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Applications of artificial intelligence in B2B marketing: Challenges and future directions

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ABSTRACT

With the growing popularity of artificial intelligence (AI) transforming business-to-business (B2B) marketing, there is a growing demand to comprehensively understand the adoption and application of AI to advance B2B marketing. This study examines AI methods and their applications in B2B marketing across the four customer life cycle stages of reach, acquisition, conversion, and retention. The paper also analyzes and synthesizes the findings of five B2B industry surveys conducted to do the following: 1) examine B2B marketers' knowledge and attitudes toward using AI in their businesses, 2) determine the various ways in which AI is used in B2B marketing, and 3) investigate the perceived merits and challenges of using AI in B2B marketing. The findings reconcile various machine learning (ML) techniques suitable for use by B2B marketers. Employing the technology acceptance model (TAM), the paper identifies how B2B marketers perceive the benefits of AI adoption. Furthermore, this study discusses the perceived barriers to AI adoption, including data privacy challenges and the replacement of human workforces. To further highlight the benefits of AI, the study showcases three examples of successful AI adoption in B2B marketing. The paper concludes by summarizing the theoretical and managerial implications of AI adoption in B2B marketing and directions for future studies.

1. Introduction

The digitization of business-to-business (B2B) marketing has resulted in the generation and curation of big data. These centralized databases consist of structured data (e.g., sales data, customer information) and unstructured data (e.g., videos, pictures) that require advanced artificial intelligence (AI) models for analysis. These AI models, generally referred as machine learning (ML) models, are growing in popularity (Ongsulee, 2017; Paschen, Kietzmann, & Kietzmann, 2019; Paschen, Wilson, & Ferreira, 2020; Ribeiro & Reis, 2020; Sterne, 2017). Various factors influence the application and need for AI in business. The most significant factor is that AI is able to process enormous amounts of information and discover novel patterns hidden within the information. These newly discovered patterns can then be used to generate new insights (Cortez & Johnston, 2017), increase efficiencies (Bag, Gupta, Kumar, and Sivarajah (2021), and assist the process of decision-making (Borges, Laurindo, Spínola, Gonçalves, & Mattos, 2021). Examples of the practical AI advantages for B2B companies include targeted advertising (Jabbar, Akhtar, & Dani, 2020), sales force training (Sleep, Dixon, DeCarlo, & Lam, 2020), marketing strategies development (Katsikeas, Leonidou, & Zeriti, 2019), and knowledge creation and management (Bag et al., 2021). Research on segmentation and profiling (Dwivedi et al., 2021; Dwivedi et al., 2021), lead identification and scoring (De Bruyn, Viswanathan, Beh, Brock, & von Wangenheim, 2020), and customer support are other examples of business procedures that can be automated with the help of AI.

While AI is currently being used with numerous business-to-consumer (B2C) interfaces, such as social networking sites, B2B marketing professionals, although lagging behind, are also looking forward to the ways these new generation techniques could help in simplifying processes and generating profits (Kaplan & Haenlein, 2019). Several reasons could prevent B2B companies from applying AI solutions. First, it is more difficult to predict the decisions in B2B markets because of the complexity and human heterogeneity involved in buying decisions (Nyadzayo, Casidy, & Thaichon, 2020), and AI might be considered an unreliable method to manage this level of complexity and subjectivity. However, AI is specifically designed to predict these types of complex systems with many contributing variables; therefore, B2B marketers can benefit even more from AI than B2C marketers. Additionally, since the buying cycle for B2B transactions is typically longer and more

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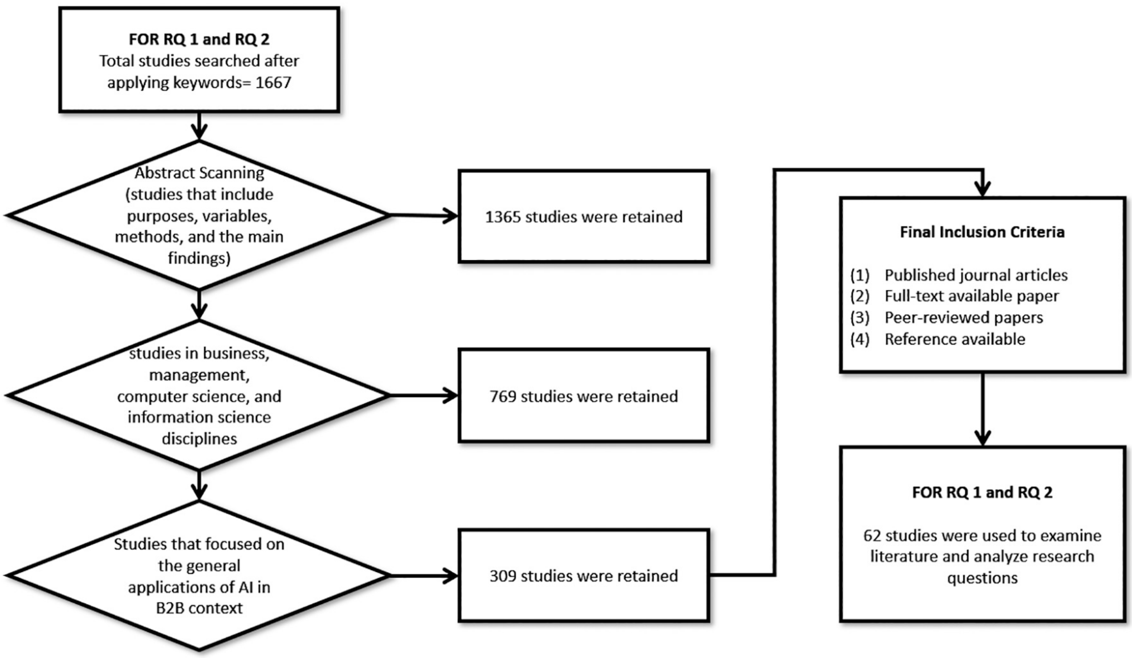

Fig. 1. Flowchart of the methodology.

complicated than that of B2C transactions, it is particularly valuable for B2B marketers to use AI models, which enable them to gain in-depth knowledge of their customers and respond to decision-makers to close sales as quickly and effectively as possible (Marr, 2017). Second, because of the complexity of B2B purchases, B2B companies might assume that human interaction is crucial for managing B2B processes (Aichner & Gruber, 2017). However, humans can be more creative and effective in their activities to the extent that businesses are able to shift more of their workload to machines, namely those tasks that are repetitive or analytical in nature and that computers are superior to humans at performing. While machines can recognize patterns and process data quickly, humans can use their time more efficiently and apply the knowledge obtained from machines to become more effective in managing B2B businesses' complex processes.

Third, B2B companies usually have fewer customers to serve, and this limited network may result in smaller datasets available to B2B marketers for analyzing and applying AI solutions. However, several powerful ways of incorporating AI, such as automation and business process optimization (Pham, 2017), do not necessarily need large datasets. In addition, when B2B companies deal with smaller datasets, they have the advantage of fully monitoring the output of the models and providing comprehensive feedback to the system through reinforcement learning (Salehi & Burgueño, 2018) which ultimately optimizes the performance of the model. Fourth, although B2B purchasers are starting to expect the same on-demand buying experience that is available to B2C customers, it is difficult for B2B companies to trust machines in dealing with their important customers' queries. However, AI has the potential to close this expectation gap (Koskinen, 2021) because AI algorithms are very well developed in providing personalized content (e.g., messages, emails, quotes). Any business that caters to other businesses but does not take a substantial interest in customization solutions, particularly AI, will be found wanting. Fifth, the ability of B2B organizations to benefit from the promises of AI is dependent on their access to essential technology and knowledge resources and the ability to query algorithms (Li, Hou, Yu, Lu, & Yang, 2017). However, the purpose of implementing AI is not limited to analyzing large datasets. As mentioned, an AI application such as automation (i.e., automating repetitive processes) is one way of incorporating AI into a system. These types of models place less emphasis on data analysis and data volume. Moreover, as a result of the progress made in enhancing the efficiency of AI algorithms (Li, Zhao, Li, & Zhang, 2018), B2B enterprises are now able to create a number of AI models using personal computers. Therefore, the absence of access to powerful computers should not prevent B2B organizations from using AI solutions.

Nevertheless, surveys reveal that several B2B companies are not utilizing AI methods. For example, according to the Demandbase 2018 report, less than one-fifth of B2B firms employ AI's machine learning tools in their sales and marketing. In other words, AI's practical implementation has been low compared to the collective and growing interest. Because implementing advanced AI solutions is perceived as costly and resource-consuming, we need to investigate the various applications and benefits of AI solutions (Dwivedi, Hughes, et al., 2021; Dwivedi, Ismagilova, et al., 2021; Han et al., 2021) to assist B2B companies in conducting a cost-benefit analysis of AI return on investment (ROI). This paper uses a literature review approach to assess the scope and use of AI in B2B marketing. First, we conducted a literature review using the Technology Acceptance Model (TAM) framework (Davis, Bagozzi, & Warshaw, 1989) to consolidate the latest information about AI's methods, benefits, drawbacks, and applications for B2B marketing. Second, we analyzed and synthesized the findings of five B2B industry surveys to determine the drivers behind and hindrances to AI adoption by B2B marketers. Finally, we summarized three success stories of AI applications in the B2B industry. In so doing, we sought to answer the following research questions:

RQ 1. What AI methods and techniques have practical applications for B2B marketers?

RQ 2. How do B2B marketers perceive the advantages and challenges of using AI?

The contributions of this paper are threefold. First, it explains the importance of AI in B2B marketing and identifies the available AI methods and techniques that enable B2B marketers to benefit their companies. The TAM framework is used to identify these tools and group them across the four stages of the B2B customer life cycle: reach, acquisition, conversion, and retention. The paper explains the important AI methods and techniques across these life cycle stages. Second, the paper describes how B2B marketers perceive AI advantages, how they consider its potential uses, and whether they are ready to adopt this technology. This is important as these insights highlight the gap between the expectations of AI and the actual use of AI among B2B marketers. Consequently, our findings should motivate B2B marketers to incorporate and deploy AI methods and processes into their business models. In addition to the literature review, we present three success stories to further motivate B2B marketers to use AI in their problem-solving processes. Finally, we classify the benefits, drawbacks, opportunities, and threats of AI adoption among B2B marketers and lay the foundation for a roadmap for future research perspectives.

2. Methodology

While academic attention has been paid to the use of AI, there is still much to explore in order to assist B2B marketers in fully realizing AI's potential. Therefore, we independently formulated the search strategy with an experienced librarian to identify the current use of AI by B2B marketers. The initial search included the following AI-related keywords: Artificial Intelligence, AI, machine learning, ML, propensity model, PM, deep learning, DL, neural network, artificial neural network, ANN, supervised learning, unsupervised learning, semi-supervised learning, reinforcement learning, natural language processing, NLP, and computer vision. In the next step, AI-related keywords and business-related keywords (i.e., firm, organization, customer, business, process (es), manager, management, marketing, marketer, business-to-business, B2B) are used with the boolean operator "AND" to get the intersection set of paper covering AI and business. We favored Scopus—a website monitoring top-level journals in science, social science, and the arts and humanities—over Google Scholar and Web of Science. Initially, Scopus identified 1667 papers. We then independently screened the titles and abstracts of each to ensure they covered the study's purposes, essential variables, methods, and main findings. This allowed us to identify and exclude 302 studies, leaving us with 1365.

Next, we excluded papers that were purely mathematical or programming-oriented. Therefore, studies focusing on the managerial implications of AI in business, management, computer science, and information science were retained, reducing the number to 769. We then retained those studies that referred to the applications of AI specifically in B2B marketing, thereby reducing the sample to a manageable categorization of 309 papers. The studies were further evaluated using the following inclusion criteria. Each study had to: (1) be a published journal article; (2) have its full-text available; (3) be peer-reviewed; and (4) have its reference available. Consequently, the sample was reduced to 62 studies.[1] The methodological process is summarized in Fig. 1.

