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Research article

The impact of artificial intelligence adoption for business-to-business marketing on shareholder reaction: A social actor perspective

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ABSTRACT

While AI applications are becoming ever more important in B2B marketing operations, there is a lack of research to examine whether and how shareholders react to firms' AI-enabled B2B marketing initiatives. Accordingly, the purpose of this study is to explore this process by theoretically building on the social actor perspective of the firm and investigating the impact of AI-enabled B2B marketing initiatives on shareholder reaction measured by abnormal stock returns. By adopting a propensity score matching (PSM) method to generate an artificial control group of firms without adopting AI-enabled B2B marketing initiatives, we conduct an event study based on 174 sample firms (87 treatment firms and 87 matched control firms) publicly listed in the US between 2011 and 2020. The test results suggest that firms implementing AI for B2B marketing receive greater stock returns than their industry peers without AI implementation. In addition, the stock return is more remarkable for firms operating in turbulent environments and with less complex customer bases. A qualitative focus group discussion was conducted to further complement and enrich the findings. This study provides the first empirical evidence regarding the shareholder reaction to AI-enabled B2B marketing initiatives. The results reveal the significance of the fit between AI-enabled B2B marketing values and firms' business environments. It encourages future studies to investigate AI implementation from the social actor perspective.

1. Introduction

Nowadays, the adoption of emerging technologies has contributed substantially to firms' capability to effectively interact and collaborate with their partners, overcome operational challenges, and create new opportunities for growth (Vannoy & Palvia, 2010; Gupta et al., 2023; Kaartemo & Nyström, 2021; Lam et al., 2019). Notably, the use of artificial intelligence (AI) in business-to-business (B2B) marketing has attracted increasing attention, owing to the data available from various sources, the advance in big data analytical techniques, increased computing power and lower costs (Dwivedi et al., 2021a; Huang & Rust, 2021; Lui et al., 2021). A recent study conducted by MIT Technology Review Insights (2018) in association with Google collected data from 1419 marketing executives and identified that B2B marketing services ranked among the top fields regarding the AI adoption for innovation. For instance, Lexus adopted IBM Watson to create its B2B commercial scripts "Driven by Intuition" (IBM, 2018); Barclays implemented AI to improve and facilitate their transaction banking services through chatbots (Barclays, 2019). Siemens Healthineers used AI to support clinical decision-making by improving customized product performance and reducing costly downtime (Siemens Healthineers, 2021). It has even been argued that AI will considerably reshape the future of B2B marketing (Han et al., 2021; Paschen et al., 2019).

In spite of the notable advancements in AI development over the last decade, extant research remains insufficient in providing a comprehensive understanding of the optimal strategies for harvesting AI's potential to drive significant impacts on B2B marketing. Particularly, most studies of AI implementations pay specific attention to its technological features in the area of business-to-customer (B2C) marketing (Belanche et al., 2019; Chung et al., 2020; Kumar et al., 2019). Meanwhile, although the business implications of AI-enabled B2B marketing have gained importance, most of the literature only offers conceptual

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frameworks and qualitative discussions about its values, barriers and socio-economic impacts (Martínez-López & Casillas, 2013; Paschen et al., 2019; Mikalef et al., 2021; Sung, 2021). For instance, Martínez-López & Casillas (2013) highlight the historical overview, current and future insights regarding the application of AI in industrial marketing. Mikalef et al. (2021) further conduct three case studies in Norway that use AI for B2B marketing and identify several AI-specific micro-foundations of dynamic capabilities. In terms of quantitative studies of AI-enabled B2B marketing, certain research has investigated the function of computer-mediated AI agents in identifying crises related to events through data mining techniques (Farrokhi et al., 2020) or examined the consequences and antecedents of AI-enabled B2B activities applying surveys (Baabdullah et al., 2021). Nonetheless, given the shareholders are the owner of the company who plays important roles (both direct and indirect) in companies' operations, there is a lack of empirical research studying whether shareholders reward or penalize firms for their AI-enabled B2B marketing initiatives. Investigating how shareholders perceive and respond to AI-enabled B2B marketing initiatives is critical because it directly impacts a firm's strategic decisions, financial health, access to resources, competitive positioning, and overall success (Huang & Rust, 2021). This is particularly relevant in the B2B marketing context, where the dynamics of AI adoption may differ significantly from consumer-focused marketing. Addressing this gap in the empirical literature can provide a more comprehensive understanding of the dynamics between AI investments, shareholder value, and the unique challenges and opportunities within B2B marketing. Accordingly, this study attempts to address this critical issue.

Moreover, it is unlikely that companies operating in different business environments will receive the same results from their AI adoption for B2B marketing. For instance, while the use of AI for B2B may enable companies to harvest the values from fluctuating market demands and changing consumer needs to gain a competitive edge (Soel & Muhanna, 2009; Lui et al., 2021; Wamba, 2022), companies operating in less turbulent environments may receive fewer business opportunities in adopting AI for innovation. Also, companies with a more complex customer base may experience higher uncertainty and rely more on AI implementation to gain competitive advantages by meeting the demands arising from the markets (Prentice & Weaven, & Wong, 2020; Schmitz & Ganesan, 2014). In this way, apart from investigating whether shareholders reward or penalize firms for their AI-enabled B2B marketing initiatives, it is important to further explore how shareholders' reaction differs across companies operating in various business environments. This leads to our research question:

> How does the adoption of AI in B2B marketing initiatives impact shareholder reactions, and to what extent do these impacts vary across different business environments?

We applied a social actor perspective to address the research question. Although most of the studies focusing on the role of AI implementation in B2B marketing have referred AI as a technique for problem-solving, this study investigates the symbolic nature of AI implementation for B2B marketing and its social impacts. This study argues that the focal firm of AI implementation in B2B marketing can be considered as a social actor who takes actions purposefully and intentionally (Whetten & Mackey, 2002). Viewing the relationship between AI-enabled B2B marketing and shareholder reaction from a social actor perspective reveals how firms use AI as an effective way to enhance their legitimacy of social identity and be a symbol to improve stakeholders' confidence. Mainly, this research addresses a significant gap in the literature by studying the effect of AI adoption for B2B marketing on shareholder reaction, which is measured by stock returns. The measure of stock returns can be referred to as a proxy for general market value and represents the full performance effect due to AI Adoption. This study performs an event study based on 174 sample firms (87 treatment firms and 87 matched control firms) regarding AI implementation for B2B marketing made by the US publicly listed companies between 2011 and 2020. The findings show that firms implementing AI for B2B marketing receive greater stock returns than their industry peers without AI implementation. In addition, the stock return is more remarkable for firms operating in turbulent environments and with a less complex customer base. Then, a qualitative focus group discussion was conducted following the data analysis to provide a more comprehensive view of the complex relationships within the context of AI adoption and shareholder reactions in B2B marketing. These results reveal the significance of the fit between AI-enabled B2B marketing values and firms' business environments.

This study has made several contributions. First of all, to the best of our knowledge, this is the first study that empirically investigates the impact of AI implementation for B2B marketing on shareholder reaction, referred to as stock returns. The significant positive effect identified from the analysis offers empirical evidence for firms to implement AI technology for better B2B marketing performance. Secondly, the analysis further illustrates the moderating effect of different business environments (i.e., industry dynamism and customer complexity) in influencing the impact of AI implementation for B2B marketing. Hence, it provides insights for companies to consider their business environments to reap more value from their AI implementation for B2B marketing. Thirdly, this study integrates the social action theory and provides a more comprehensive view to investigate whether shareholders reward or penalize firms for their AI-enabled B2B marketing initiatives. From a social actor perspective, it explains how AI implementation for B2B marketing can enable firms to gain competitiveness via improved social identities for innovation and how the competitiveness can be further enhanced in different business environments. It is believed that the social actor perspective can be used as an insightful theoretical lens for future research in this area. It extends the existing literature on AI adoption to consider the social attributes of technological artefacts in the approach through which prescribed information technologies are transformed into 'information technologies-in-use' (Cunha & Carugati, 2011; Orlikowski, 2010).

2. Literature review and hypothesis development

2.1. Exploring AI in B2B marketing through a social actor perspective

AI has generated increasing interest in future work discussions and is considered the next frontier for innovation, competition, and productivity (McKinsey, 2020; Dwivedi et al., 2021b; Hradecky et al., 2022). Considering the socio-technical nature of AI and the truth that actions are conducted in an organizational and social context, this study argues that the AI implementation for B2B marketing can be seen as social actions, i.e., meaningful activities for organizations and associated with and are affected by the activities of others (Hedström et al., 2013; Kling & Lamb, 1999). For example, AI-based techniques used in B2B marketing can be referred to as a series of tools and resources for facilitating firms' leadership-generated communications and employee interactions to affect shareholders' perceptions. Although research has led to theoretical models (Ngwenyama & Lyytinen, 1997; Vannoy & Palvia, 2010; Van Osch & Coursaris, 2017), more remains to be conducted on investigating and theorizing the social traits of AI implementation for B2B marketing. In other words, the issue remains unaddressed as to what extent AI-enabled B2B marketing will affect shareholders' perceptions. Although some recent studies have suggested a positive relationship between the adoption of emerging technologies and firms' overall performance (Sheel & Nath, 2019; Lam et al., 2019; Wamba et al., 2017), research about the social impact of AI adoption for B2B marketing is still in its infancy.

