than small, and from small to medium [16].

5.3 Predictive capability

Stone-Geiser's Q^2, predictive relevance of endogenous variables, was also used to assess the model. The indicator is used for measuring "how well-observed values are reproduced by the model and its parameter estimates, verifying as such the model's predictive validity through sample re-use" [59]. The Q^2 values found for the constructs AI capabilities (Q^2=0.810), marketing information management capability (Q^2=0.884), marketing planning capability (Q^2=0.870), marketing implementation capability (Q^2=0.846), and organizational performances (Q^2=0.888), are greater than zero leading to satisfactory predictive relevancy. In addition, criterion estimates q^2 values are all above 0.35 meaning there is substantial effect size of predictive relevance in the research model. Lastly, the model fit was assessed using composite-based standardized root mean square residual (SRMR). The SRMR for the model is 0.044, which is less than the threshold 0.08 and hence the research model is correct and appropriate [59].

Chapter 6

Discussions

This study assessed the institutional pressures prompting organizations to invest in artificial intelligence and their further impact on marketing capabilities and organizational performances by employing a well-established institutional theory as theoretical lens. With promising artificial intelligence benefits, and with increasing institutional pressures from customers, governments, and competition for utilizing artificial intelligence in the marketing field, the results indicate that building AI capabilities for the purpose of augmenting marketing capabilities indeed presents an opportunity for companies to increase their organizational performances. In line with multiple prior research using the institutional theory [3, 6, 10, 12, 16], I argue that the institutional perspective for adopting artificial intelligence for marketing purposes in B2B context is relevant as it explains organizational behavior. Prior studies have also used the RBV (Resource-based view) perspective [3, 63], dynamic capability perspective [7, 16], and even a combination of RBV and institutional perspective [3, 6] to explain the adoptions of artificial intelligence in B2B context. Using RBV alone has previously been criticized "for being inattentive to contexts" [3, 6, 12, 16], and hence make a good combination with the institutional theory. However, for the purpose of this study and the time limitation, only the institutional perspective was chosen to examine the institutional pressures influencing organizations to adopt AI for B2B marketing purposes. Following are the main findings from the empirical study.

Firstly, drawing on institutional pressures it was hypothesized that coercive, mimetic, and normative pressures will influence a firm's AI capabilities and adoption of AI for B2B marketing context. Using the data collected, the analysis indicates that both coercive and mimetic pressures play a significant role in influencing adopting both the AI capabilities and the AI; which was also highlighted by other studies [5, 12, 16]. However, the empirical analysis did not support the normative pressures' positive influence on AI capabilities and AI adoption. This can be explained by that the norms and other established standards may not influence firms' adoption of AI as much as the other two institutional pressures do. This is also the case for the study conducted by Lin et al. [18], however for that study Lin et al. [18] were examining the institutional pressures' effect on social media usage instead of AI. Other prior studies also suggest that norms are often not the most important motivators for decisions involving adoption of new technology [15, 18]. Secondly, the paths AI capabilities and marketing information management, AI capabilities and marketing planning, and AI capabilities and marketing implementation all are positive and significant. AI has a great proven influence on marketing activities, as supported by several studies e.g., [5, 54, 55, 64], however this study has extended the knowledge by examining AI's influence on three specific marketing capabilities.

Finally, it was found that the marketing information management capability and marketing implementation capability are positively and significantly associated with organizational performances, which clearly support the previous studies examining impacts of marketing activities on organizational performances e.g., [40, 41, 43, 45, 58]. Contrary to theorized relationship between marketing planning and organizational performances, the results found that marketing planning has a negative but significant effect on the organizational performances. Previous marketing planning capability research suggests some unclear results pattern [65, 66]. Most of the results from previous studies [40–43, 45–47, 50, 58] indicate a positive and significant marketing planning's influence on business performances while some few studies also point out the marketing planning paradox. Slotegraaf et al. [67] suggests that "an emphasis on marketing planning capability presents managers with a paradox – how to capitalize on the benefits associated with planning capability without suffering from its rigidity-inducing effects". Furthermore, Pulendran et al. [65] suggested through their empirical research that the impact of marketing planning capability on company performances is indirect, rather than what was theorized in this study, which may explain the negative significant effect. In the case of study conducted by Pulendran et al. [65], it was suggested that high quality marketing planning indeed provides benefits for the organizations, however these benefits flow through the creation of a market orientation and not directly. For this study's research model, it is possible that the benefits of marketing planning may either flow through marketing information management, marketing implementation or both. Nonetheless, this requires further investigation.