3. Findings

3.1. The importance of AI in business

The term "artificial intelligence" was coined in 1955 by John McCarthy, professor of mathematics at Dartmouth College, at a time when numerous claims were made about a computer's capabilities to surpass human intelligence (Andresen, 2002). Liebowitz (2001) argued that AI encourages integrating internal and external knowledge of an organization on a larger platform, improving managers' efficacy by supporting them in generating required business outputs fast. AI is now considered a source of knowledge generation in return for information input. AI uses existing data or knowledge to innovate upon the existing models, generate new knowledge platforms, and develop new products, processes, and practices, all of which serve to improve knowledge management systems. This upsurge can be seen in such diverse domains as healthcare, education, agriculture, transport, and aviation, primarily because management is the underlying base for every industry or trade, either profitable or non-profitable (Di Vaio, Palladino, Hassan, & Escobar, 2020; Di Vaio, Palladino, Pezzi, & Kalisz, 2021).

Although AI and big data began to gain prominence in the early 2000s, their real power has become evident to businesses in recent years (White, 2015). The potential of analytical tools in contributing to real business value has been evolving over the years (Jans, Lybaert, & Vanhoof, 2010). Today, data from numerous sources is being fed and processed by algorithms embedded in statistical, econometric, and AI tools (Hiebert, 2003). Vera-Baquero, Colomo-Palacios, and Molloy (2014) recommended that the real-time availability of business performance indicators will be critical to a competitive enterprise's operation and evolution. Dubey et al. (2020) asserted that data could reveal beneficial concealed patterns and relationships contributing to informed decision-making.

Janssen, van der Voort, and Wahyudi (2017) recommended that leveraging the benefits of big data is an evolutionary process involving acquiring a gradual understanding of its potential before embedding it into organizational processes. The current business context requires that managers find and use a data-driven system to reduce outcome uncertainty and significantly enhance growth (Casillas, Martínez-López, & Corchado Rodríguez, 2012; Martínez-López & Casillas, 2009). AI is one such system that provides automated solutions to problems that otherwise require human intelligence (Negnevitsky & Intelligence, 2005). The growth of AI as a system that would make appropriate decisions and frees up human resources for other value-adding activities has elevated the business domain's interest in its applications. Companies attempt to implement AI to make more effective, precise, and timely decisions. The discipline of marketing is also actively pursuing such intelligent systems.

Digitalization and the implementation of new technologies are crucial for developing a sustainable and innovative business model (Del Giudice, Di Vaio, Hassan, & Palladino, 2021). Di Vaio et al. (2020) focused on how AI can play a role in developing sustainable business models. They systematically reviewed 73 studies from 1990 to 2019, the majority of which were conceptual articles presenting the challenges and opportunities for the future uptake of AI from all spheres of life. They concluded that the success of AI exclusively depends on the user's level of knowledge and understanding (Di Vaio et al., 2020). Technology is a double-edged sword that must be controlled lest it lead to devastation. Hence, along with advancing AI technology, researchers must advocate for its wise usage to maintain harmony with humans and the environment (Di Vaio et al., 2020; Di Vaio et al., 2021).

Martínez-López and Casillas (2013) suggested that AI has applications in areas such as segmenting and targeting, managing customers' relationships, marketing channel relationships, organizational buying and supply chain management processes, business intelligence and knowledge management, managing personal selling, B2B communications decisions, B2B pricing strategies, product development, innovation and creativity, services management in business markets, and web intelligence and B2B e-commerce applications. Davenport, Guha, Grewal, and Bressgott (2020) cautioned that AI could have a disruptive impact on marketing and highlighted questions related to AI privacy, bias, and ethics. The modern markets are shaped by volatility, uncertainty, complexity, and ambiguity (VUCA), meaning that B2B professionals need intelligent solutions for establishing the processes of structuring, standardizing, aligning, and customizing data (Fensel et al., 2001; Jabbar et al., 2020). Furthermore, Jabbar et al. (2020) asserted that effectively leveraging AI to one's benefit will prove to be a definitive and invaluable competitive edge that will be visible in subsequent customer behavior.

3.2. TAM framework and the role of AI in B2B markets

Davis et al. (1989) proposed the TAM framework to explain the intention to use technology and new technology adoption. The model considers a technology's perceived utility and ease of use as central to influencing a person's behavioral intention to use it. Indeed, Schepers

[1] List of journals available upon request

Table 1
Summary of extant research on applications of AI in B2B marketing.

No.	Author	Purpose of study	Findings
1	Liebowitz (2001)	Examine the potential of AI in integrating knowledge	The use of AI encourages the integration of internal and external knowledge on a bigger platform, improving the managers' efficacy
2	Fensel et al. (2001)	Examine the need for AI in marketing	To overcome current bottlenecks in B2B e-commerce, we need intelligent solutions for mechanizing the process of structuring, standardizing, aligning, and personalizing data
3	Martínez-López and Casillas (2013)	Identify areas in marketing where AI can be utilized	AI may have an application in about 12 areas of marketing activity, from segmenting to web intelligence and B2B e-commerce applications
4	Sila (2013)	Analyze the factors affecting the adoption of Internet-enabled business-to-business electronic commerce (B2B EC)	The paper found that scalability is the most significant contributor to B2B EC usage. The results also showed that contextual factors influence adoption behavior
5	Järvinen and Taiminen (2016)	Investigate how to integrate content marketing with B2B selling processes.	The paper found that marketing automation can generate high-quality sales leads through behavioral targeting and content personalization. The study also showed how content marketing could be combined with B2B selling processes via marketing automation to achieve business benefits
6	Vera-Baquero, Colomo-Palacios, & Molloy (2016)	Improve decision support systems in organizations	Real-time availability of business performance indicators will be a critical element in operating and help a competitive business evolve with time
7	Gordini and Veglio (2017)	Develop a churn prediction model tailored for B2B e-commerce industry	The study showed that the support vector machine based on the AUC parameter-selection technique (SVMauc) points out good generalization performance when applied to noisy, imbalance and nonlinear marketing data outperforming competitive methods
8	Paschen et al. (2019)	Explain the technological phenomenon of Artificial Intelligence (AI) in the B2B setting	The paper proposed a set of six building blocks of an AI system for an organization. It also discusses how the combination of the building blocks transforms data into information and knowledge
9	Farrokhi et al. (2020)	Examine the role of computer-mediated AI agents in detecting crises related to events in a firm	The paper suggested that knowledge extracted from day-to-day data communications such as email communications of a firm can lead to the sensing of critical events related to business activities
10	Jabbar et al. (2020)	Design a real-time framework to guide future marketing decision-makers	The paper developed interdisciplinary dialogues that overlay computer-engineering frameworks such as Apache Storm and Hadoop within B2B marketing viewpoints and their implications for contemporary marketing practices
11	Liu (2020)	Investigate whether user-generated content (UGC) has differential impacts on stock performance	The paper suggested that UGC significantly impacts firms' stock performance. While consumers' positive sentiment does not play a significant role in stock performance, consumers' negative sentiment and WOM significantly impact stock prices
12	Paschen et al. (2020)	Describe how AI affects the B2B sales funnel	The paper found that combining AI and human intelligence maximizes value throughout the B2B sales funnel. The importance of employing highly skilled sales professionals remains high, yet there is potential for added value in the use of AI throughout all stages of the sales process
13	Zhang, Wang, Cui, and Han (2020)	Investigate the driving forces of a firm's assimilation of big data analytical intelligence (BDAI) and how the assimilation of BDAI improves customer relationship management (CRM) performance	The paper suggested that BDAI enables an organization to develop superior mass-customization capability, positively influencing its CRM performance. In addition, a firm's marketing capability can moderate the impact of BDAI assimilation on its mass-customization capability
14	Bag et al. (2021)	Create an integrated AI framework for knowledge creation and B2B marketing rational decision-making for improving firm performance	The paper suggested that knowledge gained from Big data-powered AI technology (BDAI) applications can keep firms up-to-date in terms of their competitive position. Also, knowledge generated through BDAI can help B2B marketers to be cautious about their brands and eliminate any threats that arise from fake news
15	Grewal et al. (2021)	Classify the benefits and dark side of AI in both B2C and B2B settings	The paper discussed that in B2C settings, AI benefits are primarily via customized experiences, while B2B AI benefits manifest via business efficiencies. The paper

(continued on next page)

Table 1 (*continued*)

No.	Author	Purpose of study	Findings
			also identifies the drivers of the dark side of AI - lack of trust and power asymmetries, with lack of trust being a stronger factor in B2C settings and power asymmetries being a stronger factor in B2B settings
16	Han et al. (2021)	Investigate the approaches that AI can be used for enabling B2B marketing innovation	The study discussed the AI-enabled B2B marketing literature within five domains for innovation: 1) AI-enabled customer relationship management, 2) B2B sales forecasting through AI, 3) the use of AI for value co-creation, 4) AI-enabled operations management, and 5) conceptual frameworks for AI in B2B marketing
17	Mikalef et al. (2021)	Identify how AI can prompt dynamic capabilities, which in turn impact B2B marketing activities	The paper identified a number of AI-specific micro-foundations of dynamic capabilities, essentially highlighting how organizations can use AI to manage B2B marketing operations in dynamic and uncertain environments
18	Rohaan et al. (2021)	Present a method to use advance demand information (ADI), taking the form of a request for quotation (RFQ) data, in B2B sales forecasting	The paper presented step-by-step guidance on incorporating AI in B2B sales forecasting and revealing potential pitfalls along the way. Furthermore, the research indicated that performance improvement could be expected when adopting supervised machine learning into B2B sales forecasting
19	Saura et al. (2021)	Develop a literature review on the application of AI in B2B digital marketing	Using a statistical approach known as Multiple Correspondence Analysis (MCA), the paper classified the types of Customer Relationship Management (CRM) and their typologies and explored the main techniques and uses of AI-based CRMs in B2B digital marketing

and Wetzels (2007) performed a meta-analysis of the use of the TAM as a model for explaining the intent and found the above-mentioned factors had strong roles in influencing users' attitudes toward and intention to adopt new technology. Consistent with the TAM, in B2B markets, businesses must first evaluate to what extent AI is useful and easy to use before embracing it. The TAM framework directly associates AI benefits with the usefulness element of the framework and its challenges with the ease-of-use component. To organize the findings, we adopted the TAM to examine the perceived benefits and challenges of using AI by B2B marketers that impact the actual use of AI systems.

Regarding the AI benefits (i.e., usefulness in TAM), the primary value driver of AI-enabled solutions for B2B firms is that AI enhances efficiency (Grewal, Guha, Satornino, & Schweiger, 2021). There are many examples of how AI can be used in B2B settings to enhance efficiency and how such efficiencies enhance customer relationships. Farrokhi, Shirazi, Hajli, and Tajvidi (2020) illustrated how AI assists businesses by analyzing email communications which highlight scandals and/or critical organizational events, acting as an early-detection measure of crisis. Guha et al. (2021) discuss how retailers use Tally – an AI-enabled, shelf-scanning robot – to make restocking easier. Within the realm of sales, AI increases productivity by either displacing human salespeople with chatbots or enhancing the effectiveness of human salespeople by supplying them with supplementary data and analysis in real-time throughout a sales call (Bharadwaj & Shipley, 2020; Davenport et al., 2020), or by training salespeople directly (Luo, Qin, Fang, & Qu, 2021). Luo, Tong, Fang, and Qu (2019) discovered that chatbots could be more effective than novice workers when using highly organized outbound sales conversations. Similarly, Luo et al. (2021) found that providing a combination of human and AI coaches for sales training can be effective. Specifically, when human managers communicated the findings from AI coaches, salespeople performed more effectively than when either AI coaches or human coaches conducted the training.