Consistent with the existing literature, this study identifies the metatheoretical underpinnings that form the basis for conceiving an organization in the role of a social actor. According to King et al. (2010), social actors are organizations which identifiable due to how they are interpreted and perceived by others. This point of view is different from conventional perspectives, which generally refer to the focal firm as structurally distinctive but essentially rooted in the market or in communities of organizations (Van Osch & Coursaris, 2017). The social actor perspective posits that organizations within a social context actively engage in roles and behaviors influenced by their perceptions, interactions, and social norms (Whetten & Mackey, 2002). In the context of our study, this perspective informs our examination of how shareholders perceive and respond to organizations' adoption of AI in B2B marketing initiatives. Notably, this study applies Goffman's dramaturgical theory of social action - it perceives social life as a stage on which individuals play various roles of performers, attempting to impress their target audience through their actions (Goffman, 1970; Schimmelfennig, 2002). Goffman's dramaturgical theory complements the social actor perspective by framing social interactions as performances on a metaphorical stage. It emphasizes the idea that organizations strategically manage their public image and actions to shape perceptions (Schimmelfennig, 2002). In our study, we apply this theory to explore how organizations strategically communicate and present their AI-enabled B2B marketing initiatives to shareholders, recognizing that these presentations are, in essence, performative acts that can influence shareholder reactions.

Together, these theoretical foundations guide our research by providing a framework for understanding the dynamics of AI adoption, shareholder perceptions, and the organizational business contexts. They allow us to delve into the complex interplay between actors, roles, and business conditions within the context of B2B marketing, ultimately contributing to a deeper comprehension of the impact of AI adoption on shareholder reactions. This study theorizes that the focal firm's AI implementation for B2B marketing can be seen as an action delivered by the firm (i.e., performer) to present its IT proficiency and future business opportunities to its shareholders (i.e., audience). Following this logic, adopting the social actor perspective to explain how AI implementation for B2B marketing presents their underlying capabilities or competencies to shareholders, affecting shareholders' perception and influencing the firm's market value. In addition, this study further argues that the shareholders' reaction to the implementation of AI for B2B marketing relies on different business conditions, such as the characteristics of firms' industry type (i.e., industry dynamism) and operational environments (i.e., customer complexity). In this way, it offers an insightful lens for situating firms in a broader social landscape and investigating the relationships between their AI-enabled B2B marketing and shareholder reaction in different environments. The conceptual model of this study is illustrated in Fig. 1.

2.2. Hypothesis development

The theorization of AI implementation as valuable techniques for B2B marketing activities in organizational contexts is supported by Habermas' theory of social action (Habermas, 85, 2001), which identifies a range of social tools and resources required for individuals to perform their everyday work. Specifically, this study uses a dramaturgical view and defines the AI implementation for B2B marketing as a theatrical performance through which firms present themselves to their shareholders according to the social values, rules, and expectations

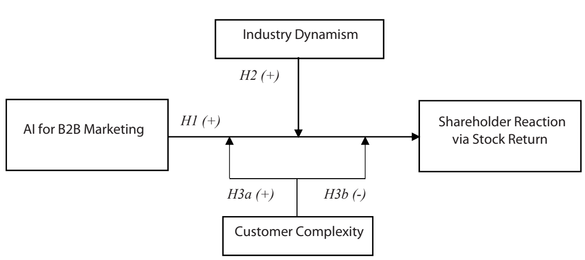

Fig. 1. Conceptual model.

(Schimmelfennig, 2002). Thus, the focus of AI implementation for B2B marketing is on how firms should deliver this information to impress their shareholders and support their daily operations. According to Cunha and Carugati (2011), performance is a social behavior where the objective is acceptance from the audience via thoughtfully performed activities that interpret, if successful, a well-defined self-image.

To better understand how shareholders react to AI implementation for B2B marketing, it is crucial to acknowledge the meanings individuals place on AI. Consistent with recent B2B marketing literature (Baabdullah et al., 2021; Bag et al., 2021; Borges et al., 2021a, 2021b; Huang & Rust, 2021), this study argues that firms' AI implementation for B2B marketing projects two interrelated messages to shareholders: a symbol for a more significant managerial influence and a higher likelihood for achieving long-term competitiveness. Specifically, Sowa et al. (2021) found that AI implementation is often seen as a social status symbol, especially among professionals, to represent a tremendous managerial influence. For example, the existing literature has well-documented how AI can support organizations' decision-making by analysing data from various sources (Jarrahi, 2018; Shrestha et al., 2019; Farrokhi et al., 2020; Dwivedi et al., 2021b). Also, studies such as Davenport and Ronanki (2018) and Sowa et al. (2021) refer to AI as a managerial tool to support fields where humans have shortcomings and help broaden cognitive limitations. This is in line with the information systems literature, which suggests a tool metaphor – the use of appropriate tools will result in more significant managerial impacts and business performance (Leonard-Barton & Deschamps, 1988; Benbya et al., 2019).

Moreover, beyond the technical nature of AI, its implementation for B2B marketing can also be considered a symbol of firms' long-term competitiveness. Studies suggest that AI implementation for B2B will lead to great competitive gains, and the expenditures are just temporary (Kumar et al., 2019; Han et al., 2021; Saura et al., 2021). Therefore, shareholders may view AI implementation for B2B marketing as a positive social symbol for firms. Additionally, world-leading companies such as Apple, Autodesk, Amazon and FedEx have successfully implemented AI as part of their B2B marketing for automating business operations (Forbes, 2020). These anecdotal evidences further project a positive image of the firm to shareholders while allowing them to have high expectations of AI implementation for B2B marketing. As a result, since the implementation of AI for B2B marketing creates a good social image of the firms with a more significant managerial influence and a higher likelihood of long-term competitiveness, shareholders may consider them attractive and pay particular attention to selecting these firms' stocks. Nonetheless, it is worth noting that many other companies such as IBM's Watson, despite its early promise, faced substantial challenges in healthcare applications, particularly in medical diagnostics (Lohr, 2021). The difficulties in accurately processing complex medical data led to questions about its practical utility and return on investment. These examples collectively show that AI can offer significant benefits in B2B marketing, but its implementation is not without risks and challenges that can impact a firm's reputation and shareholder perception.

To measure firms' competitive edge, the existing literature has applied various performance indicators such as business profitability, market growth, and operations efficiency (Morgan & Rego, 2006; Bag et al., 2021). In this study, we have chosen to measure shareholder reaction through abnormal stock returns, a pivotal financial metric that captures the direct impact of specific firm-level initiatives on shareholder value (Fama, 1970). The rationale behind using abnormal stock returns, as computed via the event study method detailed in Section 3, lies in their ability to reflect the immediate market reaction to a firm's strategic decisions. Unlike traditional performance metrics, abnormal stock returns provide a real-time indicator of investor sentiment and expectations. They represent the difference in stock returns between firms that adopt AI for B2B marketing and their non-adopting industry peers, offering a more direct and quantifiable measure of competitive gains as conceptualized in the literature. This metric is particularly useful in our study as it captures the market's response to AI adoption in a timely and specific manner, aligning with our focus on understanding the immediate impact of such technological advancements on shareholder perception and firm valuation. Thus, we propose the first hypothesis:

H1. Shareholders react positively to the announcement of AI implementation for B2B Marketing.

2.3. The moderating effect of industry and operational environments

Although the study expects shareholders react positively (via abnormal stock returns) to the announcement of AI implementation for B2B marketing, the extent to which the shareholders' reaction can be incremented may differ across firms in different business environments. From a social actor's view, the effectiveness of the announcement regarding firms' AI implementation for B2B marketing is based on the external social environments (Habermas, 1984; King et al., 2010). Recent research has illustrated how the application and adoption of emerging technologies in firms to study human behavior in different organizational settings (Vannoy & Palvia, 2010; Li & Li, 2014; Kaartemo & Nyström, 2021). Nevertheless, the social action literature has committed little attention to investigating the moderating role of business environments on firms' technology adoption effectiveness. Accordingly, this study considers the business environment a significant factor in exploring the shareholders' reaction to AI implementation for B2B marketing. In particular, this study examines how the business environment in terms of firms' industry dynamism and customer complexity may influence the effectiveness of the AI implementation for B2B marketing in increasing/mitigating firms' abnormal stock returns.

Industry dynamism refers to the instability of firms' business environment (Stoel & Muhanna, 2009; Lam et al., 2019). Typically, dynamic industries are featured by perceived technological uncertainty, unpredictable customer requirements, changeable market demand and unstable political conditions (Henderson et al., 2006). It is believed that such a turbulent business environment can cause firms' AI implementation for B2B marketing to become a more effective social symbol to shareholders and thus increasing stock returns. For example, the technology sector is rapidly evolving and NVIDIA - originally known for graphics processing units - has become a leader in AI technology. When NVIDIA announced further investments in AI for B2B marketing, shareholders reacted positively, recognizing that NVIDIA's enhanced AI capabilities would not only improve their marketing efficiency but also showcase their AI prowess to other businesses in the tech sector, potentially leading to more B2B collaborations (Fender, 2021). This is aligned with studies (e.g., Karasek & Bryant, 2012; Lam, 2018) that suggest the signal effect will be most vital when the market uncertainty is most remarkable. This is because firms' turbulent environment increases uncertainty and information asymmetry between shareholders and firms, making it more difficult for the shareholders to understand the firms' ongoing business and associate with the firms' future value. In this way, shareholders are more likely to rely on other notable symbols, such as the activity of AI implementation for B2B marketing, making it a more effective way to reduce the shareholders' uncertainty about the firms' future business, improving investors' confidence, and therefore increasing firms' market value via stock returns. As a result, it is argued that the higher the instability of firms' business environment, the greater the uncertainty and information asymmetry levels between shareholders and firms, and hence the higher the shareholders' reward for AI-enabled B2B marketing initiatives.

