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The effect of AI-based CRM on organization performance and competitive advantage: An empirical analysis in the B2B context

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ABSTRACT

Organizations have cultural-cognitive and regulative as well as normative elements that impact their employees. Organizations, by definition, cannot achieve a pure, stable state and always go through various change processes, both incremental and radical changes. Moving from legacy business-to-business (B2B) relationship management to an artificial intelligence-based customer relationship management (AI-CRM) is a gradual but paradigm change. AI-CRM leverages intelligent systems to automate the B2B relationship activities where the decision can be taken automatically without any human intervention. Relationship management in the B2B segment is considered a strategic activity of an organization. Moving from legacy to AI-CRM to facilitate B2B relationship management activities is an important decision, and proper implementation of AI-CRM is a critical success parameter for an organization. This study combines institutional theory and the resource-based view (RBV) in B2B relationship management to understand how AI-CRM could impact the firm's performance with varied firm size, firm age, and industry type.

1. Introduction

Artificial intelligence (AI) is on course to disrupt marketing management offering new prospects and challenges for marketing (Cao, Duan, Edwards, & Dwivedi, 2021; Davenport, Guha, Grewal, & Bressgott, 2019; Kumar, Dwivedi, & Anand, 2021; Mustak, Salminen, Plé, & Wirtz, 2021; Rust, 2020; Vlačić & Corbo, 2021). Especially, within the business-to-business (B2B) and industrial marketing segment, the applicability of AI-based solutions is well acknowledged and discussed (Bag, Gupta, Kumar, & Sivarajah, 2021; de Jong, de Ruyter, Keeling, Polyakova, & Ringberg, 2021; Martínez-López & Casillas, 2013; Paschen, Kietzmann, & Kietzmann, 2019; Paschen, Paschen, Pala, & Kietzmann, 2020). B2B marketers need intelligent solutions to automate the process of structuring, standardizing, aligning, and customizing data in a complex business environment (Farrokhi, Shirazi, Hajli, & Tajvdi, 2020; Fensel et al., 2001; Jabbar, Akhtar, & Dani, 2019; Syam & Sharma, 2018).

The impact of managing long-term customer relationships on business profitability has presumably influenced the academicians and practitioners to develop more understanding about customer relationship management (CRM) (Richards & Jones, 2008; Wilson, Clark, & Smith, 2007). In particular, Richards and Jones (2008, p.121) provide a holistic definition of CRM as “a set of business activities supported by both technology and processes that is directed by strategy and is designed to improve business performance in an area of customer management”. In the B2B context, CRM helps organizations in identifying customers, understanding their requirements, developing customer knowledge, and building a profit maximization portfolio by establishing deeper buyer–seller relationships (Hart, Hogg, & Banerjee, 2004; Saura, Palos-Sanchez, & Blanco-González, 2019; Zablah, Bellenger, & Johnston, 2004).

CRM integrates and analyses customer data generated from formal and informal interactions among the stakeholders, including the supplier and the customer. It also builds and maintain a profit-maximizing portfolio of customer relationships (Zablah et al., 2004). The integrated data from CRM is a living record of the firm's effectuated correspondence with its customer that is crucial to ascertain the customer's actual needs and lead management decisions (Ascarza et al., 2018; Kim, Park, Dubinsky, & Chaiy, 2012; Stein, Smith, & Lancioni, 2013). In B2B relationships, customers' data becomes vast and complex since it is

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collected from multiple customer touchpoints set up in the organization (Dwivedi et al., 2021; Shareef et al., 2021; Zhang, Pee, & Cui, 2021). Moreover, many organizations in B2B settings struggle with harnessing the CRM data and exploiting the potential value because managing and analysing voluminous customers' data precisely requires skills and resources (Stein & Smith, 2009). In recent years, AI is playing an influential role in CRM, enabling firms to quickly and accurately analyse voluminous data (Libai et al., 2020). The growing acceptance of advanced AI technologies in the business domain and the abundance of customer data in the buyer–supplier relationship management space have facilitated firms to offer personalized services and target more profitable customers via ubiquitous communication (Gupta, Leszkiewicz, Kumar, Bijmolt, & Potapov, 2020; Rust & Huang, 2014).

Therefore, in the longer run, AI-driven applications will radically reform the nature of customer service by offering widespread personalized services to customers through human-like interactions at low cost (Bag, Pretorius, Gupta, & Dwivedi, 2021; Hoyer, Kroschke, Schmitt, Kraume, & Shankar, 2020; Kaplan & Haenlein, 2019). The growing popularity of AI applications in B2B has instigated the need to integrate AI with CRM for service personalization and managerial decision making (de Jong et al., 2021). Hence, an AI-integrated CRM system implementation is essential for all organizations working in B2B settings to analyse massive data and derive useful business insights for decision making (Chatterjee, Ghosh, Chaudhuri, & Nguyen, 2019; Libai et al., 2020).

Successful implementation of AI-based CRM (hereafter, AI-CRM) in B2B organizations needs the support of different factors (King & Burgess, 2008). AI-CRM implementation quality must be effective, and the employees of the organizations must have the abilities and expertise to implement, maintain, and fine-tune the system. The organization's technological capabilities must also be conducive for successful AI-CRM implementation (Chatterjee, Rana, Dwivedi, & Baabdullah, 2021; Lipiäinen, 2015; Raman, Wittmann, & Rauseo, 2006). The factors responsible for the successful implementation of AI-CRM in the B2B context may be identified with the help of institutional theory (Scott, 1987). This theory suggests how new technology implementation in the organization becomes successful within the organization's values, expectations, and norms (Massi, Rod, & Corsaro, 2020). It is perceived that organizations act as institutions in many respects. Therefore, this study proposes that the factors related to the successful implementation of AI-CRM can be better explained using institutional theory.

Moreover, it is essential to collect the data (resources) by the organizations, which are valuable, rare, inimitable, and non-substitutable as observed in resource-based view (RBV) theory (Barney, 1991). On the availability of these data with the help of the experience and expertise of the employees, and with the use of an appropriate B2B information processing system, it might be possible to extract the best potential of the AI-CRM system to improve the organization's competitive advantage. However, to the best of our knowledge, none of the existing literature discusses how the AI-CRM implementation can be supported by different factors and how the implementation of AI-CRM would impact organizational performance to gain a competitive advantage in the B2B context. Hence, there is a solid need to advance the scholarship on AI-CRM implementation and organizational performance.