6.1 Theoretical implications

The role of institutional theory when examining the adoption of technology is well discussed in previous literature. However, there seems to be a research gap for understanding which institutional pressures effect the adoption of AI for general B2B marketing purposes, and how that further augments the company's marketing capabilities and organizational performances. Other scholars have researched specific parts of the AI adoption for B2B marketing purposes such as AI for knowledge creation and marketing rational decision-making [5, 27, 55, 68], Chen et al. [7] found barriers and outcomes of AI adoption in B2B marketing, Rahman et al. [54] examined effect marketing analytics capability has on a firm's marketing performance, Järvinen et al. [69] investigated marketing automation for B2B content marketing, and Chatterjee et al. [3] studied the effect AI-based CRM system, to automate B2B relationship activities, has on performances and competitive advantage. Marketing related previous research has also examined the marketing capabilities and their effect on organizational performances e.g., [40–43, 45, 47, 50, 58]. This study, however, tries to combine the previous research about AI and MCs by utilizing institutional theory to interpret the pressures impacting adoption of AI and AI capabilities for augmenting marketing capabilities in a B2B marketing context. And further investigating the effect it has on performances. Hence, this paper makes an important contribution to the intuitional theory, marketing capabilities literature, and their mediated relationship through AI and AI capabilities.

The results suggest that institutional pressures are guiding organizations to work within expected boundaries to enable AI adoption in marketing. More specifically, the coercive pressures followed by mimetic pressures are suggested to be very strong motivators while the normative pressures were not found to be significant. Independent of exactly which pressure influence companies to adopt AI and AI capabilities, the results indicate a very strong significant augmentation of marketing capabilities when utilizing AI; also supported by e.g. [5, 27]. This strengthens the reasons for incorporating AI in marketing activities to perform informed business decisions for achieving higher business performance levels.

6.2 Managerial implications

The findings offer some useful implications for managers. First, the role of institutional pressures offers important insights especially the coercive and the mimetic pressures appear positively related to adoption of AI and adoption of AI capabilities. Findings highlight that the stakeholders of a firm want the firm to exploit data to improve decision-making, all while using the data safely and within the boundary of regulatory norms to avoid any defamation to the firm. Privacy and fair usage of data issues are still present, and hence is something managers need to incorporate into their AI adoption plan. If the managers are uncertain about adoption of AI for marketing but are also pressurized to increase performances or competitive advantage, then they may adopt AI for augmenting their marketing capabilities making it an effective response to these pressures. As marketing information management capability and marketing implementation capability are proven by previous research to affect organizational performances positively and significantly, augmenting these capabilities with AI will further make them adapt to the everchanging customer demands and help the firm to become data driven. The results indicate that the competitors that adopt AI do indeed benefit from it and are favorably perceived by their suppliers and customers. These results were predicted by institutional theory as adopting innovative technology such as AI may help organizations to be perceived as legitimate and innovators.

Findings also indicate that the normative pressures are not significant, which may to some degree suggest the industries has yet to adopt AI for marketing. Therefore, it may be possible for firms to achieve a competitive advantage by seizing the first-mover advantage. This suggestion is both supported by the previous research [40, 46, 62, 70] and this study by a highly significant relationship between AI and augmentation of marketing capabilities.

Secondly, even though artificial intelligence (capabilities) is significantly and positively related to marketing planning capability, it is still advisable to continuously monitor the performances and gather customer feedbacks to avoid the rigidity-effect that the marketing planning poses, and if needed also dynamically adapt to avoid unnecessary losses [46]. Lastly, as also pointed by previous research about utilizing big data and AI for organizational activities by e.g., [6, 7, 10, 28, 36, 38, 52, 53, 69, 71], it is important to understand that to reap the benefits of AI for marketing, managers need to foster a data-driven decision-making culture, give proper training to relevant employees, and have a clear plan and commitment for the AI adoption.