In addition, firm performance in environments where business opportunities can be very short-lived and threats may occur unexpectedly tends to be defined based on its capability to deal with the changes and react swiftly (Bozarth et al., 2009; Mikalef et al., 2021). Wamba et al. (2017) identify the values generated from advanced analytics and technology adoptions appeared to be most significant for firms in turbulent environments and with an externally focused strategy. From a social actor perspective, although unstable business environments might need firms to provide frequent modification of their internal operations and create technological constraints, AI implementation for B2B marketing in such environments enables the firm to erect a good corporate image and social identity (of firms' strong digital power for innovation), which weakens the improvised IT support required for implementing AI for B2B marketing. This is consistent with the findings from Stoel and Muhanna (2009) about externally focused IT. Thus, it is believed that the effectiveness of AI implementation for B2B marketing will be more prominent for firms in turbulent environments as it allows firms to better respond to market opportunities through data-driven activities and timely react to the changes in customer and supplier demand. We hypothesize the following:

H2. Shareholders of firms in a more dynamic industry environment react more positively to the announcement of AI implementation for B2B marketing.

Customer complexity can be seen as the level at which marketing managers have to react to a wide range of customer demands and personnel involved with different purchasing processes in conducting their businesses (Schmitz & Ganesan, 2014). While industry dynamism measures the degrees of firms' external environment for AI implementation in B2B marketing, customer complexity indicates a more complicated business condition. Specifically, it may generate two opposite effects on the relationship between firms' AI implementation for B2B marketing and shareholder reaction. This is in line with the existing literature, which also suggested mixed findings regarding the role of complexity (e.g., Skaggs & Huffman, 2003; Bozarth et al., 2009; Schmitz & Ganesan, 2014). For instance, Skaggs and Huffman (2003) suggested that the performance of firms' service adaptability improves in complex environments, while Bozarth et al. (2009) found that supply chain complexity weakens firms' plant-level performance.

On the one hand, existing B2B literature has presented that various customer needs result from growth in the omnichannel environment, such as growing expectations for customized services and items, higher diversity among consumers, and a more significant number and more diversity of customer personnel involved in buying centers (Skaggs & Huffman, 2003; Bozarth et al., 2009). In such complex customer situations, firms are more likely to behave proactively to impress their shareholders through exploring new markets, improving customer experience and conducting product and service innovation. Specifically, AI implementation for B2B marketing can enhance innovation effectively by increasing firms' lead generation capabilities while eliminating the costs and manufacturing limitations across the entire new product development process (Paschen et al., 2019). Also, AI implementation for B2B marketing enables powerful personalization without additional changes to its operations, consequently improving consumers' perceived values and willingness to pay more for the products or services (Chung et al., 2020; Prentice & Nguyen, 2020). Therefore, the adoption of AI for B2B marketing can support firms to meet the needs emerging from their customers and convey a positive social image of the firm – capable of innovating and gaining competitiveness over their competitors. In this way, customer complexity is expected to positively affect the existing relationship between firms' AI implementation for B2B marketing and shareholder reaction. It is suggested that shareholders of firms with more complex customer bases may react more positively to the announcement of AI implementation for B2B marketing. Therefore, we hypothesize the following:

H3a. Shareholders of firms with more complex customer bases react more positively to the announcement of AI implementation for B2B marketing.

On the other hand, while shareholders are unsure about the underlying business operations in turbulent environments, customer complexity can make them more skeptical about the potential outcomes.

This is because AI implementation for B2B marketing normally requires significant investments and with great uncertainty, while its payback time and expected value are hard to evaluate (Martínez-López & Casillas, 2013; Lui et al., 2021). Despite the tremendous advantages AI could bring to change daily operations in B2B marketing, studies generally show that the current state of AI technology does not yet live up to its promise (Davenport & Ronanki, 2018; Kumar et al., 2019). Additionally, firms tend to make extra effort to identify sophisticated, diverse customer preferences, manage intra- and inter-customer expectations and deliver personalized products and services (Schmitz & Ganesan, 2014; Lam et al., 2019). Such demand uncertainty further increases firms' capital expenses and brings down their future cash flow. In other words, implementing AI for B2B marketing in high customer complexity environments may project a negative social image of firms and convey a high level of uncertainty and risk to their shareholders. In this way, shareholders may assume that the firms operating with high customer complexity to implement AI for B2B marketing are financially unfavorable in the short term and might not invest in these firms. Accordingly, shareholders of firms with more complex customer bases may react less positively to the announcement of AI implementation for B2B marketing. The above discussion indicates two conflicting roles of customer complexity in the opposite directions. Accordingly, we make another hypothesis regarding the role of customer complexity:

H3b. Shareholders of firms with more complex customer bases react less positively to the announcement of AI implementation for B2B marketing.

3. Methodology

In this study, we adopted a comprehensive two-step approach to investigate the impact of AI adoption for B2B Marketing on shareholder reaction. Firstly, we conducted a quantitative analysis to test the hypotheses developed based on a thorough review of the literature. Employing a propensity score matching (PSM) method, we generated an artificial control group of firms that had not adopted AI-enabled B2B marketing initiatives. Subsequently, we performed an event study using a dataset comprising 174 sample firms, consisting of 87 treatment firms (those implementing AI for B2B marketing) and 87 matched control firms, all of which were publicly listed in the United States between 2011 and 2020. Secondly, to further enrich our understanding and complement the quantitative findings, we collected qualitative data through a carefully conducted focus group study (Morgan, 1996). The qualitative phase encompassed in-depth discussions with two distinct groups of participants: senior managers representing firms at various stages of AI adoption for B2B marketing, and key investors and shareholders holding stakes in these firms. These discussions were designed to explore the underlying reasons, motivations, and contextual nuances behind the quantitative results. The focus group transcripts were subjected to rigorous analysis to identify recurring themes, patterns, and insights relevant to each of the hypotheses.

By adopting this mixed-methods approach, our study aims to provide a more comprehensive and holistic perspective on the phenomenon under investigation (Shi et al., 2020). This two-step methodology not only validates our quantitative findings but also uncovers the qualitative intricacies that shed light on the "why" behind the observed reactions (Cyr, 2016). By integrating both quantitative and qualitative analyses, our research offers deeper insights into the multifaceted factors influencing shareholder reactions to AI adoption in B2B marketing, including the role of industry dynamics and the complexities of customer bases. This comprehensive approach enhances our understanding of the complex interplay between AI adoption and shareholder sentiment in the B2B marketing context. The following sections will explain the research methods in detail.

4. Study one: quantitative analysis

To test the hypotheses, we follow the approaches suggested by previous studies (Faramarzi & Bhattacharya, 2021; Monfort et al., 2021) and adopt the Factiva database to search and identify firms that have implemented AI-enabled B2B marketing initiatives. However, a critical issue is that the firms' AI-enabled B2B marketing initiatives do not occur randomly, resulting in a possible selection bias and endogeneity concern. To eliminate this selection bias, we capture the counterfactual announcements regarding AI-enabled B2B marketing initiatives. Specifically, this study employs propensity score matching (PSM) to match each treatment firm (i.e., the AI-enabled B2B marketing adopting firm) to a control firm which had a similar probability of implementing AI for B2B marketing initiatives as the treatment firm but eventually did not do so. After identifying the treatment and matched control firms, we use the event study method to calculate the abnormal stock returns and consider it the dependent variable. Then, we construct a regression model to test whether AI-enabled B2B marketing initiatives can positively affect firms' abnormal stock returns and whether this positive impact is contingent on the levels of industry dynamism and customer complexity.

4.1. Data collection and sample firms

This study identifies the sample firms by searching the announcements of firms implementing AI for B2B marketing via Factiva, a database collecting all major real-time news wires and information articles worldwide such as *The Financial Times* and *The Wall Street Journal.* The keywords used for the search included the combination of a stock market index (e.g., Nasdaq and NYSE), terms related to AI technology (e.g., artificial intelligence, algorithm, automation, and machine learning), and terms related to B2B marketing (e.g., enterprise customer, corporate client, business to business, and marketing). These searching terms are the key "classifiers" identified from the previous literature regarding the use of AI technology in B2B marketing (Borges et al., 2021a, 2021b; Lui et al., 2021). The research is limited to a ten-year period from 2011 to 2020. This is because AI-enabled B2B marketing has emerged as a relatively new phenomenon in recent years. Consequently, a significant challenge in conducting this study arises from the necessity to secure a substantial number of announcements for subsequent data analysis. Therefore, this study endeavored to span an extended period (i.e., 2011 to 2020) to meticulously identify all accessible announcements related to AI-enabled B2B marketing in Factiva. We critically check through all the announcements collected, and only retain those specifically mentioning adopting AI in marketing functions for business customers rather than using AI for other purposes and individual customers. If there are multiple reports of the same announcements in Factiva, only the earliest report date is captured as the event date of the announcements. This is because stock markets should react (if any) when information about the event is made available to the markets for the first time (Ding et al., 2018). This screening process results in a final sample of 89 announcements of AI-enabled B2B marketing initiatives from 2011 to 2020. Some examples of the announcements are excerpted below:

- Baidu, the leading Chinese Internet search provider, leveraged AI technology to help its enterprise customers to enhance their advertise performance prediction and thus increase advertising revenues.
- MasterCard employed AI-assisted marketing and sales software to offer smaller merchants real-time, analytics-based market insights on revenue, market share, customer demographics and competitors in a particular location and across multiple locations.
- Rocket Fuel, a leading programmatic media-buying platform provider, uses artificial intelligence for its enterprise marketer to improve marketing ROI.
- US Bank adopted AI-based automation services for its enterprise clients to simplify their business-to-business payments and improve payment processing routines.