To fill in this research gap, this study aims to address the following research questions:

RQ1. To determine the antecedents for implementation of an AI-CRM system for B2B relationship management.

RQ2. To understand the moderating role of leadership support for managing B2B relationship management in the organization.

The remaining sections of the article are organized as follows. The following Section 2 presents theoretical debate surrounding the conceptual model for this study followed by hypotheses development. Section 3 describes the research methodology employed in this study, followed by data analysis and results in Section 4. Section 5 discusses the results against the backdrop of relevant literature and implications for theory and practice. Finally, Section 6 concludes the paper by citing some key findings of this research.

2. Theoretical background, proposed conceptual model, and hypotheses development

2.1. Institutional theory

Institutional theory offers a theoretical foundation for understanding complex change management scenarios (Currie, 2008). Researchers adopt this theory to investigate how institutions influence the design, use, and outcomes of technologies, either within or across organizations (Orlikowski & Barley, 2001; Weerakkody, Dwivedi, & Irani, 2009). Moreover, institutional factors are “ubiquitous and essential components” that play an indispensable role in understanding and explaining inter-organizational IT innovations (King et al., 1994). Within the B2B context, institutional theory is perceived to be the best fit for interpreting issues of implementation of a new technology when the different organizations function to improve their B2B relationships (Wallin & Fuglsang, 2017). Institutions can be conceptualized as social structures that could attain a high degree of resilience. This conceptualization could help cover the implementation aspects of a new system operating at different levels in a collaborative environment (Ledesma, 2014). Institutional theory is perceived to have nurtured organizational phenomena, especially when the organizations take the initiative in a collaborative environment for implementing a new system (Massi et al., 2020). This theory emphasizes maintenance and implementation towards incremental changes as well as the survival of institutions and posits that institutions are “composed of cultural-cognitive, normative and regulative elements that, together with associative activities and resources, provide stability and meaning to social life” (Scott, 1995, p.33).

This study endeavoured to establish a nexus between implementation issues in organizations and institutional theory and institutionalization process to identify the predictors for the implementation of a system in organizations. Wallin and Fuglsang (2017) highlight that in terms of institutional theory, it is always cogent for organizations to improve the implementation quality along with improvement of organizational competence as well as employees' assimilation abilities that would help in the successful implementation of a new system. Scott (1987) defined institutional theory as an extensively accepted theoretical stance that underscores reasonable mythologies, isomorphism, and legitimacy. Institutional theory further posits that organizations can hardly achieve a pure state of stability but always proceed with both implemental and discontinuous changes. In this context, the transformation from a legacy CRM system to an AI-CRM system in organizations is construed as an incremental change in the organization.

Organizations can analyse a massive volume of customers' data with the support of AI-CRM systems (Chatterjee et al., 2019; Lacka, Chan, & Wang, 2020; Libai et al., 2020). The existing literature confirms that AI effectively assists organizations in analysing a variety of massive data (Chatterjee, Ghosh, & Chaudhuri, 2020; Chatterjee, Ghosh, Chaudhuri, & Chaudhuri, 2020; Verma & Verma, 2013). The past research has revealed how institutional theory could explain organizational activities (Oliver, 1997). Institutional theory is now accepted as a dominant theory to explain organizational functionalities, and it can also explain the environmental relations among the organizations at a macro level (Oliver, 1997; Reed & Burrell, 2018). This theory also helps identify the antecedents that affect the implementation of any new technology in organizations (Oliver, 1997). Thus, the implementation of an AI-CRM system in an organization in the B2B context is perceived to positively impact the organization's performance if such implementation is supplemented by a better implementation process and organizational technology-acceptance abilities as well as employees' power of cognitive acceptance of a new system through their developed expertise (Massi et al., 2020).

Through extant research it transpires that efficacious B2B relationship management provides various benefits to organizations as it helps to increase productivity, reduce staff overload, ensure transparent audit trailing, and improve decision making (Zeng, Wen, & Yen, 2003). AI-CRM for B2B relationship management is considered helpful because the solution assists in data integration and management for fostering data-driven decision making for acquiring, developing, and retaining customers (Libai et al., 2020). For better data integration and management, AI-CRM consolidates data from multiple heterogeneous sources and applications to ensure availability of customer data in a single repository (Stein et al., 2013). In this way, AI-CRM enables effective storage of customer data for fast on-demand data retrieval and accurate predictive analysis using advanced AI techniques (Chatterjee, Ghosh, Chaudhuri, & Chaudhuri, 2020). However, effective implementation of all the standard features of an AI-CRM system is pivotal in the organizations. Moreover, the skills and abilities of the employees are also crucial in effectively using the AI-CRM system after implementation (Chatterjee, Ghosh, & Chaudhuri, 2020; Hart et al., 2004). It has been observed in different studies that different factors (such as automating routine tasks, recommendations, lead customization, virtual assistance, personalization services, and so on) are responsible for extracting the best potential of AI-CRM in organizations (King & Burgess, 2008; Ullah, Iqbal, & Shams, 2020). The extant literature also highlights that successful implementation of any technology in organizations can be best achieved by the active support of the top management, who are ready to motivate the employees to use the new system (Akkermans & Van Helden, 2002; Goodhue, Wixom, & Watson, 2002). While identifying the factors impacting the implementation of AI-CRM in a B2B context, we have adopted institutional theory (Oliver, 1997; Scott, 2008) that explains how different implementation of technologies, schemes, norms, and routines are created and diffused as well as adopted over time and space in organizations (Richard, 2004).

2.2. Resource-based view (RBV)

RBV is considered as a managerial framework used to determine the strategic resources essential for organizations to achieve competitive advantage (Barney, 1991; Wu, Yeniyurt, Kim, & Cavusgil, 2005). RBV emphasizes the resources of organizations for identifying abilities, assets, and competencies that would help to achieve competitive advantage by improving performance (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016; Wernerfelt, 1984). In the context of B2B relationship management, sources of competitive advantage start with the notion of the resources of different organizations working together, which may be immobile and heterogeneous (Barney, 1991). RBV theory mainly deals with the resource management abilities of organizations collaborating with each other in the B2B context (Kozlenkova, Samaha, & Palmatier, 2014).