6.3 Limitations and future research

Despite the contributions made to institutional theory, AI and AI capabilities, and marketing capabilities, there are several limitations with this study. First, the theoretical lens could be extended with RBV theory for explaining how some strategic resources and/or capabilities can help organizations achieve competitive advantage [16], but as the RBV also has issues such as context insensitivity [16], contingency theory can also be used for identifying internal and external conditions that may be influencing the adoption of AI for marketing purposes in the B2B context. Second, the model's discriminant validity is not achieved as the square roots of AVEs values and HTMT values are not acceptable. For the purpose of this study, the model was not tweaked to achieve the discriminant validity, something future research should address. Furthermore, the study may also be subject to response bias since the data were collected from only one respondent at a single point in time within a firm. Future research can mitigate the response bias by sampling multiple respondents and taking measurements at different intervals. Thirdly, the future research can further examine the augmentation effect of AI for other marketing capabilities, e.g., CRM (customer relationship management) capabilities or brand management capabilities, and then in turn examine their effect on the organizational performances. Fourth, future studies can also seek to consider different organization features that could impact the adoption of AI for marketing. Examples for such features are organization size, age, market uncertainty level and risk-taking capabilities they are currently operating with. Lastly, the limited collected sample may affect the generalizability of the results. Even though a well-represented sample may be difficult to collect, it is still something future research should seek to address.

Chapter 7

Conclusion

Using the institutional theory, this study developed a research model for examining pressures influencing adoption of AI and AI capabilities among organizations, and how they further augment marketing capabilities that help achieve organizational performances. Despite higher interest among companies and researchers for AI and strategic marketing, there is still a lack of theory-based research on adopting AI for augmenting marketing capabilities. The results indicate that coercive and mimetic pressures, as also indicated by previous literature, indeed influence companies to adopt AI for marketing purposes, and by doing so they can effectively augment their marketing information management capability, marketing planning capability, and marketing implementation capability for improving their performances. Lastly, this paper contributes to the institutional theory, marketing capabilities literature, and their mediated relationship through AI and AI capabilities.

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Appendix A

Survey instrument

Measure	Item
Coercive pressures	COER1. The data protection law requires our firm to use data safely.
	COER2. The industry association requires us to use data within the boundary of regulatory norms.
	COER3. The stakeholders of our firm want us to exploit data to improve decision making without interfering into privacy of any individuals, which may attract defamation to the firm.
Normative pressures	NORM1. The extent to which your firm's suppliers use AI for decision-making.
	NORM2. The extent to which your firm's customers use AI for decision-making.
	NORM3. The extent to which industry associations' (such as CII or FICCI) promotion of big data and predictive analytics influences your firm to use AI for decision-making.
Mimetic Pressures	MIMET1. Our competitors who have adopted AI have greatly benefitted.
	MIMET2. Our competitors who have adopted AI are favourably perceived by the others in the same industry.
	MIMET3. Our competitors who have adopted AI are favourably perceived by their suppliers and customers.

AI Infrastructure capability	AIINFR1. Data management services and architectures for AI. AIINFR2. Network communication services and cloud services. AIINFR3. AI application portfolio and services (e.g. Microsoft Cognitive Services, Google Cloud Vision). AIINFR4. AI facilities' operations/services (e.g., servers, large-scale processors, performance monitors). AIINFR5. AI infrastructure to ensure that data is secured from to end to end with state-of-the-art technology.
AI Business Spanning Capability	AIBUSINE1. Developing a clear vision regarding how AI contributes to business value. AIBUSINE2. Integrating business strategic planning and IT planning. AIBUSINE3. Enabling functional area and general management's ability to understand value of IT investments. AIBUSINE4. Establishing an effective and flexible AI planning process and developing a robust AI plan.
IT proactive stance	AIPROACT1. We are capable of and continue to experiment with new AI tools and techniques as necessary. AIPROACT2. We have a climate that is supportive of trying out new ways of using AI. AIPROACT3. We constantly seek new ways to enhance the effectiveness of AI use. AIPROACT4. We constantly keep current with new AI innovations.
Marketing information management	MARKETINF1. Gathering information about customers and competitors. MARKETINF2. Using market research skills to develop effective marketing programs. MARKETINF3. Tracking customer wants and needs. MARKETINF4. Making full use of marketing research information.