- Visa Inc. introduced an artificial intelligence platform to increase automation, convenience and security for the B2B transactions of small to medium-sized business clients.

After the data collection, panel A of Table 1 presents the characteristics of the sample firms. For instance, the mean of the sample firms' net income and total assets are $3292.382 million and $ 139,398 million, respectively. At the same time, the mean of sales, total liabilities and employee number of the sample firms are $ 24,361.830 million, $ 11,933.500 million, and 66,487, respectively. Panel B and C of Table 1 show the distribution of the sample firms by industry (via its two-digit SIC codes) and year. It illustrates that AI-enabled B2B marketing activities are most popular in the services industry (i.e., SIC 70–89), which takes 56.18% of the total sample. The distribution panel shows that most of the firms only started using AI for their B2B marketing practices during 2016–2020, with 2017 as the peak year.

4.2. Matching firm selection

This study uses propensity score matching (PSM) to identify firms without adopting AI-enabled B2B marketing initiatives (i.e., matched control firm group) but have very similar probabilities as our sample firms to implement AI-enabled B2B marketing initiatives. PSM has been widely used in marketing research (e.g., Liu et al., 2019) and to study the adoption of emerging technologies (e.g., Lui et al., 2016). To implement PSM, we first construct a binary logistic regression model with a dummy dependent variable indicating whether the firm has undertaken AI-enabled B2B marketing initiatives (i.e., coded as 1) or not (i.e., coded as 0) between 2011 to 2020. Marketing efficiency, firm debt, profitability, size, liquidity, financial slack, and R&D intensity are included in the logistic regression model as independent variables. This is because the firms with a high level of firm profitability, large firm size, high level of firm liquidity, high level of slack resources, and high level of R&D intensity tend to have more resources and related infrastructure to support AI-enabled B2B marketing initiatives and thus are more likely to undertake these initiatives (Matzler et al., 2015; Zuo et al., 2019). In contrast, a high level of marketing efficiency and debt ratio can decrease firms' motivation to implement AI-enabled B2B marketing initiatives due to unnecessary resources investment and financial constraints (Lui et al., 2016; Singh & Faircloth, 2005). Particularly, by obtaining financial and accounting data from Compustat, we measure various control variables, as shown in Table 3, such as marketing efficiency (Modi & Mishra, 2011), firm debt (Eriotis et al., 2007), firm profitability (Appio et al., 2019), firm size (Parker & Ameen, 2018), firm liquidity (Eriotis et al., 2007), firm financial slack (Lui et al., 2016) and R&D intensity (Guldiken & Darendeli, 2016).

After performing the binary logistic regression model, we acquire the propensity score, which indicates the probability of implementing AI-enabled B2B marketing initiatives for all firms included in the model. Then, we use a nearest-neighbor one-on-one matching method to identify the control firms. To improve the matching quality, we set a predetermined caliper of 0.02, which measures the absolute distance between the control and treatment firms' propensity scores (Ye et al., 2020). As shown in Model 1 (pre-match model) of Table 2, the number of firms included in the regression model is 1423, consisting of 89

Table 2
Logistic Regression Results.

Independent Variable	Model 1 (Pre-Match)	Model 2 (Post-Match)
Intercept	-4.462 *** (−10.14)	-0.826(−1.417)
Marketing Efficiency	-0.697 *(−1.701)	-0.233(−0.967)
Firm Debt	-0.387 (−0.601)	-0.057(−0.058)
Firm Profitability	0.439(0.842)	-0.163(−0.470)
Firm Size	0.471 *** (8.150)	-0.019(−0.234)
Firm Liquidity	0.276 **(2.406)	0.355(1.541)
Financial Slack	0.233(0.388)	0.489 (0.801)
R&D Intensity	2.236 **(2.398)	0.107(0.083)
Control Firms	1334	87
Treatment Firms	89	87
Log Likelihood	-426.663	-117.137
Pseudo-R^2	0.107	0.029

Notes: *p < 0.1, **p < 0.05, and ***p < 0.01 (two-tailed tests). z-statistics are in parentheses.

Table 1
Descriptive Statistics of Sample Firms.

Panel A: Characteristics of Sample Firms

Variable	Unit	Mean	Standard Deviation	Min	Max
Net Income	Millions (USD)	3292.382	6027.965	-546.494	32,474.000
Total Assets	Millions (USD)	139,398.000	393,777.900	23.944	2,622,532.000
Sales	Millions (USD)	24,361.830	46,033.770	18.956	280,522.000
Total Liabilities	Millions (USD)	11,933.500	352,735.700	10.226	2,366,017.000
Number of Employees	Thousands	66.487	118.775	0.042	798.000

Panel B: Distribution of Samples Across Industries

Industry	2-Digit SIC Codes	Frequency	Percentage
Services	70-89	50	56.180%
Finance, Insurance, & Real Estate	60-67	19	21.348%
Manufacturing	20-39	7	7.865%
Retail Trade	52-59	7	7.865%
Transportation & Public Utilities	40-49	4	4.494%
Wholesale Trade	50-51	2	2.247%
Total		89	100%

Panel C: Distribution of Samples Across Year

2011	3	3.371%
2012	2	2.247%
2013	5	5.618%
2014	3	3.371%
2015	4	4.494%
2016	12	13.483%
2017	25	28.090%
2018	9	10.112%
2019	15	16.854%
2020	11	12.360%
Total	89	100%

treatment firms collected from Factiva, 1334 potential control firms with the same 4-digit SIC codes as the treatment firms. 87 out of the 89 treatment firms are matched successfully through the above-mentioned matching procedures and criteria. Therefore, the total sample size for this research reached 174, including 87 treatment firms and 87 matched control firms. Model 1 shows that the coefficients of marketing efficiency are negatively significant, while the coefficients of firm size, liquidity and R&D intensity are positively significant. This result indicates that firms with lower marketing efficiency, larger firm size, higher firm liquidity and greater R&D intensity tend to be more likely to employ AI technology for their B2B marketing practices. Also, we further check the matching quality by comparing the results of pre-match and post-match logistic regressions. As shown in Model 2 (post-match model) in Table 2, there are no statistically significant predictors, thus indicating a satisfying matching quality is achieved.

4.3. Variables measurement and model

We developed a cross-sectional regression model with the CARs as the dependent variable to test our proposed hypotheses. The regression model is presented as Eq. (1). The β1 determines whether the stock market reacts differently for the firms with and without AI-enabled B2B marketing initiatives (H1). β2 and β3 indicate how this impact is contingent on different levels of industry dynamism (H2) and customer complexity (H3). The measurements of the variables included in the regression model are summarized in Table 3 and discussed below.

$$CAR_i = \beta_0 + \beta_1\text{AI-enabled B2B Marketing}_i + \beta_2\text{AI-enabled B2B Marketing}_i \times \text{Industry Dynamism}_i + \beta_3\text{AI-enabled B2B Marketing}_i \times \text{Customer Complexity}_i + \beta_4\text{Industry Dynamism}_i + \beta_5\text{Customer Complexity}_i + \beta_6\text{Marketing Efficiency}_i + \beta_7\text{Firm Debt}_i + \beta_8\text{Firm Profitability}_i + \beta_9\text{Firm Size}_i + \beta_{10}\text{Firm Liquidity}_i + \beta_{11}\text{Firm Financial Slack}_i + \beta_{12}\text{R\&D Intensity}_i + \beta_{13}\text{Firm Reputation}_i + \beta_{14}\text{Goods or Services}_i + \beta_{15}\text{Time Trend}_i \quad (1)$$

CAR. Our dependent variable is shareholder reaction measured by the firm's abnormal stock returns estimated from a standard event study method (Eilert et al., 2017). The event study methodology quantifies the impact of AI-enabled B2B marketing initiatives by examining abnormal stock returns. The abnormal stock returns were computed as the difference between the actual stock return associated with the occurrence of an event and the expected stock return in the hypothetical scenario where the event did not occur (Ding et al., 2018). Specifically, within the context of our research, the abnormal stock return represents the difference between the actual stock return when a firm announces an AI-enabled B2B marketing initiative and the expected stock return under the assumption that the firm did not engage in such AI-enabled B2B marketing. Eq. (2) subsequently illustrates how the abnormal stock return (AR) is calculated.

$$AR_{it} = R_{it} - E(R_{it}) \quad (2)$$

where R_{it} is the daily stock return of firm i on day t, $E(R_{it})$ signifies the expected stock return of firm i on day t, and AR_{it} represents the abnormal stock return of firm i on day t.