The organizations' performance differs due to their distinctive capabilities and resource management abilities (Wernerfelt, 1984). RBV posits that organizations should best use their resources and exchange views to improve their B2B relationship (Galbreath, 2005). Exchange of views, expertise, and experience among employees of different organizations involved in B2B relationships will help to strengthen their relationship further (Crick & Crick, 2020). Effective implementation of the AI-CRM system and appropriate use will help to improve the B2B relationship (Chatterjee, 2019; Libai et al., 2020). It will also facilitate extracting the best potential from the technology used in organizations to impact organizations' performance (Ji-Fan Ren, Fosso Wamba, Akter, Dubey, & Childe, 2017; Mikalef, Boura, Lekakos, & Krogstie, 2019). In terms of RBV, the organizational performance and growth in the B2B context depends on the internal stock of resource mix that includes physical capital, human capital, and organization capital resources (Barney, 1991).

From the perspective of B2B relationship management, internal resources include the experience level of the employees, finance, information processing system capability, engineering, and production interface along with cross-functional product development (Auh & Menguc, 2009). However, in addition to the organization's internal resources and capabilities, researchers have empirically proved the importance of complementary external resources such as value chain network resources (Lavie, 2006) and external information (Moorman & Slotegraaf, 1999). These complementary external resources support the complete value chain and are acquired through networks of B2B relationships involving the inter-organizational vendors' alliances (Deeds & Hill, 1996). These organizations-specific resources are instrumental in impacting the performance of the organizations (Cainelli, De Marchi, & Grandinetti, 2015). Successful implementation of AI-CRM in organizations impacts organizational performance by fostering cooperation and collaboration in their inter-organizational relationships in the competitive environment (Chatterjee, Ghosh, Chaudhuri, & Chaudhuri, 2020; Josiassen, Assaf, & Cvelbar, 2014).

However, unless the employees of the organizations are given the proper training, it will be difficult to use the new system (Chatterjee, Ghosh, & Chaudhuri, 2020; Lawson-Body, Willoughby, Mukankusi, & Logossah, 2011). Moreover, this study supports the view that RBV can be used for explaining how different factors mediate in impacting organizational performance as a result of successful AI-CRM implementation. This view is justified because RBV deals with how organizations' resources help to sustain competitive advantage that triggers organizational performance (Kipley, Lewis, & Jeng, 2012). It appears that no extant literature could indicate how AI-CRM implementation could impact different factors of organizational performance to gain competitive advantage in the B2B context (Mikalef & Gupta, 2021; Pillai et al., 2021). The main objective of this study is to contribute to the growing body of literature in B2B relationship management. Therefore, based on the above discussion, this study integrates two well-established theories, such as institutional theory and RBV, to develop a conceptual model, as shown in Fig. 1.

2.3. AI and its capability in business organizations

In the four years prior to 2019, organizations using AI grew by 270% (Rowell-Jones & Howard, 2019). There is a lot of enthusiasm about the business values that AI can deliver. But organizations implementing AI face entangled challenges preventing them from realizing the performance gain (Fountaine, McCarthy, & Saleh, 2019; Hu, Lu, Pan, Gong, & Yang, 2021; Nishant, Kennedy, & Corbett, 2020). For instance, Ransbotham, Khodabandeh, Fehling, LaFountain, and Kiron's (2019) study among more than 2500 executives on their AI initiatives highlighted that significant challenges remain in AI implementation as 70% of organizations surveyed reported minimal or no impact from their AI investments. This minimal impact is due to implementational and restructuring lags (Gursoy, Chi, Lu, & Nunkoo, 2019; Mikalef & Gupta, 2021). Thus, organizations need to develop their complementary resources to be able to leverage their AI investment. If these are aptly done, AI can fuel creativity in organizations when integrated with CRM (Bag, Gupta, et al., 2021; Balakrishnan & Dwivedi, 2021; Borges, Laurindo, Spínola, Gonçalves, & Mattos, 2021) and support making swift intuitive decisions based on real-time data and data-driven predictions (Dwivedi et al., 2021; Grover, Kar, & Dwivedi, 2020). AI can handle massive datasets accurately for extending assistance to the professionals in performing repetitive work processes as well as creative tasks that include designing, engineering, and enhancing the input information to provide recommendations in complex situations (Mazzone & Elgammal, 2019). Various researchers have proposed eight resources that could constitute an AI capability (Chui & Malhotra, 2018; Mikalef & Gupta, 2021). These are classified into tangible resources (data, basic resources, technology), human resources (technological skills and business skills), and intangible resources (coordination, risk-taking ability, and organizational change capability).

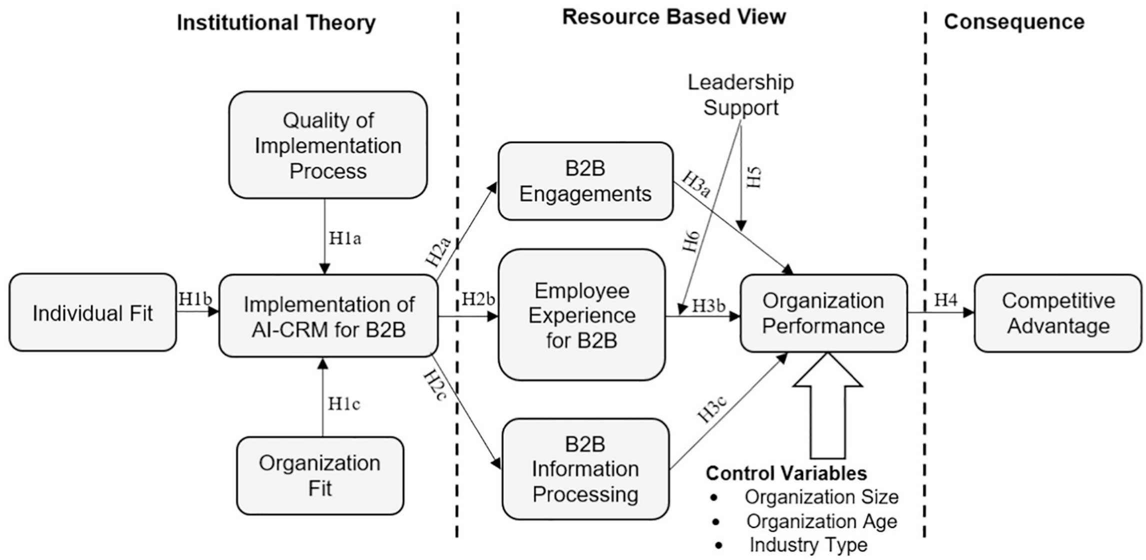

Fig. 1. Proposed conceptual model (Adapted from Barney (1991) and Currie (2008)).