In addition to the discussed benefits, Paschen et al. (2019) used an input-throughput-output system, proposed an AI system's building blocks for an organization, and elaborated upon the AI benefit in knowledge creation in B2B marketing. They also highlighted key areas requiring further research, such as the role of AI in capturing customer knowledge, the movement of consumer knowledge in B2B marketing, and how AI can be leveraged to enhance market understanding abilities using external information. Previous research also discussed the effect of AI on business value and firm performance. For example, Mikalef, Kieran Conboy, and Krogstie (2021) highlighted how AI could be used in B2B marketing in an uncertain environment and identified interrelated concepts impacting business value. Similarly, Bag et al. (2021) proposed an integrated AI framework for customer-rated decision-making, linking AI with customers, users, and external market knowledge creation with firm performance in a B2B market. Table 1 summarizes the recent literature on applications of AI in B2B marketing.

It is important to note that, in the B2B setting, not all relationships are of the buyer-seller type; instead, it is feasible for other types of partnerships to exist. For example, a store and an analytics company may have a partnership. In this model, the retailer provides the analytics firm with access to substantial sales and other data and even grants the organization the ability to manage retail store displays; in exchange, the analytics company guarantees to deliver customer insights and overall sales growth (Gooner, Morgan, & Perreault Jr, 2011). Imagine a situation in which an analytics organization firm uses AI to analyze customer behavior and provide customer insights more effectively and efficiently—applying AI in this scenario results in value creation for both the retailer and the analytics company. Since the analytics company can utilize AI technologies to provide richer and deeper customer insights, the retailer receives increased value as a result of providing its data. This could potentially result in the retailer generating relatively higher sales. The analytics firm receives a significantly higher value by utilizing its AI applications to generate increased sales for the analytics company. Therefore, applications of AI have the potential to improve both profitability and relationships with clients. This is true across a wide range of B2B relationships, including buyer-seller relationships.

Regarding AI challenges (i.e., ease of use in TAM), Dwivedi, Hughes, et al. (2021) and Dwivedi, Ismagilova, et al. (2021) propose that organizations encounter challenges unique to AI technology and ask for empirical studies that investigate AI applications in marketing. The issues posed by AI are comparable to those posed by other new and unproven technologies. According to Dwivedi, Hughes, et al. (2021), and Dwivedi, Ismagilova, et al. (2021), "technical requirement" is one such challenge that must be addressed for AI to operate at its full capability (Han et al., 2021). To be more specific, businesses will not be able to maximize the opportunities presented by AI if they do not have a digital infrastructure and have access to the high-quality datasets required for uncovering insights (Dimitrieska, Stankovska, & Efremova, 2018). Another obstacle to overcome is the question of whether or not AI is suitable for specific types of marketing functions. Although it is generally accepted that AI is better suited for jobs that demand repetition than ones that require intuition (Huang & Rust, 2021), many B2B marketing challenges require the latter type of talent (De Bruyn et al., 2020). Therefore, there is a possibility that firms reject the use of AI and want to invest in human resources instead (Longoni, Bonezzi, & Morewedge, 2019).

It is important to note that although it is anticipated that the implementation of AI-based solutions will result in a reduction in operating expenses, even the most basic AI solution may call for a considerable initial expenditure (Canhoto & Clear, 2020). Therefore, companies may have difficulty developing these digital assets internally and may be forced to outsource them, thereby becoming dependent on their service suppliers (Quinn, Dibb, Simkin, Canhoto, & Analogbei, 2016). In addition, Delponte and Tamburrini (2018) asserted that AI awareness among organizational stakeholders is a significant determinant of AI readiness and that organizational stakeholders need to be provided with appropriate knowledge regarding AI for them to be able to use the technology to the advantage of the organization. Therefore, the acceptance of AI techniques by B2B companies primarily depends on the degree to which these companies are knowledgeable about AI applications and have sufficient information regarding the advantages of such new systems. To address this challenge, in the following sections, we discuss the main AI methods and the possible applications of AI in B2B marketing.

3.3. AI methods and techniques in marketing

AI has been defined as "the use of computational machinery to emulate capabilities inherent in humans, such as doing physical or mechanical tasks, thinking, and feeling" (Huang & Rust, 2021, p. 31). In other words, AI is a broad term that describes all algorithms through which a machine mimics human behavior, such as learning and problem-solving. There are two types of AI, namely (1) Narrow or Weak AI - practical applications of AI that we observe and use in data-to-day life and (2) Artificial General Intelligence (AGI) – flexible and adaptable intelligence similar to human intelligence that is currently in a conceptual stage (Yao, Zhou, & Jia, 2018). Machine learning (ML), categorized as Narrow or Weak AI, is the fastest-growing form of AI. Instead of being explicitly programmed, machines may learn to construct models by recognizing patterns in data themselves, which is referred to as machine learning. The term "learning" refers to the training process that these systems go through to function at an optimal rate. The machine learning algorithms find patterns in large amounts of data and then use those patterns to modify the model to produce more accurate outputs each time. In general, there are two types of machine learning algorithms depending on how the "learning" of the patterns in the data takes place. They are (1) propensity models (PM) and (2) deep learning (DL) models.

Propensity models (PM) use traditional statistical methods (Khan, Baharudin, Lee, & Khan, 2010; Kotsiantis, Zaharakis, & Pintelas, 2006; Somvanshi, Chavan, Tambade, & Shinde, 2017) to analyze quantitative data, build predictive models, and identify the likelihood of a user taking a specific action (e.g., making a purchase) or the probability of a person falling into a specific cluster of customers. In general, these predictive models (e.g., classification and clustering models) convert a series of features received as inputs (e.g., customers demographics, reviews, past purchase behavior) to outputs (e.g., customer clusters, sentiments, probability of making a purchase) using statistical estimation processes such as a maximum likelihood and least-squares estimation to learn the data patterns. Such predictive models are also used in natural language processing (NLP) algorithms that enable the computer to understand how sentence components relate to one another (Jurafsky & Martin, 2014). This type of ML helps marketers analyze large amounts of qualitative data (e.g., textual data). For example, Lee and Bradlow (2011) initiated data harnessing by analyzing 8226 online product reviews of products using text mining to generate a market structure analysis. Since then, unstructured data have been analyzed using text mining methods and content analysis to, for example, classify data into positive and negative sentiments. Another example, Liu (2020) who analyzed a large dataset of 84 million tweets from 20.3 million Twitter accounts and eight years of stock data from 407 companies and found that negative sentiment expressed in social media posts has a significant impact on firms' stock performance. B2B marketers can use NLP to understand and cluster their clients' opinions and sentiments by analyzing website data, social media posts, and keywords. They can also evaluate the effectiveness of their branding strategies using NLP tools, such as IBM Watson Natural Language Understanding (Wignell, Chai, Tan, O'Halloran, &

Table 2
Applications of AI techniques in B2B marketing across the customer life cycle.

AI techniques	Customer life cycle applications		
	Reach & acquisition	Conversion	Retention
Supervised Learning (for classification & regression)	▪ *Predictive analytics* ▪ *Lead scoring*	▪ *Dynamic pricing*	▪ *Customer churn prediction*
Examples: Decision Trees Support Vector Machine Random Forests Linear/Logistic Regressions	Input(s)/Output: Use input variables such as time of year, historical sales, historical promotions, and contract sizes to predict sales/leads	Input(s)/Output: Use customer characteristics as input variables to predict the optimal price for each customer	Input(s)/Output: Use customer characteristics as input variables to predict the probability of churn
Unsupervised Learning (for clustering & association)	▪ *Programmatic media buying* ▪ *Ad targeting*	▪ *Web & app personalization* ▪ *Re-targeting*	▪ *CLV prediction*
Examples: K-means Clustering Hierarchical Clustering Apriori Algorithm	Input(s)/Output: Use demographic variables/sales data as input variables to either segment customers and target them or find frequent associations among sold items and target customers with promotions related to the predicted purchases	Input(s)/Output: Use demographic variables, past purchases, and browsing behavior as input variables to segment customers and send them personalized messages	Input(s)/Output: Conduct customer segmentation based on a set of customer characteristics to classify customers into different groups with different CLV levels
Semi-supervised / Reinforcement Learning (for agent-based models)	▪ *AI-generated content* ▪ *Smart content curation* ▪ *Voice search*	▪ *Chatbots*	▪ *Marketing automation*
Examples: Markov Decision Processes Dynamic Programming Deep Reinforcement Learning	Input(s)/Output: Use potential client's online activities, this algorithm can target the potential clients with tailored and customized AI-generated content (texts/images/videos), which can be modified based on the feedback it receives from clients' actions	Input(s)/Output: Use customer's queries as inputs and responds to them accordingly using natural language processing (NLP) and sentiment analysis. Chatbots might also use ANNs to process visual data.	Input(s)/Output: Use demographic variables and online customer activities as input variables and predict the optimal business decision, such as determining the most constructive time for communicating with clients

Lange, 2021). Other PM examples (e.g., classification and clustering models) are reported in Table 2.

Deep learning (DL) is another subfield of ML that uses artificial neural networks (ANN) as the backbone of the "learning" process (Ongsulee, 2017). ANNs are modeled after the human brain and use a network of interconnected neurons, or nodes, to analyze data (Arel, Rose, & Karnowski, 2010). ANNs are hierarchical systems used to process large amounts of data in a non-linear way, having data pass through layers of interconnected nodes, which is called deep learning (Ongsulee, 2017). Computer vision is a popular field in deep learning, where the computer can examine images and videos (i.e., visual data) through mathematical representations of three-dimensional shapes and appearances. Furthermore, the computer is able to understand the embedded subject matter in the visual data. Although the practical application of this technique is still under development, B2B marketers can use this method to analyze their websites and social media images to understand what specific objects or content results in higher views or social media engagement. They can thus design their online platforms accordingly. They can also run the same analyses on their advertising videos to identify the most attractive type of video content. In addition, Google has developed a new DL algorithm called Bidirectional Encoder Representations from Transformers (BERT) that is used for NLP and now works as the underlying process of the Google Search Engine (Devlin, Chang, Lee, & Toutanova, 2018). Therefore, new applications of DL also help with profound text and audio analysis (i.e., beyond sentiment analysis). Some of these new DL methods (e.g., text analysis) overlap with the PM techniques but provide a deeper analysis of the user's intent, words, and sentences. Chatbots, converting speech to text, correcting grammar, and the ability to identify meaning within texts are all examples of DL applications (Balducci & Marinova, 2018; Kieser, Baylis, & Luyens, 2021).

In all AI models (e.g., ML models), computer programs learn and improve by using datasets, usually referred to as training datasets. Once the computer has learned to produce the correct output using specific datasets or variables, a testing dataset is provided to test its ability. This is how computer programs are trained, tested, and improved several times before they are trusted to analyze large amounts of data. There are four different ways through which an AI model learns:

a. *Supervised learning*: The most common and widely used form of learning, wherein an algorithm is generated using a set of training datasets to predict the correct output. The training dataset consists of two data values: input variables and the output variable (the latter of which is predicted by the former). After analyzing the training data, the system produces a predictive function. A testing dataset (consisting of only input variables) is given to the algorithm to predict the output. It can then modify this predictive function by comparing the output to the correct result (Khan et al., 2010; Kotsiantis et al., 2006; Somvanshi et al., 2017). This type of learning solves problems of classification (i.e., predicting a discrete output) and regression (i.e., predicting a continuous output). Other examples of methods that follow this type of learning are decision trees, support vector machines, random forests, and linear and logistic regressions (Haldorai, Ramu, & Khan, 2020).