It should be noted that only a firm's actual stock return can be calculated directly using its actual stock price, while the expected stock return can only be estimated. To estimate the expected stock return, we employed the Fama-French three-factor model over a period of 210 days, ending 11 days prior to the event date (Eilert et al., 2017). Additionally, we require that a firm must have a minimum of 50 days of stock returns data during this estimation period. Eq. (3) below illustrates how the expected stock return is estimated. We obtained the firm's daily stock returns and the Fama French Three Factors data, utilized to calculate expected stock returns, from the CRSP database.

$$E(R_{it}) = \alpha_i + \beta_i RM_t + \gamma_i SMB_t + \delta_i HML_t \quad (3)$$

Where RM_t denotes the equal-weighted market return on day t, and SMB_t equates to the size risk that accounts for the return of publicly-traded companies on the small minus-big portfolio. HML_t accounts for the return of publicly-traded companies on the high-minus-low portfolio.

Finally, consistent with previous studies (Jacobs, 2014; Hendricks & Singhal, 2003), we use a two-day event window (i.e., one day before the event day and the event day) to calculate the cumulative abnormal returns (CAR) by summing the individual abnormal returns across this event window, to better capture the overall stock market reaction to the event and keep provision for any information leakage before the event

Table 3
Variable Measurements.

Variable	Measurement	Reference	Data Source
Dependent Variable			
CAR	The sum of abnormal stock return (AR) over the event window based on Fama-French Three factors model.	Eilert et al. (2017)	CRSP
Independent Variables			
AI-enabled B2B Marketing	Dummy variable based on whether the company has implemented AI-enabled B2B marketing or not.	Xiong et al. (2021)	Press Release
Industry Dynamism	Industry sales are regressed on year (according to five years before the event year) to obtain standard error, which is divided by the mean of industry sales.	Jacobs et al. (2015)	Compustat
Customer Complexity	The number of focal company's business customers (log-transformed).	Bozarth et al. (2019)	Bloomberg
Control Variables			
Marketing Efficiency	The ratio of Sales-to- selling, general, and administrative expenses (SGA) minus mean industry Sales-to-SGA, and divided by the standard deviation of industry Sales-to-SGA.	Modi and Mishra (2011)	Compustat
Firm Debt	A company's total liabilities divided by total assets.	Eriotis et al. (2007)	Compustat
Firm Profitability	A company's return on asset (ROA) ratio, calculated as "net income divided by total assets".	Appio et al. (2019)	Compustat
Firm Size	A company's total number of employees (log-transformed).	Parker and Ameen (2018)	Compustat
Firm Liquidity	A company's current assets divided by current liabilities.	Eriotis et al. (2007)	Compustat
Firm Financial Slack	A company's current assets divided by total assets.	Lui et al. (2016)	Compustat
R&D Intensity	A company's R&D expense divided by total sales.	Guldiken and Darendeli (2016)	Compustat
Firm Reputation	Dummy variable based on whether a company is included in America's Most Admired Companies list.	Beckers et al. (2018)	Fortune
Goods or Services	Dummy variable based on companies' two-digit SIC code distinguishing companies primarily operating in goods or services setting (SIC 70-89).	Beckers et al. (2018)	Compustat
Time Trend	Assigning an integer number between 1 and 10 to a firm depending on the announcement year (i.e., 2011 =1, 2012 =2, … 2020 =10).	Luffarelli and Awaysheh (2018)	Press Release

day.

4.3.1. AI-enabled B2B marketing

We measure AI-enabled B2B marketing as a dummy variable, indicating whether the firms included in the regression model have implemented AI for B2B marketing purposes. Specifically, treatment firms (i.e., firms with AI-enabled B2B marketing announcements) are coded as 1, and matched control firms (i.e., firms without such announcements) are coded as 0. We relied on the AI-enabled B2B marketing announcements to identify our treatment firms. Matched control firms are identified using the previously mentioned PSM method. This measure allows us to compare the stock returns of these two groups (i.e., treatment firms and matched control firms) in terms of adopting AI-enabled B2B marketing.

4.3.2. Industry dynamism

Following the study of Jacobs and Singhal (2014), we measure industry dynamism by regressing industry sales (four-digit SIC codes) on year (according to five years before the event year) to obtain standard error, which is divided by the mean of industry sales. Based on this estimation, a higher standard error indicates that actual industry sales deviate more widely from predictions, implying greater unpredictability and higher dynamism for overall market demands. Moreover, normalizing this standard error by the mean of industry sales (i.e., standard error divided by the mean of industry sales) scales the measure of volatility to the average size of the industry, ensuring that the measure of dynamism is not disproportionately influenced by the industry's size. As noted by previous studies (Henderson et al., 2006; Stoel & Muhanna, 2009; Lam et al., 2019), a high level of industry dynamism typically reflects an unstable business environment with unpredictable customer requirements and changeable market demand. Therefore, our measurement aptly captures the nature of industry dynamism.

4.3.3. Customer complexity

Customer complexity pertains to the level at which managers must respond to a wide range of customer demands (Schmitz & Ganesan, 2014). Thus, a company with more business customers should exhibit a higher level of customer complexity. Based on the study of Bozarth et al. (2019), we operationalize the customer complexity as the firms' number of business customers. According to this measurement, a higher number of customers likely introduces a wider array of demands and amplifies the complexity of customer management, thereby presenting a major facet of customer complexity. We utilize the Bloomberg SPLC database to identify the firms' number of business customers. Given the skewness distribution of business customer numbers across firms, we employ logarithm transformation to measure customer complexity.

4.3.4. Control variables

We also incorporate several control variables to capture the potential impact on abnormal returns. First, we control for firm-specific factors, including marketing efficiency, firm debt, firm profitability, firm size, firm liquidity, firm financial slack, R&D intensity, and firm reputation. To control for the effects of industry and year-specific factors on firms' stock returns, we also include two control variables corresponding to goods or services (whether companies primarily operate in goods or services industries) and time trend (assigning an integer number to a firm depending on the announcement year). The detailed measurements of these control variables are shown in Table 3.

4.4. Results

Table 4 shows the descriptive statistics, including means and standard deviations, and the correlations of all variables in Eq. (1). Table 5 presents the results of cross-sectional regression analysis with CAR over the event window (−1, 0) as the dependent variable. More specifically, model 1 is the basic model and only includes all control variables. In model 2, the direct effect of AI-enabled B2B marketing is introduced.

Table 4
Correlation Matrix and Descriptive Statistics.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) CAR (−1, 0)	1.000													
(2) AI-enabled B2B Marketing	0.145 *	1.000												
(3) Industry Dynamism	-0.114	0.086	1.000											
(4) Customer Complexity	0.100	0.108	0.187 **	1.000										
(5) Marketing Efficiency	0.108	-0.084	-0.062	0.180 **	1.000									
(6) Firm Debt	-0.086	-0.031	-0.052	0.046	-0.096	1.000								
(7) Firm Profitability	0.188 **	-0.037	-0.070	0.190 **	0.197 ***	-0.083	1.000							
(8) Firm Size	-0.149 **	-0.011	-0.069	0.251 ***	0.286 ***	0.291 ***	0.311 ***	1.000						
(9) Firm Liquidity	0.148 *	0.148 *	0.105	0.061	0.081	0.003	0.080	-0.126 *	1.000					
(10) Firm Financial Slack	-0.007	0.120	0.186 **	0.038	0.068	-0.420 ***	0.055	-0.182 **	0.347 ***	1.000				
(11) R&D Intensity	0.083	0.021	-0.018	0.150 **	0.101	-0.209 ***	0.049	-0.331 ***	0.048	0.297 ***	1.000			
(12) Firm Reputation	-0.140 *	0.110	0.174 **	0.247 ***	0.236 ***	0.123	-0.110	0.415 ***	-0.029	-0.018	-0.078	1.000		
(13) Goods or Service	-0.131 *	-0.172 **	0.004	-0.178 **	0.005	0.196 ***	-0.020	0.330 ***	-0.099	-0.198 ***	-0.339 ***	0.200 ***	1.000	
(14) Time Trend	-0.012	0.000	-0.068	-0.103	-0.037	0.054	0.137 *	0.073	-0.070	-0.007	-0.009	0.172 **	0.046	1.000
Mean	0.003	0.500	0.105	3.192	0.153	0.173	0.025	2.172	1.581	0.446	0.101	0.157	0.511	6.908
Standard Deviation	0.029	0.501	0.038	1.749	0.960	0.186	0.141	2.226	0.793	0.195	0.195	0.365	0.501	2.284

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (two-tailed tests).

Table 5
Results of Regression Analysis.