2.4. Hypotheses development

2.4.1. Antecedents of AI-CRM implementation in B2B relationship management

The accounting and information systems model (A&IS model) revealed that the implementation process has established a relationship between the quality of the process of implementation and the extent of success of such implementation (Zand & Sorensen, 1975). The quality of the implementation process is determined by the effects of the intersection of users' and designers' characteristics, which is perceived to impact better implementational outcomes (Ginzberg, 1980). It leads to the formulation of the following hypothesis:

H1a. The quality of the implementation process impacts significantly and positively the outcomes of the implementation of AI-CRM for B2B context in organizations.

Besides, the theoretical evidence highlights that users' characteristics and system characteristics determine the individual capacity to influence the implementation of a new system in an organization (Ginzberg, 1980). The previous research has found a consistent link between individual fit as well as outcomes of the implementation of a new system in organizations (McKenney & Keen, 1974). The individual capacity, otherwise known as the individual fit, is often defined in the context of skills, attitudes, and abilities of the employees in the organizations (Nadler & Tushman, 1977). These discussions lead us to hypothesize H1b as follows:

H1b. Employees' individual fit significantly and positively impacts the outcomes of the implementation of AI-CRM for B2B context in the organizations.

The organization's existing technological competence, which is also known as organization fit, is determined by the intersection of system characteristics and organizational characteristics, as is found from the study of the A&IS model (Ginzberg, 1980). The organization fit is also conceptualized by the four major components of organizations in the context of the implementation of a new technology. The components are its structure, task, the technology it employs, and its people (Leavitt, 1964). Nadler and Tushman (1977) added another component, i.e. organizational environment, to it. These discussions lead to the perception that organization fit helps to achieve better outcomes by the implementation of a new system in organizations. This leads to the following hypothesis:

H1c. Organization fit significantly and positively impacts the outcomes of the implementation of AI-CRM for B2B context in the organizations.

2.4.2. Descendants of AI-CRM implementation in a B2B context

Information is shared with the help of collaborative CRM in organizations. Collaborative CRM is defined as “a software that allows real-time access to information about a company, its suppliers, its development and any other information offered to the third parties interested in contracting products or services from that company” (Saura et al., 2019, p.471). However, in the B2B context, such collaborative CRM processes information is large in volume and complex in nature (Stein et al., 2013). It is difficult to manage such a huge volume of information manually. For this, AI comes to the rescue (Chatterjee, 2019). Thus, by the implementation of AI-CRM in a B2B context, it is possible to share a large amount of information among the different organizations in an automated manner. It has already been discussed how institutional factors such as quality, organization, and individual abilities impact the outcomes of AI-CRM implementation. Institutional theory posits that organizations never attain a state of pure stability but always enjoy incremental or discontinuous changes (Scott, 2008). In line with these arguments, migration from legacy CRM to AI-CRM is construed as an incremental change supplementing the concept of institutional theory.

If the implementation of AI-CRM is successful, organizations can improve their B2B engagement process. Mainly, the B2B engagement process is the connections and transactional interactions between the various organizations involved in B2B activities (Nyadzayo, Casidy, & Thaichon, 2020). The quality of processing better and effective B2B engagement is considered as an external resource as envisaged by the RBV theory (Barney, 1991; Wu et al., 2005). B2B engagement strategy is a concept where the organizations are trying to develop a long-term strategic B2B relationship with the customers by delivering more value (Lacka et al., 2020; Mikalef, Pappas, Lekakos, & Krogstie, 2020). These insights from the literature help in construing that a successful implementation of AI-CRM technology in B2B context will considerably improve the B2B engagement process. This discussions leads to the formulation of the following hypothesis:

H2a. Implementation of AI-CRM for B2B relationship management significantly and positively impacts the B2B engagements.

Employees working in an organization in developing B2B relationships often use different tools to know their customers and initiate long-term relationships with employees of other organizations to ensure a higher degree of mutual cooperation and collaboration (Ford, 1990; Lindgreen, Palmer, Vanhamme, & Wouters, 2006; Sheth & Parvatiyar, 2000; Spekman & Carraway, 2006). However, if the tools do not work effectively, that is, in the present context, if the implementation of an AI-CRM system in B2B relationship management does not work successfully, it will not be possible for the employees to develop any new relationship with employees of other organizations effectively, nor they will be able to efficiently maintain their existing B2B relationships (Lacka et al., 2020). Thus, if the implementation of a new CRM technology is successful, the employees will be able to use the system appropriately to develop a long-term relationship in the B2B context, and their experience in managing a B2B relationship effectively will be improved. This argument leads to the following hypothesis:

H2b. Implementation of AI-CRM for B2B relationship management will significantly and positively improve the employee experience for B2B relationship management.

Business firms need *facilitating capabilities* to maintain collaborative B2B relationships as shifting B2B relationships from competition to collaboration is hindered by information asymmetry (Spekman & Carraway, 2006). IT-based applications and tools come under these *facilitating capabilities*, which are also known as competencies of the firm. To sustain a relationship in a B2B environment, employees are found to use different tools for improving relationships with the employees of other organizations. These tools can be advanced by an AI-CRM system that can process voluminous information efficiently (Chatterjee, 2019; Chatterjee, Ghosh, Chaudhuri, & Chaudhuri, 2020). If these tools are found to not work efficiently, it becomes difficult for the organizations to maintain a proper business relationship with the other organizations. Consequently, B2B relationships are hampered (Demlehner, Schoemer, & Laumer, 2021; Dubey et al., 2020). Appropriate implementation of an AI-CRM system for managing a B2B relationship is perceived to improve B2B information processing systems (Lacka et al., 2020). Accordingly, it is hypothesized as follows:

H2c. Implementation of AI-CRM for B2B relationship management will significantly and positively improve the B2B information processing system.