	MARKETINF5. Analyzing our market information.
Marketing planning	MARKETPLA1. Marketing planning skills. MARKETPLA2. Ability to effectively segment and target market. MARKETPLA3. Marketing management skills and processes. MARKETPLA4. Developing creative marketing strategies. MARKETPLA5. Thoroughness of marketing planning processes.
Marketing implementation	MARKETIMPL1. Allocating marketing resources effectively. MARKETIMPL2. Organizing to deliver marketing programs effectively. MARKETIMPL3. Translating marketing strategies into action. MARKETIMPL4. Executing marketing strategies quickly. MARKETIMPL5. Monitoring marketing performance.
Operational performance	PERFOP1. In the past year our productivity has exceeded that of our competitors. PERFOP2. In the past year our profit rate has exceeded that of our competitors. PERFOP3. In the past year our ROI (return on investment) has exceeded that of our competitors. PERFOP4. In the past year our sales revenue has exceeded that of our competitors.
Financial performance	PERFFINA1. Over the past year, our financial performance has been outstanding. PERFFINA2. Over the year, our financial performance has exceeded our competitors'. PERFFINA3. Over the past year, our sales growth has been outstanding. PERFFINA4. Over the past year, we have been more profitable than our competitors.

Market Performance	PERFMARK1. Revenues are higher than competitors. PERFMARK2. Our new products/services are more profitable than competing ones. PERFMARK3. Sales of products/services are higher than competitors. PERFMARK4. Our new products/services are successful.

Appendix B

Cronbach's Alpha (CA), Composite Reliability (CR), and Average Variance Extracted (AVE)

	Cronbach's Alpha (CA)	Composite Reliability (CR)	Average Variance Extracted (AVE)
AICAP	0.987	0.988	0.868
COERPR	0.972	0.982	0.947
MARIMPL	0.979	0.984	0.923
MARINFMAN	0.981	0.985	0.931
MARPLAN	0.970	0.977	0.893
MIMETPR	0.973	0.982	0.949
NORMPR	0.989	0.993	0.979
ORGPR	0.990	0.991	0.912

Appendix C

Cross loadings

	AICAP	COERPR	MIMETPR	NORMPR	MARINFMAN	MARPLAN	MARIMPL	ORGPR
AIBUSINE1	**0.965**	0.920	0.924	0.856	0.920	0.972	0.934	0.937
AIBUSINE2	**0.937**	0.890	0.844	0.809	0.900	0.909	0.841	0.843
AIBUSINE3	**0.925**	0.916	0.941	0.885	0.892	0.934	0.910	0.936
AIBUSINE4	**0.938**	0.947	0.889	0.847	0.931	0.938	0.927	0.917
AIINFR1	**0.840**	0.882	0.864	0.856	0.860	0.820	0.835	0.853
AIINFR2	**0.948**	0.905	0.932	0.928	0.953	0.918	0.869	0.920
AIINFR3	**0.981**	0.919	0.881	0.874	0.942	0.959	0.928	0.926
AIINFR4	**0.842**	0.801	0.686	0.786	0.838	0.805	0.808	0.777
AIINFR5	**0.984**	0.923	0.893	0.886	0.958	0.976	0.931	0.929
AIPROACT1	**0.957**	0.910	0.897	0.895	0.955	0.935	0.885	0.914
AIPROACT2	**0.948**	0.929	0.878	0.838	0.891	0.954	0.955	0.929
AIPROACT3	**0.936**	0.865	0.850	0.865	0.915	0.944	0.902	0.895
AIPROACT4	**0.897**	0.876	0.872	0.800	0.878	0.916	0.914	0.902
COER1	0.977	**0.982**	0.908	0.900	0.953	0.972	0.971	0.961
COER2	0.910	**0.964**	0.921	0.856	0.919	0.913	0.894	0.919
COER3	0.928	**0.973**	0.915	0.942	0.919	0.934	0.927	0.929
MIMET1	0.928	0.922	**0.983**	0.947	0.927	0.932	0.898	0.944
MIMET2	0.909	0.920	**0.969**	0.915	0.908	0.907	0.904	0.944
MIMET3	0.905	0.904	**0.970**	0.873	0.925	0.916	0.865	0.915
NORM1	0.916	0.919	0.919	**0.987**	0.922	0.905	0.885	0.904
NORM2	0.917	0.926	0.936	**0.995**	0.936	0.912	0.885	0.924
NORM3	0.895	0.899	0.925	**0.987**	0.923	0.896	0.892	0.932
MARKETIMPL1	0.891	0.893	0.843	0.800	**0.860**	0.909	0.957	0.922
MARKETIMPL2	0.902	0.915	0.876	0.931	**0.930**	0.915	0.939	0.949
MARKETIMPL3	0.886	0.894	0.853	0.794	**0.860**	0.913	0.964	0.934
MARKETIMPL4	0.981	0.954	0.911	0.918	**0.957**	0.983	0.967	0.959
MARKETIMPL5	0.957	0.941	0.899	0.858	**0.913**	0.977	0.978	0.952
MARKETPLA1	0.878	0.880	0.813	0.749	0.845	**0.909**	0.913	0.863
MARKETPLA2	0.984	0.923	0.893	0.886	0.958	**0.976**	0.931	0.929
MARKETPLA3	0.944	0.924	0.919	0.887	0.980	**0.950**	0.903	0.928
MARKETPLA4	0.925	0.916	0.941	0.885	0.892	**0.934**	0.910	0.936
MARKETPLA5	0.945	0.922	0.885	0.903	0.932	**0.955**	0.967	0.959
MARKETINF1	0.917	0.887	0.910	0.884	0.939	0.886	**0.818**	0.884
MARKETINF2	0.914	0.927	0.914	0.906	0.958	0.935	**0.942**	0.961
MARKETINF3	0.967	0.923	0.889	0.890	0.971	0.968	**0.933**	0.935
MARKETINF4	0.945	0.947	0.918	0.915	0.970	0.951	**0.932**	0.941
MARKETINF5	0.972	0.928	0.926	0.924	0.986	0.966	**0.914**	0.944