Variable	Model 1	Model 2	Model 3	Model 4
AI-enabled B2B Marketing		0.161 * * (2.045)	0.154 * * (2.000)	0.154 ** (2.023)
AI-enabled B2B Marketing × Industry Dynamism			0.217 * ** (2.589)	0.251 * ** (2.963)
AI-enabled B2B Marketing × Customer Complexity				-0.158 * * (−1.975)
Industry Dynamism	-0.128 (−1.570)	-0.141 * (−1.733)	-0.226 * ** (−2.620)	-0.234 * ** (−2.758)
Customer Complexity	0.205 * * (2.336)	0.203 ** (2.340)	0.202 * * (2.370)	0.196 * * (2.328)
Marketing Efficiency	0.056 (0.680)	0.060 (0.749)	0.047(0.594)	0.076(0.955)
Firm Debt	-0.117 (−1.334)	-0.116 (−1.330)	-0.149 * (−1.727)	-0.146 * (−1.702)
Firm Profitability	0.161 * (1.930)	0.164 ** (1.995)	0.165 * * (2.038)	0.150 * (1.861)
Firm Size	-0.091 (−0.871)	-0.088 (−0.846)	-0.099 (−0.976)	-0.118 (−1.178)
Firm Liquidity	0.142 (1.651)	0.129 (1.517)	0.159 * (1.879)	0.144 * (1.713)
Firm Financial Slack	-0.142 (−1.400)	-0.146 (−1.452)	-0.167 * (−1.689)	-0.175 * (−1.786)
R&D Intensity	-0.015 (−0.154)	-0.025 (−0.255)	-0.024 (−0.255)	-0.069 (−0.719)
Firm Reputation	-0.087 (−0.972)	-0.110 (−1.224)	-0.076 (−0.858)	-0.058 (−0.659)
Goods or Service	-0.042 (−0.478)	-0.014 (−0.157)	-0.059 (−0.667)	-0.097 (−1.079)
Time Trend	0.019 (0.236)	0.026 (0.329)	0.024(0.317)	0.019(0.258)
Number of Observations	162	162	162	162
R-squared	0.141	0.164	0.201	0.221
Adjusted R-squared	0.071	0.091	0.124	0.141
F-value	2.031 * *	2.236 * *	2.635 * **	2.768 * **

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (one-tailed tests for hypothesized variables). Standardized coefficients are reported. t-statistics are in parenthesis.

The interactions between AI-enabled B2B marketing and industry dynamism and customer complexity are sequentially included in models 3 and 4. The F-tests ($p < 0.05$) show that these four models are significant, with adjusted R-squared values between 0.071 and 0.141. To test for multicollinearity, we calculate the full model's variance inflation factor (VIF). The maximum and mean values of VIF are 1.93 and 1.40 (much lower than the threshold of 10), thus suggesting that multicollinearity is not a concern in our models (Kennedy, 1998).

As shown in Table 5, all variables remain consistent across these four models. We thus employ the full model (model 4) to interpret the testing results of the hypotheses. Model 4 reveals that the coefficient of AI-enabled B2B marketing is significantly positive ($\beta = 0.154$, $p < 0.05$). This implies that the stock market reacts more positively to the firms with AI-enabled B2B marketing practices, supporting H1. The results of model 4 also show that the coefficient for the interaction between AI-enabled B2B marketing and industry dynamism is significantly positive ($\beta = 0.251$, $p < 0.01$). This finding confirms H2 that industry dynamism positively moderates the relationship between AI-enabled B2B marketing and firms' market value via abnormal stock returns. By contrast, customer complexity negatively moderates the relationship between AI-enabled B2B marketing and firms' market value ($\beta = -0.158$, $p < 0.05$). This finding suggests that shareholders react less positively when firms with more complex customer bases adopt AI for B2B marketing, supporting H3b but rejecting H3a.

In summary, we find support for the positive impact of AI-enabled B2B marketing on shareholder reaction measured by firm value. Moreover, this positive impact is stronger for the firms operating with a higher level of industry dynamism and weaker for firms with greater customer complexity. Model 4 also shows that the direct effects of industry dynamism and customer complexity on CAR are significantly negative and positive, respectively. Besides, regarding other control variables, we also find that firm profitability and firm liquidity can positively affect abnormal stock returns. In contrast, firm debt and financial slack tend to exert a negative impact.

5. Study two: qualitative analysis

While secondary data analysis provides valuable insights, it is important to acknowledge its limitations, including potential data gaps and the inability to capture contextual nuances and participant perspectives (Johnston, 2014). To complement the findings, we extended our research methodology by conducting a focus group study. This qualitative phase enabled us to delve deeper into the underlying factors and nuances related to the three hypotheses examined in our quantitative analysis. The advantages of applying the focus group method in our research context, exploring the impact of AI adoption for B2B marketing on shareholder reaction, are noteworthy. For instance, the focus group setting fostered open and interactive discussions among participants, allowing for the exploration of diverse perspectives and the emergence of rich insights. Also, it provided a platform for shareholders, senior managers, and investors to share their experiences and perceptions, offering a nuanced understanding of the intricate dynamics at play. Besides, the qualitative data obtained from the focus group discussions enriched our research by elucidating the "why" behind the quantitative results (Cyr, 2016), thereby providing a more comprehensive view of the complex relationships within the context of AI adoption and shareholder reactions in B2B marketing.

5.1. Method

For the collection of qualitative data through focus group discussions, we adopted a purposive sampling approach to ensure the inclusion of participants who could provide valuable insights into the impact of AI adoption for B2B marketing on shareholder reaction. Our sampling strategy targeted two distinct groups: company managers actively involved in AI adoption for B2B marketing and shareholders and investors representing the companies. To identify prospective participants, we leveraged our professional network and collaboration with a prominent global innovation incubator center. In total, we identified 19 prospective participants and extended invitations via email to participate in a half-day focus group workshop dedicated to facilitating in-depth discussions on the subject. Clear communication of the workshop's purpose, venue and schedule was provided, accompanied by assurances of strict anonymity preservation.

Of the 19 prospective participants, 12 confirmed their attendance, thereby contributing to the richness of our qualitative data. Importantly, the selection process prioritized diversity, ensuring representation from firms at various stages of AI adoption and spanning diverse industry contexts. Among the 12 participants, we engaged with 7 managers representing four different firms, encompassing two manufacturing companies and two IT services firms, alongside 5 key shareholders and investors from these organizations. This purposive sampling strategy enabled us to gather diverse and comprehensive qualitative insights that further enriched our study's depth and breadth.

To facilitate our focus group discussion, we meticulously framed our research objectives to provide clear guidance on the purpose of our study, as outlined in Table 6. These predefined objectives served as a framework for our inquiries during the workshop. The discussion revolved around the examination of the three hypotheses central to our research. For Hypothesis 1, participants engaged in conversations addressing questions such as "*Could you share your thoughts on why shareholders generally react positively to AI implementation in B2B marketing?*" and "*What specific benefits or expectations do you associate with AI*

Table 6
Objectives of the qualitative study.

Findings	Objectives
Hypothesis 1 (Positive Reaction)	Explore the specific reasons and emotions behind shareholders' positive reactions to AI implementation in B2B marketing. Investigate whether there are common themes or differences among participants' responses.
Hypothesis 2 (Dynamic Industry Concerns)	Probe into shareholders' perceptions of industry dynamics and how these dynamics influence their reactions to AI implementation. Identify key industry concerns and their impact on shareholder sentiment.
Hypothesis 3 (Complex Customer Bases)	Investigate why shareholders of firms with more complex customer bases might react less positively to AI implementation. Explore their concerns, expectations, and factors that contribute to this reaction.

adoption in B2B marketing?" Hypothesis 2 prompted discussions with questions such as "*From your perspective, how do industry dynamics and concerns affect your perception of AI adoption in B2B marketing?*" and "*Do you believe that firms in more dynamic industries have unique considerations when it comes to AI implementation? Please elaborate.*" Hypothesis 3 guided participants to respond to queries like "*What challenges or complexities do you perceive in firms with more complex customer bases when implementing AI in B2B marketing?*" and "*Could you provide examples of situations where shareholders may have concerns about AI adoption in such firms?*".

The focus group workshop, spanning approximately 4 hours, was organized to foster open and in-depth discussions. We structured the workshop into three sessions, each corresponding to one of our research hypotheses. To ensure thorough exploration and engagement, each session was carefully timed to last about 60 minutes. To maintain participant engagement and facilitate reflection, a 15-minute break was placed between the sessions. During each session, we provided a concise introduction to frame the topic, followed by a period dedicated to participant responses. This was complemented by a summarizing segment at the end, summarizing key insights and reflections from the discussion.

Rather than recording the session, we chose to capture insights through detailed notes, ensuring participants' anonymity and comfort. Throughout the workshop, we were assigned specific roles in notetaking to document key points, unique perspectives, and the overall essence of the discussions. These notes included quotes on critical points and summaries of arguments, providing a rich view of the discussions. After the workshop, the notes were collectively checked and transcribed to ensure accuracy and completeness. This transcription process involved cross-referencing notes from different members to capture a comprehensive and unified account of the discussions. The transcribed data were then systematically analysed to generate insights relevant to our research hypotheses. During the workshop, we took on the role of a facilitator, ensuring that the discussion remained focused among the participants. This approach fostered an open and informal discussion setting, encouraging participants to freely express their perspectives and insights.