2.4.3. RBV and organization performance

The organizational resources impacting performance also include the information processing systems apart from the extent of B2B engagement of the involved organizations through their employees as well as extent of experience gained by the employees (Auh & Menguc, 2009). In the B2B context, RBV theory posits that performance of organizations depends on resource-mix and these resources may be classified as physical capital, human capital, and organization capital resources (Barney, 1991). However, from the perspective of B2B relationships, internal resources are considered as experience level of the employees, information processing system ability, and so on (Auh & Menguc, 2009; Duan, Edwards, & Dwivedi, 2019; Pillai, Sivathanu, & Dwivedi, 2020). The complementary external resources acquired through networks of B2B relationships are related to the value chain enabled by the alliances of the suppliers and vendors offering organization-specific external resources, which also impact performance of the organizations (Cainelli et al., 2015; Deeds & Hill, 1996). Hence, effective B2B engagement abilities, experience level of the employees, and effective information processing systems are perceived to have considerable impact on the overall performance of the organizations. With all these discussions, the following hypothesis is proposed:

H3a. Effective B2B engagement leads to an improved organization's performance.

Sharing of experience among the employees of various organizations involved in a B2B relationship will help the involved organizations to effectively extract the best potential from an AI-CRM system (Lin, Yip, Ho, & Sambasivan, 2020). In the context of B2B relationship management, the experience level of the employees comes under the category of internal resource of the organizations (Auh & Menguc, 2009). The sharing of experience of employees of different organizations involved in B2B relationship management can be further improved by successfully and effectively implementing AI-CRM systems in the organizations. This will also ensure better performance gain of the organizations (Mikalef et al., 2019). Accordingly, it is hypothesized as follows:

H3b. A higher level of employee experience in B2B relationship management leads to improved organization performance.

A process is considered as a unique combination of materials, tasks, people, and methods that results in an assessable outcome. An information processing system in the B2B context provides critical information (Auh & Menguc, 2009). For the output of a specific process, an information processing system provides a calibrated measure of variability, and it also helps to detect the specific problem areas that impede the information flow among the organizations involved in B2B relationship management (Akter et al., 2016; Farrokhi et al., 2020). Organizations implementing an AI-CRM system are perceived to improve their B2B relationship management performance provided the organizations' information processing systems function properly (Dwivedi, Hughes, et al., 2021; Zhang et al., 2021). The above discussion leads to the formulation of the following hypothesis:

H3c. B2B information processing capability positively influences organization performance.

2.4.4. Organization performance and competitive advantage

The organization performance is measured by the assessment of net outcomes the organizations derive. These outcomes include consideration of financial and marketing aspects, market share, return on investment, and sales growth along with net profit (Kreye & Perunovic, 2020). Moreover, satisfaction level is also considered as an effective measure of organization performance (Keramati, Mehrabi, & Mojir, 2010). Organization performance is also assessed in terms of how an organization can successfully achieve its goal (Li, Ragu-Nathan, Ragu-Nathan, & Rao, 2006). Besides, performance of organizations working in a B2B context is also associated with subjective measure on how the organizations involved together could effectively manage their successful B2B relationship (Sin, Tse, & Yim, 2005). As already stated, RBV theory helps to identify the predictor of organizational performance, which depends on how the organizations could acquire valuable, inimitable, rare, and non-substitutable (VIRN) information. These abilities are perceived to influence the competitive advantage of the organizations. By achieving these, the organizations are perceived to gain competitive advantage over other existing contemporary organizations functioning in the market. Competitive advantage is the degree to which the performance of an organization working in the B2B context could achieve greater benefits compared to other organizations functioning in similar conditions (Rogers, 1983, 1985). The above discussion leads to the formulation of the following hypothesis:

H4. Organization performance significantly and positively impacts the organization's competitive advantages.

2.4.5. Moderating effects of leadership support

Donate and Guadamillas (2011) observed that the support of the top management in any organization working in a B2B context helps to stimulate the employees in one organization to share knowledge and any other essential information with the employees in the other organization. This sharing of knowledge develops a strong B2B relationship, which further influences the performance of organizations (Gupta, Drave, Dwivedi, Baabdullah, & Ismagilova, 2019). Besides, support of the top management of their subordinates is perceived to influence new idea generation practices and development of their experience regarding usage of a new technology that eventually impacts organizational performance (Kreye & Perunovic, 2020). The above discussion leads to the formulation of the following hypotheses:

H5. Leadership support moderates the relationship between B2B engagement and organization performance.

H6. Leadership support moderates the relationship between employees' experience for B2B relationship management and organizational performance.

In this study, we have considered organization size, organization age, and organization type as control variables for organization performance.

3. Research methodology

This section will delineate the research strategy used. This study employed quantitative research methodology and collected data by means of a survey (Wang & Jeong, 2018).

3.1. Sample and data collection

This study randomly selected 39 manufacturing and service organizations from Bombay Stock Exchange (Mumbai, India) for data collection. On contact with the top executives of the 39 organizations through emails and telephone calls, it was learnt that out of these 39 organizations, only 27 organizations are known to be functioning in B2B relationship management using AI-CRM or contemplating implementing an AI-CRM system for B2B relationship management soon. The top executives of these 27 organizations were requested more than once through telephone calls and emails to allow their different managers to participate in the survey. The attempts to target the prospective respondents for the survey were not encouraging as most of the executives were found to be reluctant to cooperate even though they were made aware that the survey would be done for purely academic purposes, with strict anonymity and confidentiality regarding the participants. With such persuasion, eventually top executives of 16 organizations allowed their managers to participate in the survey. Only those managers of different hierarchy were contacted who were directly involved in the context of B2B relationship development. Through this approach, initially 709 managers were selected from these 16 organizations. All these 709 managers were provided with the response sheets along with other documents. They were requested to respond within 60 days from the date of receipt of the communication made through emails. In the intermediate period, all of them were persuaded to expedite the replies within the stipulated time. Eventually, 366 replies were obtained within the time with a response rate of 51.6%. These 366 responses were scrutinized. It was observed that out of 366 replies, 17 replies were incomplete and hence were removed from the overall responses. Partial least squares structural equation modelling (PLS-SEM) analysis was undertaken for 349 responses for a total of 36 questions. This is within the allowable range (Deb & David, 2014). Respondents' demographic statistics are shown in Table 1.