Supervised learning can be used in the B2B context for sales forecasting (Rohaan, Topan, & Groothuis-Oudshoorn, 2021). Specifically, B2B marketers can use input variables such as time of year, historical sales, historical promotions, and past contract sizes with their customers to predict sales. Additionally, this method can help B2B marketers prioritize sales leads, develop dynamic pricing strategies, and discover cross-selling opportunities. It also has applications in other fields, such as medicine, where it can be used to develop algorithms for assigning the cause of death by giving information on various signs and symptoms of illness as input variables.

b. *Unsupervised learning*: This algorithm trains an AI system by giving it a set of unlabeled training data. The system learns and analyzes the training data for trends, structures, and relationships between variables, then creates a function to predict the output from the inputs. This type of learning can solve problems of clustering (i.e., grouping a set of objects) and association (i.e., finding associations among items within large commercial databases). Examples of methods that follow this type of learning are K-means clustering, hierarchical clustering, and the apriori algorithm (Haldorai et al., 2020). This type of learning is beneficial for B2B companies in conducting customer segmentation based on a broad set of factors as inputs (e.g., industry, company size, location, revenue). B2B customers need personalized and tailored services. This granular level of customization requires hyper-segmentation that can be implemented by unsupervised learning algorithms (i.e., grouping and slicing every piece of large customer data).

c. *Semi-supervised learning*: This technique employs a mix of supervised and unsupervised learning. To develop this algorithm, a small set of labeled data (e.g., customers who have previously purchased product A) is provided with a large set of unlabeled data (e.g., new customers who have yet to purchase product A). This algorithm finds a pattern in the labeled data and, using this pattern, predicts the behavior of the unlabeled data. This method is both time- and cost-effective in that no separate dataset must be provided to predict output precisely. B2B companies can use this method for both prediction and hyper-segmentation. As this method capitalizes upon all the available information in the data, it can be highly accurate when using only half of the training data (Al-Azzam & Shatnawi, 2021).

d. *Reinforcement learning*: This algorithm generates reinforcement signals as a reward for an AI system for producing the desired output in the absence of a training dataset. The operating system identifies which outputs are optimal for its performance and thus learns from its own experiences rather than from any training dataset inputs. This type of learning can be used to develop agent-based models. In these models, agents determine the behavior (e.g., sending an automated message to a customer). Then, the agent receives a reward as a reinforcement signal that encodes the success of an action. The goal of the agent is to take actions that maximize rewards. Examples of methods that follow this type of learning are Markov decision processes, dynamic programming, and deep reinforcement learning (Salehi & Burgueño, 2018). B2B marketers can use this method to develop website recommendation systems to target their customers with the most relevant solutions (Tang, Chen, Li, Liu, & Ying, 2019). After recommending products to customers, the system will monitor customers' reactions. These reactions will be used as feedback to modify the recommendations. The reinforcement process enhances the accuracy of these systems over time.

3.4. Applications of AI in B2B marketing

AI techniques can be used in B2B marketing for different purposes, such as customer attraction and retention. These purposes can be organized around B2B customer life cycles: customer reach, acquisition, conversion, and retention (Chaffey & Patron, 2012). A summary of the applications of AI techniques in B2B marketing is presented in Table 2. To discuss the use of AI within B2B marketing, we can relate the findings to these life cycle stages.

3.4.1. Customer reach and acquisition

For the first two stages (i.e., reach and acquisition), AI's main applications are as follows.

AI-generated content: AI writing programs (Miroshnichenko, 2018) are expected to grow in popularity in the coming years. In this application, AI content writing programs use a dataset to pick essential product or service elements and compose a human-sounding article. These are useful for reporting regular data-focused events, such as sports, stock market data, and company quarterly reports. This feature can help B2B marketers promote their brands on social media platforms and reduce human effort. They can also use this type of ML, which is reinforcement learning, to target their potential clients with tailored and personalized AI-generated messages. This algorithm can generate texts, images, and videos (e.g., through PM and DL techniques) relevant to potential clients by analyzing online clients' activities. The system will modify itself based on the feedback it receives from clients' actions (e.g., whether they like the message or take certain actions after receiving the message).

Smart content curation: This technique is highly effective for brand promotion based on users' activities and enables marketers to track customers who bought products of a specific category (e.g., auto accessories) on individual websites. B2B companies can tap these potential customers by providing them with exclusive discounts and offers and by approaching them with personalized content (Amatriain & Basilico, 2015). Using AI, it is possible to assess each piece of content (i.e., textual and visual data) on a B2B company's website. The users that visited their websites and the data collected about them may be evaluated to tailor the content that should be delivered to those users. In addition, B2B companies will be able to give prospective customers relevant content at the proper time and based on where they are in the buying cycle. In general, social listening techniques enable B2B marketers to monitor their real-time reputation, initiate dialogues with customers, and even customize the creation of leads by analyzing keywords and mentions across numerous social networks.

Voice search: This technology allows people to perform searches by speaking. The most popular examples include Alexa, Google, and Siri. However, its use has not been widely adopted by B2B marketers (Jurafsky & Martin, 2014; Kaplan & Haenlein, 2020). Statista predicts that by 2024, 8.4 billion voice assistants will be used worldwide (Tankovska, 2020). Therefore, B2B marketers should start improving their search engine optimization (SEO) strategies to ensure that their B2B content ranks high in voice search results.

Programmatic media buying: This uses ML-generated propensity models to effectively target advertisements to the most relevant customers. This method can help B2B marketers automatically segment customers (e.g., based on demographics) and target the most valuable groups instead of negotiating with customers directly (Samuel, White, Thomas, & Jones, 2021). This process can reduce organizational costs and enhance brand performance.

Predictive analytics: This propensity modeling application predicts the likelihood of a customer being converted into a value-added client, estimates at what price a customer is likely to convert, and helps determine which customers are most likely to make repeat purchases. This application can be used by both B2C organizations and B2B marketers (Hair, 2007; Nyce & Cpcu, 2007).

Lead scoring: This is another application of propensity modeling that generates score leads to help the sales team determine the heat of a given lead from its score and, thus, whether or not they should devote their time to it. For example, a propensity model can form lead scores from the time customers spend exploring websites or products (Järvinen & Taiminen, 2016). The normal process of finding new leads for B2B organizations might take hundreds of hours to complete. Not only can machines aid with the initial gathering of information for lead generation, but AI can also quickly scan unstructured data such as emails, phone conversations, and social posts to establish trends and define a good prospect (Marr, 2017). This information is necessary for running successful advertising campaigns. This is particularly important for B2B businesses with consultative sales processes, for which each sale consumes a considerable amount of time.

Ad targeting: ML algorithms can use customer data to examine product buying trends over different periods. Accordingly, the creative content can be shared at a particular time with customers. Examples of this include video ads (i.e., targeting customers at their most relevant time and place) and real-time bidding (i.e., showing a particular advertisement to a specific user based on their past browsing behavior) (Choi & Lim, 2020). This technique can also be used to predict the subsequent purchase of a customer by analyzing sales data and finding frequent associations among items in previous transactions. As a result, the customer can be targeted with advertising and promotions related to the predicted purchase.

3.4.2. Customer conversion

The next stage of the B2B customer life cycle is customer conversion, i.e., targeting lethargic customers to convert them to value-added customers. The following AI applications can be used to further this goal.

Dynamic pricing: Dynamic pricing helps sellers adjust the prices of products/services at the individual customer level by using customer characteristics (Ban & Keskin, 2021). This type of ML allows B2B marketers to build predictive models to estimate the most likely price at which a lethargic client can be converted into a value-added one, thereby promoting sales (Kaminsky & Fiore, 2001). More importantly, if a B2B company's pricing strategy cannot adjust to evolving market conditions, the question of whether or not the company will be disrupted has been replaced by the question of when it will be disrupted. There are still many B2B organizations that rely on old technology or analog solutions, but investing in modern digital pricing solutions can often yield a rapid return on investment. For instance, frontline sales teams may still be quoting customers using spreadsheets that have little to no connection to the ever-shifting underlying price drivers. B2B firms require a quoting tool that can adjust prices across numerous customer categories, value propositions, and multiple sites. To develop the capabilities necessary for dynamic pricing, B2B firms will need to invest in modernizing their data, tools, processes, and governance.

Web & app personalization: It should come as no surprise that today's B2B buyers have become accustomed to having a more individualized shopping experience. AI-powered technology can assist B2B organizations in meeting this expectation. Using a propensity model to predict a customer's stage in the buyer's journey enables firms to serve that customer, either on an app or a web page, with the most relevant content. This keeps the customer engaged and updated about the product and allows them to be subsequently converted into a potential buyer (Chaffey & Ellis-Chadwick, 2019).

Chatbots: Chatbots mimic human intelligence by interpreting consumers' queries and completing orders for them. A recent example of a chatbot in B2B marketing is PayPal, where the software understands the customer's queries and responds to them accordingly. This highly effective communication method allows for cost-effective 24/7 customer support. Hence, a cost-benefit model of B2B marketing can be developed (Arsenijevic & Jovic, 2019). Chatbots can, in most cases, quickly direct customers to the resources they need and answer a significant number of customer questions. If they cannot do so, the question is forwarded to the marketing team for more examination. After investigating the issues, the team will enhance the chatbot through the reinforcement learning process (i.e., giving feedback) so that chatbot will handle similar inquiries in the following interactions with customers. A chatbot can also process visual data (e.g., customer IDs) with the help of deep learning models. Therefore, companies need to incorporate both PM and DL techniques into developing these bots.

Re-targeting: This technique functions similarly to advertisement targeting in that it encourages customers to return to the site based on historical data. Re-targeting is the process of converting a potential buyer into an actual customer after initial interactions with a firm's website. This method helps B2B marketers estimate the future conversion rate of potential customers (Lee, Jung, Lee, Kim, & Park, 2021) and focus their efforts onadding new customers without labeling them as laggers.

3.4.3. Customer retention

This final stage of the customer life cycle minimizes the churn rate (Gordini & Veglio, 2017). This is another area where AI has already been applied in marketing.

Customer churn prediction: Initial attempts at predicting the B2B marketing churn rate were made in the early 1990s through statistical techniques such as logistic regression. However, little progress was made due to the lack of large datasets and the limited number of variables to be modeled for churn. The churn phenomenon is widespread in e-commerce due to high market competition, which leads to a

Table 3
Matrix showing characteristics of five surveys conducted among B2B marketers.

	Everstring and Heinz (2019)	MIT Technology Review (2018)	BrightEdge (2018)	Demandbase (2018)	Salesforce (2017)
Sample Size (n)	300	600	500	111	3500
% B2B marketers currently using AI	37	90	4	18	51
% B2B marketers having no knowledge of AI	32	NA	60	40	76
Expectations of AI					
(% of respondents who expected each factor to be an application of AI)					
Customer identification	59	74	32	52	72
Improving revenue generation	53	70	8	NA	NA
Identify account opportunity	41	NA	NA	64	NA
Identify macro market opportunity	40	NA	14	67	NA
provide campaign analysis	31	NA	NA	54	NA
Make marketing tasks easier	37	NA	28	NA	NA
Most useful applications					
(% of respondents who mentioned each factor as their current usage of AI)					
Data processing	55	NA	NA	NA	60
Personalization	71	74	29	56	65
Customization	58	NA	NA	NA	67
Pricing	21	NA	NA	NA	60
Identifying trends	63	NA	NA	NA	59
Confidence in using AI					
(% of respondents who were confident using AI)					
Not at all confident	7	NA	58	NA	NA
Roadblocks in using AI					
(% of respondents who perceive each factor as a roadblock in using AI)					
Cost	NA	NA	60	55	70
Data quality/analysis issues	77	NA	58	52	52
Customer privacy concerns	NA	NA	NA	58	31

NA: That item was not measured in the study.

considerable loss of customers (Gordini & Veglio, 2017). High churn rates can pose a significant threat to a company. Accordingly, companies have consistently striven to reduce the churn rate and promote customer retention. To achieve this, industrialists and marketers approach data analysts to predict churn propensity predictions and identify the causes for this phenomenon. In an attempt to develop an optimized churn prediction model, Gordini and Veglio (2017) analyzed 80,000 transactional records of business customers. They developed a new ML model (i.e., a support vector machine model) to predict the churn rate and identify the most critical factors leading to this phenomenon. Their model was able to identify 85% of churners correctly, thus outperforming logistic regression, ANNs, and conventional ML models. This was regarded as a breakthrough in B2B marketing since it addressed the churn issue (Gordini & Veglio, 2017) and helped marketers to do the following: 1) identify the number of churners correctly out of the total number of customers, 2) develop personalized strategies to retain potential churners by acquiring information about the factors leading to churn, and 3) save cost and time.