5.2. Results

5.2.1. Why shareholders embrace AI adoption in B2B marketing (H1)

During our focus group discussion, managers representing different firms, shareholders and investors provided valuable insights into why shareholders typically react positively to AI adoption in B2B marketing. The consensus among participants was that AI adoption in B2B marketing holds the promise of enhanced operational efficiency, increased competitiveness, and improved profitability, a sentiment supported by concrete examples. For instance, participants shared examples of how AI-driven predictive analytics used by companies such as Maersk, P&G, Walmart and DHL can enable businesses to streamline their supply chain operations. By accurately forecasting demand and optimizing inventory levels, companies can reduce carrying costs and avoid stockouts, thereby enhancing operational efficiency. Moreover, from a shareholder and investor perspective, the positive reaction to AI adoption is grounded in its potential to impact the bottom line. They emphasized their expectations of improved market positioning and revenue growth resulting from more effective and targeted marketing strategies powered by AI. For example, participants highlighted how AI can analyse vast datasets to identify precise customer segments for tailored marketing campaigns. This approach not only minimizes wasted advertising spend but also leads to higher conversion rates, aligning with the social actor perspective, where organizations strategically utilize AI to optimize their interactions and performance.

Additionally, participants highlighted how AI's ability to continuously learn and adapt can lead to ongoing improvements in product development and customer experience, fostering brand loyalty and, subsequently, long-term profitability. These all support the belief that AI adoption in B2B marketing has the potential to create tangible business value, strengthen market positions, and drive financial performance in the B2B marketing context, aligning with the perspectives of firms' investors and shareholders.

5.2.2. Do firms in dynamic industries have distinct AI implementation considerations, impacting shareholder reactions (H2)

Participants concurred that industry-specific dynamics and concerns exert a profound influence on the perception of AI integration. For instance, in highly regulated sectors like finance or healthcare, our participants underscored the heightened importance of AI-driven compliance and data security. In these domains, where privacy and regulatory compliance are paramount, AI serves as an indispensable tool for meticulously adhering to stringent guidelines. Financial institutions employ AI to detect fraudulent activities and ensure compliance with ever-evolving financial regulations, while healthcare organizations rely on AI to safeguard patient data and enable precise diagnoses. Conversely, industries characterized by rapid technological advancements, exemplified by agile tech startups, uniformly viewed AI as an imperative for maintaining competitive relevance. These firms operate in ecosystems where innovation is the lifeblood of success. Participants emphasized that AI is not merely an asset but a necessity to swiftly adapt to changing market landscapes. Tech startups leverage AI to gain a competitive edge through product personalization and real-time decision-making. For instance, AI-powered recommendation engines enhance user experiences in e-commerce startups, while fintech startups harness AI-driven predictive analytics to optimize lending decisions.

This perspective inherently aligns with our hypothesis that shareholders of firms subject to more dynamic industry environmental concerns react more positively to AI implementation in B2B marketing. The rationale behind this alignment is that in dynamic industries, the imperatives for AI adoption are often inextricably tied to maintaining competitiveness and capitalizing on rapid market shifts. Consequently, shareholders in such sectors recognize AI as a strategic asset to fortify market positions and drive revenue growth. In contrast, in less dynamic sectors, the considerations around AI are often centered on operational efficiency rather than competitive survival. This illuminates the nuanced relationship between industry dynamism, AI adoption, and shareholder reactions. It suggests that shareholders in dynamic industries exhibit a more positive disposition towards AI implementation in B2B marketing due to its centrality in navigating their industry's unique challenges and opportunities. The insights emphasize the indispensability of tailoring AI strategies to meet the unique needs and challenges posed by different industries.

5.2.3. Why shareholders of firms with complex customer bases react less positively to AI adoption in B2B marketing (H3)

A recurring theme was the formidable task of aggregating and harmonizing vast datasets from diverse customer segments, each with its unique preferences and behaviors. Participants noted that achieving a unified customer view for effective AI-driven targeting and personalization can be arduous when confronted with a complex customer landscape. Additionally, managing the privacy and data security concerns inherent to complex customer profiles emerged as a significant challenge. Participants emphasized the need to ensure compliance with data protection regulations, especially when dealing with sensitive information from varied customer segments.

A main concern was the risk of unintended consequences from AI-driven decisions, particularly in industries with diverse and multifaceted customer groups. For instance, in the pharmaceutical sector, where customers range from healthcare providers to insurers and patients, the implementation of AI in pricing could inadvertently result in inconsistent pricing strategies. Such inconsistencies might not only provoke regulatory actions but also risk alienating key customer segments, potentially damaging the brand's reputation and worrying shareholders about possible long-term financial repercussions. Furthermore, in environments with complex customer interactions, the transparency and interpretability of AI algorithms become important. Stakeholders expressed unease over scenarios where AI models make critical business decisions, such as credit scoring in financial services, without a transparent and understandable rationale. This lack of clarity raises ethical concerns, such as fairness in decision-making, and could lead to regulatory compliance issues. Shareholders are particularly wary of the legal and reputational risks that may arise from these opaque AI practices.

These concerns are magnified in firms where customer complexity is heightened, as they face challenges in aggregating and harmonizing diverse data sets, along with ensuring data security. Thus, while AI holds the promise of streamlining operations and offering tailored customer solutions, its adoption in firms with multifaceted customer structures can lead to negative shareholder perceptions, dominated by fears of regulatory, legal, and reputational challenges. On the other hand, in industries where customer needs are more uniform, and data handling is less convoluted, the adoption of AI might be viewed more favorably, with shareholders anticipating benefits from efficient operations and enhanced customer engagement.

6. Discussion

Nowadays, many studies have investigated the potential benefits generated from AI implementation for B2B marketing, with a few early research empirically examining such impacts (Martínez-López & Casillas, 2013; Farrokhi et al., 2020; Wamba, 2022). Generally, the existing literature on AI in B2B marketing can be categorized into three main streams. The first literature stream associates with a controversial debate regarding how AI can support firms in automating their production and facilitating their existing operations process (Campbell et al., 2020; Saura et al., 2021; Li et al., 2021). AI has been demonstrated to enable organizations to automate various B2B processes, such as better identifying the targets for outward and inward marketing initiatives, simplifying customer relationship management, and creating new consumer experiences via digital devices. For instance, Campbell et al. (2020) develop a theoretical model to explain how AI can improve marketing through intelligent automation across different stages. Our study, building on this literature stream, provides empirical insights into how AI adoption in B2B marketing influences shareholder reactions, thus advancing our understanding of the impacts and practical implications of AI integration in production automation and operations process improvements.

The second stream of literature relates to the implementation of AI for better marketing decision support (Syam & Sharma, 2018; Farrokhi et al., 2020; Bag et al., 2021). For example, Syam and Sharma (2018) investigate how AI technologies can support managers in making better decisions in personal selling and sales management. Bag et al. (2021) offer a conceptual framework to demonstrate the effect of AI-enabled B2B marketing on firm performance through rational decision-making paths. The findings from our study bridge the gap between AI technology and B2B marketing-specific initiatives, aligning with studies like those by Kumar et al. (2019) and Huang and Rust (2021), which explore how AI techniques can enhance various aspects of B2B marketing, including targeting, segmentation, and customer relationship management. Through empirical evidence, our study contributes to a deeper understanding of how AI's impact on these decision-making processes resonates with the perspectives of key stakeholders.

The third stream of literature focuses on the impacts of AI on society and the workplace. Specifically, studies show that AI technologies such as recommendation systems and intelligent agents can offer fantastic experiences and interactive engagements with consumers and employees (Kot & Leszczyński, 2019; Prentice & Nguyen, 2020; Sung et al., 2021). Examples include in-store technologies like augmented reality and intelligent displays, real-time personalized customer interactions, and machine learning techniques for better marketing predictions (Morgan & Rego, 2006; Lee et al., 2013; Davenport et al., 2018). Our study extends this literature stream by providing empirical insights into how AI adoption in B2B marketing influences shareholder reactions, thereby bridging the gap between AI's societal and workplace impacts and its implications for key stakeholders in different B2B context. By examining shareholder perspectives in response to AI-enabled marketing initiatives, our research adds a valuable layer of understanding to the multifaceted effects of AI technology adoption in contemporary business environments.

In summary, the three literature streams examined in this study converge to suggest that the implementation of AI in B2B marketing can yield substantial benefits and potentially lead to competitive advantages. Our study's findings align with a significant portion of prior technology-focused literature, which has consistently identified positive returns on investment (Lam et al., 2019; He et al., 2020; Mikalef et al., 2021). However, it's worth noting that our results diverge from certain technology-focused event studies, some of which have reported negative stock returns on the day of implementation (Lui et al., 2021; He et al., 2020), or insignificant returns following adoption (Im et al., 2001; Dos Santos et al., 1993). These findings hold timely and practical relevance for both managers and industry practitioners, particularly given the recent proliferation of AI applications. Managers typically make IT investment decisions with the goal of maximizing firms' business value. However, estimating the impact of such investments can be challenging, as measurements like productivity and profitability often remain unavailable for several months post-implementation. Moreover, the true financial impact of AI adoption may not be immediately apparent, as financial performance is frequently subject to managerial planning and manipulation.

While our use of event study and focus group discussion methodology may not entirely capture all precise business value of AI implementation, it does provide insights into shareholders' concerns regarding AI adoption in B2B marketing and the associated financial risks. Consequently, our study offers a comprehensive understanding of how shareholders react to AI-enabled B2B marketing initiatives in various business contexts, thereby providing valuable support for investment decision-making in emerging technologies. Based on the findings, this research provides several important theoretical and managerial implications, as discussed in the following parts.