Table 1
Demographic statistics ($N = 349$).

Particulars	Nature of organizations	No. of units	Percentage (%)
Organization Size	< 1000 employees	96	27.50
	1000–10,000 employees	115	32.95
	> 10,000 employees	138	39.55
Organization Age	< 10 years	54	15.49
	10–25 years	181	51.86
	> 25 years	114	32.65
Industry Type	Manufacturing	11	68.75
	Service	5	31.25
Profile of Employees	Senior manager	90	25.79
	Midlevel manager	162	46.42
	Junior manager	97	27.79

3.2. Measures

Considering the nine constructs used in the proposed research model, 36 questions were inherited from the originating studies. The questions were prepared keeping in mind the AI-CRM in a B2B context to ensure that they conform to the notion and attitude of the targeted respondents (Mellahi & Harris, 2016). The opinion of five experts having experience in the domain of AI-CRM in a B2B context was sought towards enhancement of the comprehensiveness and readability of the instruments. The response sheet contained five options where each respondent was scheduled to select one option out of five for each question. The options were '1 = Strongly Disagree' to '5 = Strongly Agree'. The questions were validated using 31 managers at different levels of organizations where either AI-CRM has been implemented or the organizations were contemplating the implementation of AI-CRM. A pre-test was conducted to improve the accuracy and understanding of questions. The response sheet provided guidelines to the respondents on how to answer the survey questions. The respondents were assured anonymity and confidentiality as the aim of this study is purely academic. The refinement process involved improving readability of the questions for better understanding without compromising their uniqueness compared with the originating studies (Chidlow, Ghauri, Yeniyurt, & Cavusgil, 2015). The items for constructs along with their respective source(s) are provided in Appendix 1.

4. Data analysis and results

This study employed the PLS-SEM technique for data analysis as this technique does not require any sample restriction and allows the analysis of data that are not normally distributed (Akter, Fosso Wamba, & Dewan, 2017; Willaby, Costa, Burns, MacCann, & Roberts, 2015).

4.1. Measurement properties and discriminant validity test

Researchers verified measurement model through confirmatory factor analysis (CFA) test by examining convergent and discriminant validity of constructs (Akter et al., 2017). In line with Anderson and Gerbing (1988), three ad hoc tests such as standardized factor loadings (FL), composite reliabilities (CR) (Cho, 2016), and average variance extracted (AVE) (Fornell & Larcker, 1981) were employed to measure the convergent validity of constructs (Tamilmani, Rana, Nunkoo, Raghavan, & Dwivedi, 2020). The standardized FL values, which measure the level of association among measurement items and a single latent variable, ranged from 0.84 (BIP1) to 0.96 (EEB1, COA2), much higher than the cut-off value of 0.50 (Gefen, Karahanna, & Straub, 2003). Meanwhile, the composite reliability, an indicator similar to Cronbach's alpha (**α**) (Cronbach & Shavelson, 2004) that measures internal consistency of the latent constructs, yielded values above the threshold of 0.70 (Hair, Anderson, Tatham, & Black, 1992; Nunnally, 1978). Finally, AVE values, which is a measure of variation explained by the latent variable to random measurement error, ranged from 0.81 for quality of implementation process (QIP) to 0.89 for B2B engagements (BE). These estimates of AVE are relatively higher than the stipulated lower limit of 0.50 (Fornell & Larcker, 1981) (see Table 2). Regarding the significant values above the prescribed threshold for all the parameters according to Anderson and Gerbing (1988), three tests confirms a high convergent validity of all measurement scales and their respective latent construct.

On further assessment, it was found that the square root of all the AVEs of the constructs are greater than the bi-factor correlation coefficients. Latent variables qualify discriminant validity test, when the factor correlation among a pair of latent variables is always less than the square root of AVE of each variable in the factor correlation matrix (Fornell & Larcker, 1981). Evaluation of discriminant validity as depicted in Table 3 reveals that square root of AVE shown in bold fonts across the diagonal is always greater than the correlation value for any

Table 2
Measurement properties.

Construct|Items	LF	AVE	t-value	CR	α	No. of items
QIP		0.79		0.81	0.84	5
QIP1	0.90		29.14			
QIP2	0.95		26.12			
QIP3	0.85		38.01			
QIP4	0.85		37.77			
QIP5	0.90		22.42			
IF		0.83		0.85	0.87	3
IF1	0.94		21.21			
IF2	0.92		26.17			
IF3	0.87		29.09			
OF		0.82		0.84	0.86	4
OF1	0.88		31.47			
OF2	0.93		32.49			
OF3	0.94		37.11			
OF4	0.86		19.12			
IAB		0.81		0.83	0.85	5
IAB1	0.87		32.74			
IAB2	0.89		19.17			
IAB3	0.90		29.06			
IAB4	0.95		33.44			
IAB5	0.90		32.11			
BE		0.87		0.89	0.92	3
BE1	0.95		33.06			
BE2	0.95		37.17			
BE3	0.90		28.19			
EEB		0.84		0.87	0.89	4
EEB1	0.96		31.77			
EEB2	0.94		37.14			
EEB3	0.87		29.17			
EEB4	0.89		33.01			
BIP		0.81		0.83	0.85	5
BIP1	0.84		32.46			
BIP2	0.86		33.11			
BIP3	0.89		39.04			
BIP4	0.96		19.91			
BIP5	0.95		27.66			
OP		0.83		0.85	0.87	4
OP1	0.90		26.65			
OP2	0.94		29.11			
OP3	0.95		20.21			
OP4	0.85		32.77			
COA		0.82		0.84	0.86	3
COA1	0.85		24.11			
COA2	0.96		26.17			
COA3	0.90		32.06			

pair of variables. Therefore, the proposed research model satisfies the discriminant validity condition for all latent variables (Smith & Barclay, 1997). By another process, discriminant validity has been tested by computing loadings and cross-loadings wherein it has been observed that the values of all the cross-loadings are less than the values of the corresponding loadings. These results are provided in Appendix 2.