In summary, retaining customers is more challenging than attracting them. Customer retention is particularly important in subscription-based businesses, where a high churn rate can be too expensive. Predictive analytics (e.g., decision tree algorithms) has been used to determine which customers are most likely to unsubscribe by assessing which combinations of features are most prevalent in un-subscribers (Xie, Li, Ngai, & Ying, 2009). In addition, B2B marketers can conduct customer segmentation based on a set of customer characteristics to classify customers into separate groups with different levels of customer lifetime value (CLV) and target each group with an appropriate strategy.

Marketing automation: Through NLP algorithms, ML can help identify solutions to specific business problems, such as determining the most constructive time for communicating with previous clients or the most effective language for retaining customers. Marketing automation plays a strategic role in B2B firms because it increases efficiency, process optimization, and revenue (Pham, 2017). With the assistance of ML, repetitive tasks, such as entering data, recording a task, or sending a series of emails, can be completely removed. Machines can recognize patterns and develop methods for performing tasks efficiently, which can eliminate the need for humans to work on the task. Machine learning systems can process data, perform repetitive activities automatically, and inform humans if a specific task requires their intervention, allowing humans to focus on the core tasks of their jobs.

4. Industry surveys

Researchers have conducted surveys to assess B2B marketers' awareness of AI development, their perceptions of AI's utility for promoting their business or processes, their level of comfort with adopting this new technology, and their level of preparation for doing so in terms of resources such as manpower, cost, and infrastructure (Sila, 2013). Since the results of single siuveys are insufficient for reliable interpretation or for forming conclusions about the behavior of B2B marketers in general, we decided to examine multiple surveys to obtain a pooled percentage of the various indicators used to assess the knowledge, attitudes, and practical implications (KAP) of AI in B2B marketing. In the previous sections, we have provided insights into AI's potential applications, but examining B2B marketers' preparation levels would indicate the difference between the presence of this technology and its real-life use.

Therefore, we conducted an additional study to further explore how B2B marketers perceive the advantages and challenges of using AI. We analyzed five surveys with large sample sizes conducted between 2017 and 2019 to assess B2B marketers' knowledge, attitudes, expectations, and concerns about using AI (BrightEdge, 2018; Demandbase, 2018; Everstring and Heinz, 2019; MIT Technology Review, 2018; Salesforce, 2017). Everstring and Heinz (2019) randomly collected responses from 300 B2B marketing and sales professionals within a variety of organizations (i.e., small, medium, and large-sized) and industries. The survey explored the maximum number of factors about B2B marketers' KAP in all of the studied surveys. Salesforce (2017) collected 3500 responses from full-time marketing leaders across a variety of industries and organization sizes in nine countries. It covered the crucial aspects of benefits, drawbacks, opportunities, and challenges of using AI by B2B marketers. Demandbase (2018) collected data from 111 B2B marketing and sales professionals in organizations with annual revenues of $25 million or more. BrightEdge (2018) surveyed 500 digital marketers at different Fortune 500 brands. Finally, MIT Technology Review (2018) conducted a global survey of 600 executives in different industries and organization sizes across 18 countries. The combined sample size of all five surveys was 5011. We pooled the summary measures of knowledge, perceptions, fear, and AI acceptance (McKenzie, Salanti, Lewis, & Altman, 2013) across all the surveys. A significant advantage of this method is that it provided pooled percentages for indicators that would otherwise have had more comprehensive ranges in the individual studies. Furthermore, it rendered the information more meaningful and the results more robust for policy-level decision-making. As all the variables were in percentages or absolute numbers, we calculated the summary prevalence or percentage for marketers using AI in their businesses. Specifically, we calculated the following percentages: 1) marketers with no knowledge of AI, 2) the most prevalent use of AI as perceived by marketers, and 3) the most critical obstacles faced by firms in using AI.

We evaluated heterogeneity in the studies using Cochran's Q test, and we used I2 statistics to assess the degree of inter-study variation. We considered I2 values of 0–24.9%, 25–49.9%, 50–74.9%, and 75–100% as having no, mild, moderate, and significant thresholds, respectively, for statistical heterogeneity. Table 3 displays data from all five surveys. The variables are listed in Table 3 if they were measured by at least two of the studies.

4.1. Percentage of B2B marketers using AI

The percentage of B2B marketers using AI at the time of surveys varied between 4 and 90%. The consolidated percentage revealed that 37% (8–71%) of B2B marketers were already using AI in their business. The heterogeneity (I^2) was 100%, as the studies were conducted in various parts of the world with various methodologies. Furthermore, their sample characteristics were entirely different. For instance, the MIT Technology Review covered the majority of the B2B employees from North America (25%).

4.2. Prevalence of knowledge about AI among B2B marketers

The prevalence of no knowledge was found to be 37% (0–83%) with $I^2 = 100$, $p < 0.05$. The broad confidence interval (CI) of prevalence indicates enormous heterogeneity among studies. However, the significant fact is that the percentage of B2B marketers with no knowledge of applying AI in their business did not change considerably from 2017 to 2019. Therefore, awareness should be increased among B2B marketers regarding AI applications and their advantages.

4.3. Perceived AI applications and obstacles

The consolidated results reveal that 58% (42–74%) of B2B marketers reported that customer identification was their most common expectation of AI. Furthermore, 59% (44–74%) recognized personalization as the most useful application of AI in current use in their business. Results also reveal that 60% (49–71%) of B2B marketers cited the absence of quality data or data analysis as the major roadblock to using AI in their organization. This was followed by cost and customer privacy concerns. We have seen that almost 68% of B2B marketers were aware that AI could promote their business or simplify their processes. However, across all surveys, only 37% reported having already adopted AI. This limited real-world usage confirms that B2B marketers have some understanding of AI. However, this knowledge is very limited, so it does not convince B2B marketers to accept the costs of AI adoption.

While marketers did understand AI's use for growing their sales to a certain extent, some factors discouraged them from using AI. These included low data quality, the absence of a trained workforce to guide the data analyses, the high perceived cost of AI technology, and the perceived fear that AI could lead to privacy breaches. According to the TAM framework, perceived utility and ease of use are two critical dimensions ensuring technology adoption. The obstacles listed above refer to the perceived difficulty of use. Although B2B practitioners were aware of some AI advantages, their perceived difficulty of use was cited as the main roadblock to accepting and adopting AI. It is thus imperative at this stage to address the challenges mentioned above by 1) creating greater awareness about the existing privacy policies for managing big data and taking careful steps to prevent breaches, 2) employing technically proficient staff to store quality data and analyze it precisely, and 3) conducting cost-benefit analyses of AI adoption for B2B marketers.

5. Success stories of AI adoption by B2B marketers

The previous section revealed an urgent need for confidence-building in terms of the benefits of AI and accelerating the hiring and-training of a workforce capable of using it. This would increase the acceptance and implementation of AI in different activities across the customer life cycle. To emphasize the practical implications of AI adoption in B2B markets, in this section, we discuss three success stories in which B2B marketers have successfully used AI. Success stories of AI use must be widely propagated to encourage AI adoption.

5.1. Blast optimization by Orica

Introduction: Orica Limited is an Australia-based multinational and one of the world's largest commercial suppliers of explosives and blasting systems to the mining, oil, gas, and construction markets. It supplies sodium cyanide for gold extraction and is a specialist provider of ground support services in mining and tunneling. Orica has a workforce of approximately 11,500 employees across over 100 countries. Its explosives are used in 1500 blasts per day.

Data and Model: Before 2018, the company kept customer data on hard drives and electronic sources. In 2018, Orica digitalized its data to capture a high level of customer detail, including their reasons for purchasing blast material, the objectives and sites of the blasts, the equipment used, and the exact techniques and products employed (Orica launches next-gen BlastIQ, 2018). The data were used for propensity modeling to build pre- and post-blast measurements, packaged in a user-friendly, publicly available software called Blast IQ. When a customer enters a query about the blast material, such as the blast site, geological data, equipment data, and the desired outcome, the software runs propensity models to simulate desirable blast outcomes. This helps engineers fine-tune a high-resolution blast to produce more predictably sized rock and dirt for loading, hauling, and grinding, as well as the best blast material and quantity.

Takeaways: The precise estimation of rock size allows the company to choose the most appropriate machinery, reducing manual labor and costs. Blast IQ improves Orica's customers' cost-cutting, time management, and perfect expertise. It also boosts customer trust and dependability, addressing all the elements of a B2B marketer's valuable service (i.e., both usefulness and ease-of-use components of TAM). This software revolutionized mining and popularized Orica, which was featured in Mining magazine (Orica launches next-gen BlastIQ, 2018). This software ultimately helped Orica 1) improve personalization by identifying and attracting new customers and 2) reduce churn rates by increasing customer trust.

5.2. Invasion in agriculture: Monsanto

Introduction: Monsanto was an American-based agrochemical and agricultural biotechnology corporation that grew steadily and enhanced its chemical business by using big data to invade the agriculture industry. Monsanto's position as a leader in agricultural biotechnology and its success in contractually binding farmers to its genetically engineered seeds result from its concerted effort to control patents on genetic engineering technology, seed germplasm, and a farmer's use of its engineered seed.

Data and Model: In 2013, Monsanto acquired The Climate Corporation, which predicted and forecasted weather conditions based on 30 years of data. The goal was to provide farmers with more information about factors affecting crop performance. As agriculture was the company's economic backbone, it used soil sensors to strengthen its database and provided weather predictions to farmers. ML predictive models were implemented. Every new piece of data, such as rainfall or average heat index, helps the system gain knowledge and make more accurate predictions.

Takeaway: The acquisition combined Monsanto's R&D with The Climate Corporation's agriculture analytics and risk management. This helped Monsanto gain customers' (especially governments') trust and build successful mobile applications (Lianos and Katalevsky, 2017). Their AI solution improved TAM's usefulness and usability elements. The corporation invested in a new venture, Monsanto Growth Ventures (MGV), using data mining and predictive modeling to improve crop yields further. In sum, Monsanto began in the chemical industry and expanded into agriculture using big data management and ML for predictive analysis.

5.3. Propane industry: Mosaic analytics

Introduction: A propane industry leader, a client of Mosaic Analytics, experienced a significant increase in customer churn. Seeking to minimize additional client loss to cut costs, they investigated why consumers were canceling their accounts. They went to Mosaic, a reliable business partner that had previously assisted them in locating locations in which ML techniques would allow them to successfully target new clients. Mosaic was charged with establishing the value of employing machine learning to combat customer attrition based on our earlier work on this customer segmentation project.

Data and Model: Mosaic analyzed historical data and actual cases of consumers who had already decided to leave to gain insight into customer turnover characteristics and behaviors. Mosaic created a feature table to demonstrate customer actions by month. The team includes features in the customer's account history before they cancel their subscription. Instead of absolute numbers, features are on a relative scale to normalize client paths. Mosaic's data science consultants calibrated a churn model using three methods (i.e., Decision Tree, Random Forest, and Logistic Regression). After validation, the logit model was chosen because it predicted customer attrition with 80% precision and accuracy. Instead of using only a few churn predictors, the team leveraged all variables associated with customers' accounts.