PERFOP1	0.935	0.937	0.956	0.922	0.941	0.957	0.962	**0.990**
PERFOP2	0.938	0.930	0.905	0.890	0.923	0.947	0.979	**0.975**
PERFOP3	0.942	0.931	0.952	0.966	0.952	0.921	0.941	**0.976**
PERFOP4	0.855	0.908	0.930	0.885	0.895	0.899	0.862	**0.940**
PERFFINA1	0.972	0.928	0.926	0.924	0.986	0.966	0.914	**0.944**
PERFFINA2	0.887	0.894	0.949	0.910	0.903	0.902	0.896	**0.954**
PERFFINA4	0.890	0.900	0.833	0.827	0.851	0.923	0.972	**0.928**
PERFMARK1	0.964	0.934	0.962	0.903	0.960	0.971	0.925	**0.959**
PERFMARK2	0.890	0.904	0.893	0.823	0.870	0.912	0.958	**0.952**
PERFMARK3	0.932	0.913	0.925	0.850	0.917	0.914	0.892	**0.930**
PERFMARK4	0.934	0.934	0.913	0.914	0.954	0.930	0.930	**0.957**

Appendix D

Square roots of AVEs

	AICAP	COERPR	MARIMPL	MARINFMAN	MARPLAN	MIMETPR	NORMPR	ORGPR
AICAP	0.932							
COERPR	0.965	0.973						
MARIMPL	0.962	0.957	0.961					
MARINFMAN	0.978	0.956	0.942	0.965				
MARPLAN	0.991	0.966	0.979	0.976	0.945			
MIMETPR	0.938	0.940	0.913	0.944	0.943	0.974		
NORMPR	0.919	0.924	0.896	0.937	0.914	0.937	0.990	
ORGPR	0.965	0.963	0.982	0.967	0.977	0.959	0.930	0.955

Appendix E

Heterotrait-Monotrait ratio (HTMT)

	Construct	1	2	3	4	5	6	7	8
1	**AICAP**								
2	**COERPR**	0.985							
3	**MARIMPL**	0.977	0.980						
4	**MARINFMAN**	0.994	0.979	0.959					
5	**MARPLAN**	1.012	0.995	1.004	0.999				
6	**MIMETPR**	0.957	0.967	0.934	0.967	0.970			
7	**NORMPR**	0.930	0.942	0.910	0.951	0.931	0.954		
8	**ORGPR**	0.976	0.981	0.997	0.980	0.997	0.978	0.939	

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