4.2. Common method variance (CMV)

This research followed the guidelines of Hair, Hult, Ringle, and Sarstedt (2017), Henseler, Hubona, and Ray (2016), Hulland, Baumgartner, and Smith (2018), and Hossain, Akter, Kattiyapornpong, and Dwivedi (2020) for research design and statistical procedure. Firstly, a psychological separation between the criterion variables with their corresponding predictors was ensured to establish causality. Secondly, to gather unbiased responses, the respondents were assured that their anonymity and confidentiality will be strictly preserved as a pre-emptive measure. Finally, during the pre-test phase of instrument preparation, wordings and format were revised for reduction of social desirability bias. Moreover, the marker variable technique (Lindell & Whitney, 2001; Williams, Hartman, & Cavazotte, 2010) was applied to check the CMV validity. The results indicated that there exists a difference between the original CMV with the adjusted (marker based) CMV (0.019) ($\leq$0.06) in respect of all the concerned constructs (Hossain et al., 2020; Lindell & Whitney, 2001; Mishra, Maheswarappa, Maity, & Samu, 2018). Therefore, CMV does not distort the prediction of this study.

4.3. Moderation analysis through multi group analysis (MGA)

For scrutinizing the significance of the effects of the moderator leadership support (LS) on the two linkages H3a and H3b, MGA has been conducted by considering bias correlated and accelerated bootstrapping with 5000 resamples. The effects of the moderator LS on H3a and on H3b have been analysed by categorizing LS into strong LS and weak LS. The analysis highlighted that the concerned *p*-value differences for strong LS and weak LS on H3a and on H3b are respectively 0.03 and 0.01, both of which are less than 0.05 (Hair Jr, Hult, Ringle, & Sarstedt, 2016). This confirms that the effects of LS on H3a and on H3b are significant.

4.4. Assessment of the model by SEM

For hypotheses testing and validating the conceptual model, the PLS-SEM technique is preferred because this technology can effectively analyse an exploratory study (Hair, Sarstedt, Ringle, & Gudergan, 2018; Hair, Risher, Sarstedt, & Ringle, 2019). Besides, this technique does not impose any sample restriction while conducting a survey (Hossain et al., 2020; Willaby et al., 2015). This technique involves quantification of the replies of usable respondents while conducting the survey. In this study, this quantification of replies has been made by using a 5-point Likert scale. A survey requires the framing of a set of questions (research instruments) in the form of statements.

For examining the model, a blindfolding process has been adopted. For this, accelerated as well as bias correlated bootstrapping procedure with consideration of 5000 resamples was undertaken. To achieve this, omission separation of ‘5’ was considered for obtaining estimation of cross-validated redundancy concerning the corresponding constructs.

Table 3
Discriminant validity test.

Construct	QIP	IF	OF	IAB	BE	EEB	BIP	OP	COA
QIP	**0.89**								
IF	0.16	**0.91**							
OF	0.12	0.17	**0.90**						
IAB	0.22	0.21**	0.32	**0.90**					
BE	0.31	0.23	0.21	0.26	**0.93**				
EEB	0.19	0.26	0.17	0.24	0.19	**0.92**			
BIP	0.26	0.19	0.33***	0.22	0.21	0.17**	**0.90**		
OP	0.24	0.21	0.18	0.21*	0.28	0.30	0.33	**0.91**	
COA	0.12*	0.31	0.21	0.23	0.29	0.32	0.36*	0.31	**0.90**

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Stone-Geisser Q^2 value was found to be 0.66 (Geisser, 1975; Stone, 1974) confirming that the results possess predictive relevance. For assessing the model fit, recommendations envisaged by Henseler, Ringle, and Sarstedt (2014) have been followed. SRMR (standard root mean square residual) has been taken as a standard index. On analysis, the results of SRMR came out to be 0.061 for PLS and 0.032 for PLSc, both of which are less than 0.08 (Hu & Bentler, 1998). This led to the conclusion that the model is in order. Through this process, the values of path-coefficients for different linkages, probability (p) values, and R^2 values could also be assessed. The model after validation is shown in Fig. 2.

The estimations of path-coefficients, *p*-values, and R^2 values are presented in Table 4.

4.5. Results

This study has presented 12 hypotheses including two hypotheses covering the effects of leadership support as a moderator on the two linkages H3a and H3b. The hypotheses have been statistically validated with the help of PLS-SEM approach. It has been observed that all the hypotheses have been supported. The study highlights that out of impacts of QIP on IAB (H1a), IF on IAB (H1b), and OF on IAB (H1c), the impact of QIP on IAB (H1a) is the strongest since the concerned path coefficient is 0.41 with level of significance $p < 0.01$. Besides, the impacts of these three institutional factors on IAB from the institutional theory have received support as already mentioned. Moreover, among the influences of IAB on BE (H2a), IAB on EEB (H2b), and IAB on BIP (H2c), the causal relationship between IAB and BIP (H2c) is the maximum as the concerned path coefficient is 0.57 at the level of significance $p < 0.001$. The mediating variables BE, EEB, and BIP have influence on OP (H3a, H3b, H3c) in conformity with RBV theory as presented in Table 4. Among these three relationships covering H3a, H3b, and H3c, the impact of BIP on OP (H3c) is the strongest as the concerned path coefficient is 0.61 with the level of significance $p < 0.001$. The influence of OP on COA (H4) is significant as the concerned path coefficient is 0.59 with level of significance $p < 0.001$. The moderating effects of LS on the relationships represented by hypotheses H3a and H3b are found to be significant as appears from the values of the respective path coefficients. This has also received support from MGA. In terms of the values of R^2, it is seen that QIP, IF, and OF could explain IAB to the extent of 47% whereas BE, EEB, and BIP explain OP to the tune of 69%. Moreover, the COA is explained by OP to the tune of 76%, which is the overall predictive power of the model. This study has shown that impacts of IAB on OP considering effects of the three mediating variables and the effects of the moderator LS yielded better results compared to the direct impact of IAB on OP. This has been shown through discussions of a rival model provided in Appendix 3.

Table 4
Path coefficients, p-values, and R^2.