Takeaway: The model identified new churn drivers, such as the client's delivery method, level of spending, usage increases/decreases, and tank size. This helps the marketing team create more effective campaigns and boost customer retention (i.e., both usefulness and ease-of-use components of TAM). Data-driven companies, such as propane companies, segment their customers for value-added analyses. Now, companies can use churn rankings to inform marketing and intervention strategies. These insights can be shared with field operations leaders to create a data-driven strategy. The churn score can also be added to customer service platforms. Thus, Mosaic's customer segmentation and churn modeling efforts have produced a reliable customer lifetime value indicator. It is important to note that customer churn models should be updated periodically to maintain and improve their accuracy.

All these examples of advanced analytics are in the developmental phase, and their validity should be further established by promoting their applications. These success stories provide examples of AI applications in B2B marketing. Although the use and development of AI methods are still in their infancy (as reflected in these stories), AI has clearly demonstrated that it is able to lead to promising growth if used with clear objectives.

6. Discussion

We have used a comprehensive review approach to examine AI techniques, their applications in B2B marketing, how B2B marketers currently use AI, and their perspectives on AI's benefits and challenges. The literature discusses specific AI applications in B2B marketing (Bag et al., 2021; Di Vaio et al., 2020; Dubey et al., 2020; Farrokhi et al., 2020; Jabbar et al., 2020; Mikalef et al., 2021; Paschen et al., 2019). As recommended by various researchers (Khan et al., 2010; Kotsiantis et al., 2006; Somvanshi et al., 2017), ML (PM and DL) algorithms are broad tools that B2B marketers can utilize. These techniques enable marketers to assess the current business situation, observe trends and precedents, and make predictions. This assessment using AI will in turn assist B2B companies with reaching, acquiring, converting, and retaining customers. For example, AI-generated content (Miroshnichenko, 2018) and smart content curation (Amatriain & Basilico, 2015) can change how content is created to reach and acquire customers. Predictive analytics, lead scoring, and ad targeting effectively prompt customers to purchase products. Dynamic pricing, web and app personalization, chatbots, and retargeting engage and convert customers, and marketing automation can be used for B2B customer retention.

The analysis of the five surveys provided a reality check of the situation. 37% of B2B marketers use AI, and the same percentage are unaware of AI's applications in B2B marketing. The survey analysis revealed that marketers expected AI to help with customer identification and personalization. The most cited challenges in AI adoption were the absence of quality data and qualified data scientists for analyses; AI costs and customer privacy issues were the next significant hurdles for B2B marketers. Hence, AI's benefits, applications, and ease of use must be widely communicated to raise awareness and convince more professionals to adopt AI.

Regarding the cost of AI implementation, one of the main perceived challenges, B2B companies have the option of investing in their own data scientists or outsourcing, and must consider the benefits of AI in the long term. Although the initial cost is perceived to be high, the benefits after AI implementation outweigh the costs. Two points should be considered regarding the other main challenge (i.e., data quality/analysis). First, B2B companies can implement supervised or semi-supervised AI solutions despite poor data quality/size. They can check the model's outputs, provide quality feedback, and help the model improve over time. B2B companies can also collect better data once they decide what type of AI solution to use and what inputs (variables) they need. Second, AI is not just for analyzing large datasets. As discussed in the AI applications section, automation is another form of using AI that focuses less on data analysis or data size. Finally, as a result of recent ML algorithm efficiency advances, B2B companies are now able to build many of the suggested models on personal computers. Therefore, lack of access to powerful computers should not stop B2B companies from implementing AI solutions.

In terms of the success stories, the Orica case illustrates how personalization can attract new customers and reduce churn by building trust. Monsanto used predictive analytics, data mining, and propensity models to expand from its original chemical business into a fully-fledged agriculture company. Mosaic reduced churn by testing three methods (Decision Tree, Random Forest, and Logistic Regression) and recommending Logistic Regression for its consistency in predicting almost 80% of potentially churning customers. This breakthrough application reduced both churn and overall costs. In conjunction, the existing review, the surveys, and the success stories advance a powerful argument for enhancing AI applications in B2B marketing. With increasing efforts to use various AI tools, B2B marketing is set to witness an evolution and potential paradigm shift into AI-infused marketing.

6.1. Theoretical implications

This paper makes four theoretical contributions. First, it extends the literature by including AI applications in the B2B context. We have presented a comprehensive review of the current literature to provide an understanding of how AI can be used in B2B firms across the four customer life cycle stages of reach, acquisition, conversion, and retention (Chaffey & Patron, 2012). Second, this paper further expands the literature by exploring B2B marketers' knowledge and attitudes toward AI, laying the foundations for future B2B research. Third, we extend AI research by relating its applications to the B2B context. Indeed, our research suggests that this is the first paper to discuss AI specifically in the B2B domain and life cycle. Finally, we have built upon the TAM framework (Davis et al., 1989) by discussing how it can explain the role of AI in B2B marketing. Specifically, this study explains how marketers' evaluation of AI benefits (i.e., perceived usefulness) and challenges/costs/roadblocks (i.e., perceived ease of use) affect their decisions to adopt AI.

6.2. Managerial implications

This paper provides an outline for B2B managers on what AI applications they would benefit from adopting. Furthermore, the analysis indicates that a low percentage of B2B marketers are currently using AI. This suggests that managers should understand every potential benefit of using AI when comparing them with the obstacles (e.g., data quality, data analysis, and shortage of data scientists) and begin utilizing relevant AI applications. Simply put, they should examine their current business processes and seek opportunities to adopt relevant and cost-effective AI techniques. This paper also discusses the success stories of AI use that should motivate B2B marketers to adopt AI methods to solve their specific business problems.

6.3. Policy level implications and recommendations

Considering the strengths and opportunities of using AI (Andresen, 2002; Khan et al., 2010; Lee & Bradlow, 2011; Ongsulee, 2017; Paschen et al., 2019, 2020), policies should focus on measures to combat its possible drawbacks. These potential weaknesses include poor data quality, lack of technological infrastructure, untrained staff, and the high costs associated with AI adoption. Furthermore, the threats predominantly relate to data privacy and fear of job loss among employees. Hence, we recommend the following. First, policies should elaborate on data quality and which type of data must be collected to solve specific business problems suitably. Another consideration involves customer privacy, which can be ensured by implementing filters on which information can be stored and which type of data cannot be accessed by marketing agencies. Second, firms should digitally transform their internal communication and data-sharing processes before implementing AI tools. Third, unskilled staff should be trained in a supportive environment to uptake technology. Training should reinforce the notion that AI cannot replace human intelligence, thus building employee confidence regarding job security. Fourth, the costs of using AI should be controlled by government organizations. Persistent and effective AI should be made available in the public domain.

7. Future research directions

This section organizes all the findings and provides a research context for future B2B researchers, thus helping expand the literature in the AI domain. First, this study reveals AI's primary benefits for B2B marketers: 1) AI techniques play critical roles in the customer life cycle (i.e., reach, acquisition, conversion, and retention), 2) AI analyzes future sales, trends, pricing, and competitors to explore the competitive market, 3) AI helps serve customers with cost- and time-effective customization and personalization, 4) AI helps B2B marketers identify potential churners, supporting customer-focused strategies that reduce churn rates, 5) AI methods (e.g., semi-supervised) improve the accuracy of predictive models in organizations, and 6) AI methods improve customer lifetime value (CLV) predictions for segmentation and targeting. Therefore, future research can build on the benefits of using AI in B2B marketing by examining questions such as the following: 1) How is AI changing the value creation process for B2B customers? 2) What are the impacts of AI on B2B customers? 3) How can firms learn from the user experience through the use of AI? 4) How should businesses use AI for building market-sensing capabilities (i.e., recognize market requirements to design rapid strategies)? and 5) How much do ML methods predict CLV better than the traditional calculation of CLV?

Second, this paper shows AI's drawbacks, including 1) B2B marketers struggle to clearly understand and implement AI. As presented in the industry surveys, only 37% of B2B marketers utilize AI, showing a limited understanding of its potential, 2) Unstructured customer data makes it challenging to obtain business insights. In addition, low-quality data can skew data analyses, 3) Firms must digitally transform their internal communication and data sharing to update their technological infrastructure. This is one of the costly pre-prerequisites to AI adoption, 4) There is a shortage of qualified data analysts with AI knowledge. B2B marketers identify this as a major roadblock, and 5) Advanced AI applications are considered to be resource-intensive. Hence, small-to-midsize marketing firms are hesitant to use this technology. However, as the success stories demonstrate, AI's correct implementation can cut costs by increasing business efficiency. Therefore, future research should further discuss the drawbacks of using AI in B2B marketing by examining questions such as the following: 1) What are the benefits and costs of implementing AI in different B2B industries? 2) What are the AI requirements for small, medium, and large-sized B2B marketers? 3) What are the cost-effective, equipment-light AI techniques for small firms? 4) How can B2B marketers evaluate and ensure data quality? 5) How can B2B marketers apply AI methods to small datasets? 6) How can B2B marketers evaluate and improve AI performance? For instance, SVMs effectively reduce churn rates, but to what extent still needs to be explored.

Third, this study discusses B2B marketers' main opportunities for AI implementation: 1) A large amount of available data and a growing number of data analysis experts present the greatest opportunity to expand a business, 2) If there is a lack of big data experts in an organization, various companies are providing AI solutions services only a click away, 3) AI can enhance the quality of customer relationship management (CRM), 4) AI can help B2B marketers automatically target customers and send them customized messages, and 5) Using reinforcement learning, AI can help B2B marketers develop chatbots to address customers' queries. Therefore, future research should build on the opportunities of using AI in B2B marketing by examining questions such as the following: 1) How can B2B companies adopt AI on a wider scale? 2) Since customer relationship management (CRM) is a crucial link in the success of B2B companies (Saura, Ribeiro-Soriano, & Palacios-Marqués, 2021), how can predictive analytics be used in AI-based CRM? 3) How can B2B companies integrate B2B digital marketing and AI-based CRM? 4) How can AI be integrated with B2B digital marketing activities? 5) How can analytical CRM (i.e., collecting customer interaction data) benefit B2B marketing, and what different functionalities of AI can be leveraged? 6) How would AI enhance sales professionals' familiarity with customers? 7) With the use of AI, how can an organization account for the impacts of external environment events? 8) How can B2B marketers apply computer vision models (i.e., image/video analysis)?

Fourth, the study discusses AI threats, including 1) Phishing: rapid

Table 4
Future research directions.