6.1. Implications for research

This research provides several theoretical contributions and enriches the existing B2B marketing, social action theory, IT and Operations Management literature. The social actor perspective offers a complementary and comprehensive theoretical support of the AI-enabled B2B marketing and shareholder reaction relationship. This is aligned with Freeman (1984) stakeholder theory which suggests that firms should consider the interests of a broader group of stakeholders – everyone who can substantially affect, or be affected by, the welfare of a firm. Notably, we theorize that firms' AI implementation for B2B marketing can project two interrelated messages to shareholders: a symbol for a more significant managerial influence and a higher likelihood of achieving long-term competitiveness, eventually resulting in improved shareholder reaction via positive stock returns. This theorization allows us to investigate the symbolic nature of AI implementation for B2B marketing and its social impacts while linking firms' AI implementation practices to stock returns. We deny the 'one-size-fits-all' assumption (Braun & Clarke, 2021; Lui et al., 2021) and investigate the possible effects between AI-enabled B2B marketing practices and firms' industry and operational environments, such as industry dynamism and customer complexity. We theorize how these business situations indicate various degrees of social and environmental expectation/support for AI implementation in B2B marketing, thus moderating the effect of AI-enabled B2B marketing initiatives on shareholder reaction.

The social actor perspective enhances our understanding by examining the direct social impact of AI-enabled B2B marketing initiatives and considering the indirect moderating effect of different external business environments. It is believed that this social actor perspective can be used as an insightful theoretical lens for studying future research in this area (Cunha & Carugati, 2011; Orlikowski, 2010). Particularly, it encourages studies to change their research focus from the examination of AI's business applications and technological characteristics (Martínez-López & Casillas, 2013; Farrokhi et al., 2020; Baabdullah et al., 2021) to more operational and strategic perspectives on AI implementation in B2B marketing, investigating its ability to improve firms' social impacts and gain competitive advantage. Besides, shareholders may reward or penalize firms for their AI-enabled B2B marketing initiatives according to external business environments. While this paper pays particular attention to industry dynamism and customer complexity, more can be conducted to investigate various external environmental factors that may present different degrees of alignment with AI implementation in B2B marketing and therefore influence its social and economic impact.

6.2. Implications for practice

This study offers several practical implications to managers and industry practitioners. As our findings show that shareholders reward firms for their AI-enabled B2B marketing initiatives, companies need to pay particular attention to releasing new AI implementations for B2B marketing, given that they are important for investors and the market value of firms. Although AI adoption has attracted extensive public attention over the past decade, the current proficiency of AI implementation for B2B marketing is still in its infancy. This is partly due to managers' lack of knowledge regarding AI adoption and the difficulties of measuring its business impact (Lui et al., 2021; Huang & Rust, 2021). This research represents one of the first few studies exploring the effect of AI implementation for B2B marketing in terms of shareholder reaction measured by abnormal stock returns. It resolves the controversy over the business value of AI-enabled B2B marketing from a social actor perspective and urges firms to adopt AI for their B2B marketing to harvest the benefits. Our study's significant positive stock returns allow firms to further convince their investors and stakeholders to support their AI adoption for B2B marketing.

While this study suggests shareholders of firms react positively to the announcement of AI-enabled B2B marketing initiatives, it also encourages firms to focus on different external business environments in which the AI is adopted. The findings show that the increased stock returns due to AI-enabled B2B marketing initiatives vary across diverse business environments. Specifically, our study suggests that shareholders react more positively to the announcement of AI-enabled B2B marketing initiatives in more dynamic industries but with less complex customer bases. This is because in dynamic industries with changing consumer needs and market demands, AI-enabled B2B marketing allows firms to receive a competitive advantage from its capability to support firms by anticipating the desires and preferences of clients. It also enables firms to customize their services and products according to the customers' requirements and interests (Paschen et al., 2019; Han et al., 2021). For instance, in the dynamic consumer goods industry, Unilever adopted AI for B2B marketing to reduce the time required for production and better satisfy their ever-changing business consumers' needs (Campaign, 2019). Meanwhile, customer complexity can be seen as the level at which marketing managers react to a wide range of customer demands and personnel involved with different purchasing processes in conducting their businesses (Schmitz & Ganesan, 2014). In less complex customer situations, AI implementation for B2B marketing enables powerful personalization without additional changes to its operations, consequently improving consumers' perceived values and willingness to pay more for the products or services (Chung et al., 2020; Prentice & Nguyen, 2020). These external business environments can lead to the effective implementation of AI for B2B marketing. This is due to the privacy and data security concerns inherent to complex customer profiles, especially when dealing with sensitive information from varied customer segments. In this way, we suggest firms operating in dynamic industries and with less complex customer bases take advantage of their operating environments and harvest more values from their AI-enabled B2B marketing initiatives.

The insights gleaned from our focus group discussion carry substantial practical implications for organizations venturing into AI adoption for B2B marketing. Firstly, recognizing that shareholders are inclined to respond positively to AI initiatives when presented with tangible benefits, businesses should emphasize the potential for enhanced operational efficiency, increased competitiveness, and improved profitability. These outcomes can be showcased through concrete examples, aligning with shareholder expectations. Secondly, industry-specific considerations should inform AI implementation strategies. In highly regulated sectors, a strong emphasis on AI-driven compliance and data security is imperative, while in dynamic industries, AI should be positioned as a strategic asset for maintaining market relevance. Lastly, for firms grappling with complex customer bases, addressing challenges related to data aggregation, harmonization, and data security is paramount. Moreover, enhancing the transparency of AI algorithms can assuage shareholder concerns and mitigate potential risks. Overall, these practical implications underscore the importance of tailoring AI strategies to specific industry contexts and addressing the intricacies of data management and algorithmic transparency to foster positive shareholder reactions.

6.3. Limitations and future directions

This research has several limitations. First of all, the data applied in this study is limited to publicly listed firms in the US, which may reduce the generalizability of the results to SMEs and firms listed in other countries. Thus, it would be interesting to further investigate the role of AI-enabled B2B marketing initiatives in different business contexts and for unlisted SMEs. Secondly, this study examines the impact of AI-enabled B2B marketing initiatives on shareholder reaction measured by abnormal stock returns. While stock returns indicate the overall firm value and capture the full financial effect of the AI adoption (Lui et al., 2021), it is unclear whether AI-enabled B2B marketing initiatives affect stock returns through other measurements such as productivity growth and profitability improvement. As a result, future studies can use different measurements and methodologies to help verify the results drawn in this research. Additionally, a relatively low R-squared value (0.221) in our final regression model may highlight the limited power of AI usage in B2B marketing on stock returns and suggests that it is valuable for advancing understanding of the various factors related to AI-enabled B2B marketing practices impacting stock returns. Future studies could consider a more detailed and multifaceted exploration of AI-enabled B2B marketing practices (e.g., specific types of AI-enabled

B2B marketing practices) by using a primary data approach since the current sample-based announcements may not offer this essential data source. Last but not least, following the social action theory that emphasizes the effectiveness of firms' AI implementation for B2B marketing and external business environments (Habermas, 1984; King et al., 2010), this study considers the characteristics of firms' industry type (i.e., industry dynamism) and operational environments (i.e., customer complexity). Nonetheless, other individual-level factors such as firm size and CEO background can also influence the effectiveness of AI adoption for B2B marketing. Hence, future studies may further investigate the moderating effects of other factors to generate a more comprehensive view regarding its performance implications.

7. Conclusion

While AI applications are becoming ever more important in B2B marketing operations, there is a lack of research to examine whether shareholders are sensitive to firms' AI-enabled B2B marketing initiatives and under what conditions. The purpose of this study is to explore this process by theoretically building on the social actor perspective of the firm and investigating the social impact of AI-enabled B2B marketing initiatives on shareholder reaction. The full sample analytical results prove that firms implementing AI for B2B marketing receive greater stock returns than their industry peers without AI implementation. In addition, the stock return is more remarkable for firms operating in turbulent environments and with less complex customer bases. These results reveal the significance of the fit between AI-enabled B2B marketing values and firms' different business environments. The focus group discussion provided further valuable insights into the factors influencing shareholder reactions to AI adoption in B2B marketing. Specifically, participants uniformly recognized AI's potential to enhance operational efficiency, competitiveness, and profitability, citing examples from industry giants. This positive perception stemmed from AI's ability to optimize supply chain operations, minimize advertising expenditure through precise customer targeting, and foster continuous product improvement. Additionally, industry dynamics played a pivotal role in shaping reactions, with highly regulated sectors emphasizing AI-driven compliance and data security, while dynamic industries viewed AI as vital for competitive survival. Notably, in firms with complex customer bases, challenges centered on data aggregation, harmonization, and data security, impacting shareholder reactions. Concerns included potential unintended consequences of AI decisions and the transparency of AI algorithms. These findings underscored the nuanced relationship between industry context, AI adoption, and shareholder perspectives, emphasizing the need for tailored AI strategies to meet industry-specific demands and challenges.

CRediT authorship contribution statement

Yuanzhu Zhan: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Supervision, Writing – original draft, Writing – review & editing. **Yangchun Xiong:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing. **Runyue Han:** Data curation, Formal analysis, Investigation, Methodology, Software, Writing – original draft. **Hugo K.S. Lam:** Conceptualization, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – original draft. **Blome Constantin:** Conceptualization, Investigation, Project administration, Resources, Supervision, Writing – review & editing.

Declaration of Competing Interest

None.

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