Technology acceptance model	Current findings	Future research questions
Usefulness	• *AI plays a critical role in the customer life cycle* • *AI helps explore the competitive market* • *AI serves customers according to their specialized needs with cost and time-effective strategies* • *AI helps B2B marketers identify potential churners* • *AI methods (*e.g., *semi-supervised) significantly enhance the accuracy of the predictive models* • *AI methods enhance the accuracy of customer lifetime value (CLV) calculation and prediction* • *A large amount of data availability and a growing number of data analysis experts* • *A growing number of companies providing marketers with AI services* • *AI can enhance the quality of customer relationship management (CRM)* • *AI can help B2B marketers automatically target customers and send them AI-generated messages.* • *AI can help B2B marketers develop chatbots to address customers' questions/queries*	1. *How is AI changing the value creation process for B2B customers?* 2. *What are the impacts of AI on B2B customers?* 3. *How can firms learn from the user experience through the use of AI?* 4. *How should businesses use AI for building market-sensing capabilities (*i.e., *recognize market requirements to design rapid strategies)?* 5. *How much do ML methods predict CLV better than the traditional calculation of CLV?* 6. *How can B2B companies adopt AI on a wider scale in all departments?* 7. *Since customer relationship management (CRM) is a crucial link in the success of B2B companies, how can predictive analytics be used in AI-based CRM?* 8. *How can B2B companies integrate B2B digital marketing and AI-based CRM?* 9. *How can AI be integrated with B2B digital marketing activities?* 10. *How can analytical CRM (*i.e., *collecting customer interaction data) benefit B2B marketing, and what different functionalities of AI can be leveraged?* 11. *How would AI facilitate enhancing sales professionals' familiarity with customers?* 12. *With the use of AI, how can an organization account for the impacts of external environment events?*
Ease of Use	• *Lack of clear understanding of AI potentials among B2B marketers* • *Perceived data quality/ analysis issues* • *Digital transformation issue* • *Perception about the shortage of trained staff* • *Perceived Costs*	13. *How can B2B marketers apply computer vision models (*i.e., *image/video analysis)?* 14. *What are the benefits and costs of implementing AI in different B2B industries?* 15. *What are the AI requirements for small, medium, and large-sized B2B marketers?* 16. *What are the cost-effective, equipment-light AI techniques for small firms?* 17. *How can B2B marketers evaluate and ensure data quality?* 18. *How can B2B marketers apply AI methods to small datasets?* 19. *How can B2B marketers evaluate and improve AI performance? For instance, SVMs effectively reduce churn rates, but to what extent still needs to be explored*
	• *Phishing* • *Misleading results due to data quality* • *Jobs displacement*	20. *What guidelines should companies follow to avoid phishing and data breaches?* 21. *How much do AI models require human interaction?* 22. *To what extent will AI replace sales professionals?* 23. *What are the ethical issues involved in adopting AI?* 24. *How should data quality assurance be incorporated into the research design, including data collection, data cleaning, method selection, and data interpretation?*

technological and internet advances have created large data pools that hackers can use to access sensitive information. Banking fraud and national security leaks are examples of malicious AI effects. Most mobile apps require access to personal information (e.g., photos and documents) before installation. Hackers can access this information and create disruption, 2) Misleading findings: poor data quality can lead to biased and misleading results, and 3) Job displacement: AI can automate low-skilled tasks, leading to job displacement. Once the programming is complete, a computer program can rapidly—and near-complete perfection—analyze big data, thus making it easier for computers to replace human workforces. Therefore, future research should further discuss the threats of using AI in B2B marketing by examining questions such as the following: 1) What guidelines should companies follow to avoid phishing and data breaches? 2) How much do AI models require human interaction? 3) To what extent will AI replace sales professionals? 4) What are the ethical issues involved in adopting AI? 5) How should data quality assurance be incorporated into the research design, including data collection, data cleaning, method selection, and data interpretation (Moore, Harrison, & Hair, 2021)?

The summary of future research questions and their relationships with TAM is presented in Table 4. It seems clear that AI offers many possibilities, but B2B marketers have not yet capitalized upon them due to an incomplete understanding. Successful companies have effectively used AI to improve customer solutions, simplify tedious processes, reduce costs, decrease churn rates, and predict future sales trends. Thus, there is an urgent need to assess the requirements of B2B marketers and simplify the development and uptake of AI.

Future research should conduct extensive sample-sized market surveys among B2B marketers to assess their knowledge, expectations, and behavior toward this technological boom. Furthermore, future studies could investigate the sociodemographic factors (i.e., characteristics of decision-makers at the individual level) influencing AI uptake). Finally, while we have used a literature review, survey analysis, and success stories to examine the challenges and propose future directions for B2B managers, future studies can also employ primary data to explore the benefits, drawbacks, opportunities, and threats of adopting AI.

8. Conclusions

Leading global firms (e.g., Microsoft and Google) have started adopting and utilizing AI (Leone, Schiavone, Appio, & Chiao, 2021). The paper discusses successful B2B stories, but AI in B2B marketing is in its infancy. Previous research has paid little attention to AI's role in B2B marketing (Leone et al., 2021) and how it can benefit companies

(Kaartemo & Helkkula, 2018). Our literature review revealed that AI methods are nascent to growing in B2B marketing, but success stories have laid the foundation for marketers to use technology judiciously. Industry Survey analysis showed that 37% of B2B marketers had implemented AI. This low percentage is due to adoption obstacles and a lack of clear AI understanding. Personalization and customization for customer attraction and retention were the two main AI applications perceived by B2B marketers. However, many other AI methods and implications were unknown to them. There has never been a better time for B2B companies to use AI since it will put them ahead of the competition and allow them to see immediate benefits. When attempting to construct a business case for the technology and estimate the associated AI costs, attention should be placed on the considerable benefits that are already capable, and those benefits should be the primary focus. AI's contributions to B2B companies are unparalleled because of their capabilities, such as forecasting, lead scoring, extracting data from various sources, and providing dynamic pricing, among many others.

Data availability

Data will be made available on request.

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References*

Aichner, T., & Gruber, B. (2017). Managing customer touchpoints and customer satisfaction in b2b mass customization: A case study. *International Journal of Industrial Engineering and Management, 8*(3), 131.

Al-Azzam, N., & Shatnawi, I. (2021). Comparing supervised and semi-supervised machine learning models on diagnosing breast cancer. *Annals of Medicine and Surgery, 62*, 53–64.

Amatriain, X., & Basilico, J. (2015). Recommender systems in industry: A netflix case study. In *Recommender systems handbook* (pp. 385–419). Boston, MA: Springer.

*Andresen, S. L. (2002). John McCarthy: Father of AI. *IEEE Intelligent Systems, 17*(5), 84–85.

*Arel, I., Rose, D., & Karnowski, T. (2010). Deep machine learning-a new frontier in artificial intelligence research. *IEEE Computational Intelligence Magazine, 5*(4), 13–18.

Arsenijevic, U., & Jovic, M. (2019). Artificial intelligence marketing: Chatbots. In *Proceedings - 2019 international conference on artificial intelligence: Applications and innovations, IC-AIAI 2019* (pp. 19–22).

*Bag, S., Gupta, S., Kumar, A., & Sivarajah, U. (2021). An integrated artificial intelligence framework for knowledge creation and B2B marketing rational decision making for improving firm performance. *Industrial Marketing Management, 92*, 178–189.

*Balducci, B., & Marinova, D. (2018). Unstructured data in marketing. *Journal of the Academy of Marketing Science, 46*(4), 557–590.

*Ban, G. Y., & Keskin, N. B. (2021). Personalized dynamic pricing with machine learning: High-dimensional features and heterogeneous elasticity. *Management Science, 67*(9), 5549–5568.

*Bharadwaj, N., & Shipley, G. M. (2020). Salesperson communication effectiveness in a digital sales interaction. *Industrial Marketing Management, 90*, 106–112.

*Borges, A. F., Laurindo, F. J., Spínola, M. M., Gonçalves, R. F., & Mattos, C. A. (2021). The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions. *International Journal of Information Management, 57*, Article 102225.

BrightEdge. (2018). Future of marketing and AI survey report. Available at https://www.brightedge.com/resources/research-reports/2018-future-marketing-and-ai-survey-report.

*Canhoto, A. I., & Clear, F. (2020). Artificial intelligence and machine learning as business tools: A framework for diagnosing value destruction potential. *Business Horizons, 63*(2), 183–193.

Casillas, J., Martínez-López, F. J., & Corchado Rodríguez, J. M. (2012). Management intelligent systems. In *Proceedings of the first international symposium*. Berlin: Springer.

Chaffey, D., & Ellis-Chadwick, F. (2019). *Digital marketing: Strategy, implementation & practice* (7th ed.). New York: Pearson.

Chaffey, D., & Patron, M. (2012). From web analytics to digital marketing optimization: Increasing the commercial value of digital analytics. *Journal of Direct, Data and Digital Marketing Practice, 14*(1), 30–45.

Choi, J. A., & Lim, K. (2020). Identifying machine learning techniques for classification of target advertising. *ICT Express, 6*(3), 175–180.

*Cortez, R. M., & Johnston, W. J. (2017). The future of B2B marketing theory: A historical and prospective analysis. *Industrial Marketing Management, 66*, 90–102.

*Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science, 48*(1), 24–42.

*Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*(8), 982–1003.

*De Bruyn, A., Viswanathan, V., Beh, Y. S., Brock, J. K. U., & von Wangenheim, F. (2020). Artificial intelligence and marketing: Pitfalls and opportunities. *Journal of Interactive Marketing, 51*, 91–105.

*Del Giudice, M., Di Vaio, A., Hassan, R., & Palladino, R. (2021). Digitalization and new technologies for sustainable business models at the ship–port interface: A bibliometric analysis. *Maritime Policy & Management*, 1–37.

Delponte, L., & Tamburrini, G. (2018). *European artificial intelligence (AI) leadership, the path for an integrated vision*. European Parliament.

Demandbase. (2018). The state of artificial intelligence in B2B marketing. Available at https://www.demandbase.com/ebook/the-state-of-artificial-intelligence-in-b2b-marketing/.

Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv Preprint*. arXiv:1810.04805.

*Di Vaio, A., Palladino, R., Hassan, R., & Escobar, O. (2020). Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review. *Journal of Business Research, 121*, 283–314.

*Di Vaio, A., Palladino, R., Pezzi, A., & Kalisz, D. E. (2021). The role of digital innovation in knowledge management systems: A systematic literature review. *Journal of Business Research, 123*, 220–231.

*Dimitrieska, S., Stankovska, A., & Efremova, T. (2018). Artificial intelligence and marketing. *Entrepreneurship, 6*(2), 298–304.

*Dubey, R., Gunasekaran, A., Childe, S. J., Bryde, D. J., Giannakis, M., Foropon, C., … Hazen, B. T. (2020). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations. *International Journal of Production Economics, 226*, Article 107599.

*Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., … Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management, 57*, Article 101994.

*Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., … Wang, Y. (2021). Setting the future of digital and social media marketing research: Perspectives and research propositions. *International Journal of Information Management, 59*, Article 102168.

Everstring & Heinz. (2019). The state of artificial intelligence in B2B marketing. Available at http://results.heinzmarketing.com/R-Guide-TheStateofAIinB2BMarketing_LP.html.

*Farrokhi, A., Shirazi, F., Hajli, N., & Tajvidi, M. (2020). Using artificial intelligence to detect crisis related to events: Decision making in B2B by artificial intelligence. *Industrial Marketing Management, 91*, 257–273.

*Fensel, D., Ding, Y., Omelayenko, B., Schulten, E., Botquin, G., Brown, M., & Flett, A. (2001). Product data integration in B2B e-commerce. *IEEE Intelligent Systems, 16*(4), 54–59.

Gooner, R. A., Morgan, N. A., & Perreault, W. D., Jr. (2011). Is retail category management worth the effort (and does a category captain help or hinder)? *Journal of Marketing, 75*(5), 18–33.

*Gordini, N., & Veglio, V. (2017). Customers churn prediction and marketing retention strategies. An application of support vector machines based on the AUC parameter-selection technique in B2B e-commerce industry. *Industrial Marketing Management, 62*, 100–107.

*Grewal, D., Guha, A., Satornino, C. B., & Schweiger, E. B. (2021). Artificial intelligence: The light and the darkness. *Journal of Business Research, 136*, 229–236.

*Guha, A., Grewal, D., Kopalle, P. K., Haenlein, M., Schneider, M. J., Jung, H., … Hawkins, G. (2021). How artificial intelligence will affect the future of retailing. *Journal of Retailing, 97*(1), 28–41.

*Hair, J. F. (2007). Knowledge creation in marketing: The role of predictive analytics. *European Business Review, 19*(4), 303–315.

Haldorai, A., Ramu, A., & Khan, S. A. R. (2020). *Business intelligence for enterprise internet of things*. Cham, Switzerland: Springer International Publishing.

*Han, R., Lam, H. K., Zhan, Y., Wang, Y., Dwivedi, Y. K., & Tan, K. H. (2021). Artificial intelligence in business-to-business marketing: A bibliometric analysis of current research status, development and future directions. *Industrial Management & Data Systems, 121*(12), 2467–2497.

*Hiebert, R. E. (2003). Public relations and propaganda in framing the Iraq war: A preliminary review. *Public Relations Review, 29*(3), 243–255.

*Huang, M. H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science, 49*(1), 30–50.

*Jabbar, A., Akhtar, P., & Dani, S. (2020). Real-time big data processing for instantaneous marketing decisions: A problematization approach. *Industrial Marketing Management, 90*, 558–569.

* Studies used for literature review.

*Jans, M., Lybaert, N., & Vanhoof, K. (2010). Internal fraud risk reduction: Results of a data mining case study. *International Journal of Accounting Information Systems, 11*(1), 17–41.

*Janssen, M., van der Voort, H., & Wahyudi, A. (2017). Factors influencing big data decision-making quality. *Journal of Business Research, 70*, 338–345.

*Järvinen, J., & Taiminen, H. (2016). Harnessing marketing automation for B2B content marketing. *Industrial Marketing Management, 54*, 164–175.

Jurafsky, D., & Martin, J. (2014). Speech and language processing: Constituency parsing. In *, 3. Speech and language processing* (pp. 441–458).

Kaartemo, V., & Helkkula, A. (2018). A systematic review of artificial intelligence and robots in value co-creation: Current status and future research avenues. *Journal of Creating Value, 4*(2), 211–228.

Kaminsky, J., & Fiore, F. (2001). *U.S. patent application no. 09/816,918*.

*Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons, 62*(1), 15–25.

*Kaplan, A., & Haenlein, M. (2020). Rulers of the world, unite! The challenges and opportunities of artificial intelligence. *Business Horizons, 63*(1), 37–50.

*Katsikeas, C., Leonidou, L., & Zeriti, A. (2019). Revisiting international marketing strategy in a digital era: Opportunities, challenges, and research directions. *International Marketing Review, 37*(3), 405–424.

*Khan, A., Baharudin, B., Lee, L. H., & Khan, K. (2010). A review of machine learning algorithms for text-documents classification. *Journal of Advances in Information Technology, 1*(1), 4–20.

Kieser, R., Baylis, C., & Luyens, S. (2021). *U.S. Patent No. 11,062,094*. Washington, DC: U.S. Patent and Trademark Office.

Koskinen, P. (2021). B2B's evolution in 2021: How AI and machine learning are forever changing B2B marketing. Retrieved from Forbes website: https://www.forbes.com/sites/forbestechcouncil/2021/03/04/b2bs-evolution-in-2021-how-ai-and-machine-learning-are-forever-changing-b2b-marketing/?sh=77ceb29a7132.

*Kotsiantis, S. B., Zaharakis, I. D., & Pintelas, P. E. (2006). Machine learning: A review of classification and combining techniques. *Artificial Intelligence Review, 26*(3), 159–190.

*Lee, J., Jung, O., Lee, Y., Kim, O., & Park, C. (2021). A comparison and interpretation of machine learning algorithm for the prediction of online purchase conversion. *Journal of Theoretical and Applied Electronic Commerce Research, 16*(5), 1472–1491.

*Lee, T. Y., & Bradlow, E. T. (2011). Automated marketing research using online customer reviews. *Journal of Marketing Research, 48*(5), 881–894.

Leone, D., Schiavone, F., Appio, F. P., & Chiao, B. (2021). How does artificial intelligence enable and enhance value co-creation in industrial markets? An exploratory case study in the healthcare ecosystem. *Journal of Business Research, 129*, 849–859.

Li, B. H., Hou, B. C., Yu, W. T., Lu, X. B., & Yang, C. W. (2017). Applications of artificial intelligence in intelligent manufacturing: A review. *Frontiers of Information Technology & Electronic Engineering, 18*(1), 86–96.

Li, J., Zhao, Z., Li, R., & Zhang, H. (2018). Ai-based two-stage intrusion detection for software defined iot networks. *IEEE Internet of Things Journal, 6*(2), 2093–2102.

Lianos, I., & Katalevsky, D. (2017). *Merger activity in the factors of production segments of the food value chain: a critical assessment of the Bayer/Monsanto merger*. London, UK: UCL Centre for Law, Economics and Society. Available at http://discovery.ucl.ac.uk/10045082/1/Lianos_cles-policy-paper-1-2017.pdf.

*Liebowitz, J. (2001). Knowledge management and its link to artificial intelligence. *Expert Systems with Applications, 20*(1), 1–6.

*Liu, X. (2020). Analyzing the impact of user-generated content on B2B Firms' stock performance: Big data analysis with machine learning methods. *Industrial Marketing Management, 86*, 30–39.

*Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to medical artificial intelligence. *Journal of Consumer Research, 46*(4), 629–650.

*Luo, X., Qin, M. S., Fang, Z., & Qu, Z. (2021). Artificial intelligence coaches for sales agents: Caveats and solutions. *Journal of Marketing, 85*(2), 14–32.

*Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases. *Marketing Science, 38*(6), 937–947.

Marr, B. (2017). Why AI, machine learning and big data really matter to B2B companies. Retrieved from Forbes website: https://www.forbes.com/sites/bernardmarr/2017/11/03/why-ai-machine-learning-and-big-data-really-matter-to-b2b-companies/?sh=156c3ad81f2a.

*Martínez-López, F. J., & Casillas, J. (2009). Marketing intelligent systems for consumer behaviour modelling by a descriptive induction approach based on genetic fuzzy systems. *Industrial Marketing Management, 38*(7), 714–731.

*Martínez-López, F. J., & Casillas, J. (2013). Artificial intelligence-based systems applied in industrial marketing: An historical overview, current and future insights. *Industrial Marketing Management, 42*(4), 489–495.

McKenzie, J. E., Salanti, G., Lewis, S. C., & Altman, D. G. (2013). Meta-analysis and the Cochrane collaboration: 20 years of the Cochrane statistical methods group. *Systematic Reviews, 2*, 80.

*Mikalef, P., Kieran Conboy, K., & Krogstie, J. (2021). Artificial intelligence as an enabler of B2B marketing: A dynamic capabilities micro-foundations approach. *Industrial Marketing Management, 98*, 80–92.

*Miroshnichenko, A. (2018). AI to bypass creativity. Will robots replace journalists?(the answer is "yes"). *Information, 9*(7), 183.

MIT Technology Review. (2018). MIT executive study uncovers top 10 trends shaping IT resilience. Available at https://www.vmware.com/cio-vantage/articles/mit-technology-review-insights-report.html.

Moore, Z., Harrison, D. E., & Hair, J. (2021). Data quality assurance begins before data collection and never ends: What marketing researchers absolutely need to remember. *International Journal of Market Research, 63*(6), 693–714.

Negnevitsky, M., & Intelligence, A. (2005). A guide to intelligent systems. In *Artificial Intelligence* (2nd ed.). Pearson Education.

Nyadzayo, M. W., Casidy, R., & Thaichon, P. (2020). B2B purchase engagement: Examining the key drivers and outcomes in professional services. *Industrial Marketing Management, 85*, 197–208.

Nyce, C., & Cpcu, A. (2007). *Predictive analytics white paper* (pp. 9–10). American Institute for CPCU. Insurance Institute of America.

Ongsulee, P. (2017). Artificial intelligence, machine learning and deep learning. In *International conference on ICT and knowledge engineering*.

Orica launches next-gen BlastIQ. (2018, October 1). MiningMagazine.com. Available at https://www.miningmagazine.com/innovation/news/1347744/orica-launches-next-gen-blastiq#kre-comments-top.

*Paschen, J., Kietzmann, J., & Kietzmann, T. C. (2019). Artificial intelligence (AI) and its implications for market knowledge in B2B marketing. *The Journal of Business and Industrial Marketing, 34*(7), 1410–1419.

*Paschen, J., Wilson, M., & Ferreira, J. J. (2020). Collaborative intelligence: How human and artificial intelligence create value along the B2B sales funnel. *Business Horizons, 63*(3), 403–414.

Pham, T. H. V. (2017). *Marketing automation as an enabler in B2B: A study from customer retention perspective, Master's Thesis*. Lappeenranta University of Technology. Available at https://lutpub.lut.fi/handle/10024/135120.

*Quinn, L., Dibb, S., Simkin, L., Canhoto, A., & Analogbei, M. (2016). Troubled waters: The transformation of marketing in a digital world. *European Journal of Marketing, 50*(12), 2103–2133.

*Ribeiro, T., & Reis, J. L. (2020). Artificial intelligence applied to digital marketing. In *, 1160. Advances in Intelligent Systems and Computing* (pp. 158–169). AISC.

*Rohaan, D., Topan, E., & Groothuis-Oudshoorn, C. G. M. (2021). Using supervised machine learning for B2B sales forecasting: A case study of spare parts sales forecasting at an after-sales service provider. *Expert Systems with Applications, 188*, Article 115925.

Salehi, H., & Burgueño, R. (2018). Emerging artificial intelligence methods in structural engineering. *Engineering Structures, 171*, 170–189.

Salesforce. (2017). State of marketing. Available at https://www.salesforce.com/uk/form/pdf/2017-state-of-marketing/.

*Samuel, A., White, G. R., Thomas, R., & Jones, P. (2021). Programmatic advertising: An exegesis of consumer concerns. *Computers in Human Behavior, 116*, Article 106657.

*Saura, J. R., Ribeiro-Soriano, D., & Palacios-Marqués, D. (2021). Setting B2B digital marketing in artificial intelligence-based CRMs: A review and directions for future research. *Industrial Marketing Management, 98*, 161–178.

*Schepers, J., & Wetzels, M. (2007). A meta-analysis of the technology acceptance model: Investigating subjective norm and moderation effects. *Information & Management, 44*(1), 90–103.

*Sila, I. (2013). Factors affecting the adoption of B2B e-commerce technologies. *Electronic Commerce Research, 13*(2), 199–236.

*Sleep, S., Dixon, A. L., DeCarlo, T., & Lam, S. K. (2020). The business-to-business inside sales force: Roles, configurations and research agenda. *European Journal of Marketing, 54*(5), 1025–1060.

Somvanshi, M., Chavan, P., Tambade, S., & Shinde, S. V. (2017). A review of machine learning techniques using decision tree and support vector machine. In *Proceedings - 2nd international conference on computing, communication, control and automation, ICCUBEA 2016*.

Sterne, J. (2017). *Artificial intelligence for marketing: Practical applications*. Hoboken, NJ: John Wiley & Sons.

Tang, X., Chen, Y., Li, X., Liu, J., & Ying, Z. (2019). A reinforcement learning approach to personalized learning recommendation systems. *British Journal of Mathematical and Statistical Psychology, 72*(1), 108–135.

Tankovska, H. (2020). Number of digital voice assistants in use worldwide 2019–2024. Available at https://www.statista.com/statistics/973815/worldwide-digital-voice-assistant-in-use/.

*Vera-Baquero, A., Colomo-Palacios, R., & Molloy, O. (2014). Towards a process to guide big data based decision support systems for business processes. *Procedia Technology, 16*, 11–21.

Vera-Baquero, Alejandro, Colomo-Palacios, Ricardo, & Molloy, Owen (2016). Real-time business activity monitoring and analysis of process performance on big-data domains. *Telematics and Informatics, 33*, 793–807.

White, T. (2015). *Hadoop: The definitive guide, chapter meet Hadoop*. Sebastapol, CA: O'Reilly Media.

Wignell, P., Chai, K., Tan, S., O'Halloran, K., & Lange, R. (2021). Natural language understanding and multimodal discourse analysis for interpreting extremist communications and the re-use of these materials online. *Terrorism and political violence, 33*(1), 71–95.

*Xie, Y., Li, X., Ngai, E. W. T., & Ying, W. (2009). Customer churn prediction using improved balanced random forests. *Expert Systems with Applications, 36*(3), 5445–5449.

Yao, M., Zhou, A., & Jia, M. (2018). *Applied artificial intelligence: A handbook for business leaders*. Topbots Inc.

*Zhang, C., Wang, X., Cui, A. P., & Han, S. (2020). Linking big data analytical intelligence to customer relationship management performance. *Industrial Marketing Management, 91*, 483–494.