Linkages	H No.	Path coefficients/R^2	p-values	Remarks
Effects on IAB		$R^2 = 0.47$		
By QIP	H1a	0.41	**($p < 0.01$)	Supported
By IF	H1b	0.27	*($p < 0.05$)	Supported
By OF	H1c	0.32	*($p < 0.05$)	Supported
Effects on BE		$R^2 = 0.26$		
By IAB	H2a	0.47	***($p < 0.001$)	Supported
Effects on EEB		$R^2 = 0.32$		
By IAB	H2b	0.52	***($p < 0.001$)	Supported
Effects on BIP		$R^2 = 0.47$		
By IAB	H2c	0.57	***($p < 0.001$)	Supported
Effects on OP		$R^2 = 0.69$		
By BE	H3a	0.49	***($p < 0.001$)	Supported
By EEB	H3b	0.53	***($p < 0.001$)	Supported
By BIP	H3c	0.61	***($p < 0.001$)	Supported
Effects on COA		$R^2 = 0.76$		
By OP	H4	0.59	***($p < 0.001$)	Supported
Effects of LS				
On BE → OP	H5	0.21	*($p < 0.05$)	Supported
On EEB → OP	H6	0.32	*($p < 0.05$)	Supported

Now, we shall discuss the effects of the moderator LS (strong LS and weak LS) on the two linkages H3a and H3b graphically. In Fig. 3, the effects of strong LS and weak LS on the linkage H3a are shown graphically. The continuous line and the dotted line represent the effects of

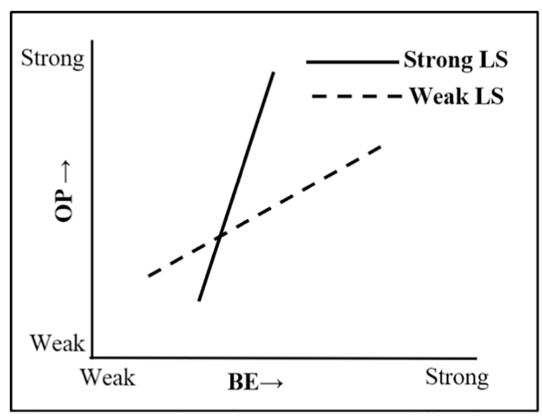

Fig. 3. Effects of LS on H3a.

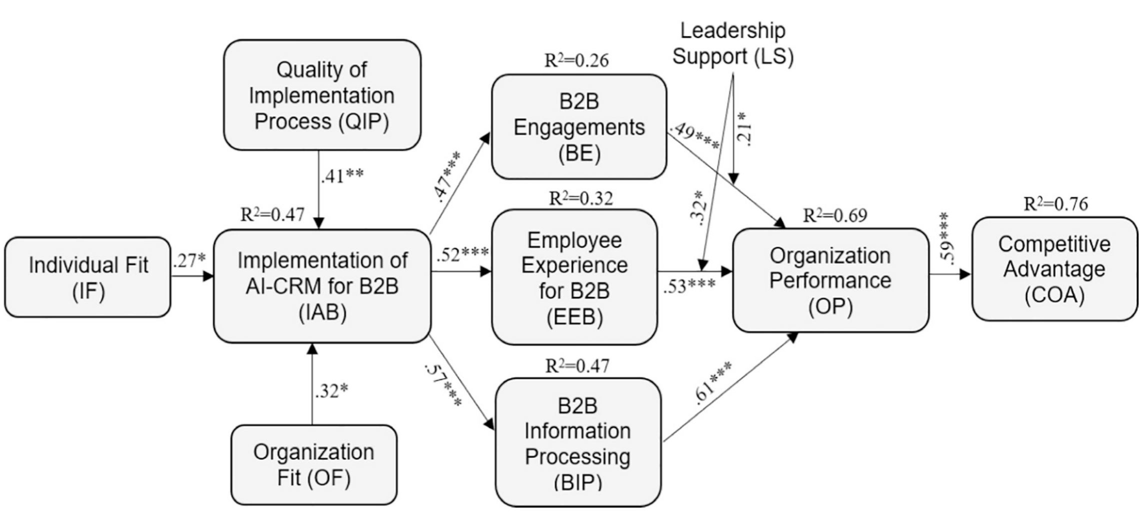

Fig. 2. Validated research model.

strong LS and weak LS respectively. With increase of BE, the rate of increase of OP is more for the effects of strong LS compared to the effects of weak LS on the linkage represented by H3a as the gradient of the continuous line is greater than the gradient of the dotted line.

In Fig. 4, the effects of the moderator LS (i.e. strong LS and weak LS) on the linkage represented by H3b are represented graphically. The continuous line and dotted line represent the effects of strong LS and weak LS on H3b respectively. From the graph, it is clearly evident that with the increase of EEB, the rate of increase of OP is more for the effects of strong LS compared to the effects of weak LS since the gradient of the continuous line is more than the gradient of the dotted line. Both the results support the MGA undertaken earlier in this study.

5. Discussion

This study assessed the impact of AI-CRM on B2B organizational performance and their competitive advantage by employing two well-established theories: RBV and institutional theory, as theoretical lens. The results revealed quality of AI-CRM implementation process as the strongest determinant of overall AI-CRM implementation in B2B organizations (H1a). This result is in conformity with other studies (Pillai et al., 2021; Syam et al., 2018). In addition, employees' skill, attitude, and ability, known as individual fit (Nadler & Tashman, 1977), had a positive impact on the outcomes of AI-CRM application for B2B relationship management (H1b). This underscores the importance of quality of implementation process and employees' abilities impact on the outcomes of AI-CRM implementation in the B2B context. These findings are in line with research by Bag et al. (2021a) that highlighted that AI integration supports knowledge creation in organizations, facilitating rational decision making in the B2B marketing context, which ultimately improves firm performance. Moreover, organization fit, comprising organizations' structure, task, technology employed, and people concerned, impact positively on AI-CRM in the B2B context (H1c) (Dubey et al., 2020).

This study has also shown that successful implementation of AI-CRM will considerably improve the B2B engagement process (H2a). Mikalef and Gupta (2021) also found similar results, that the ability of AI could improve the creative capabilities of the organization, which eventually impacts performance (Mikalef et al., 2020). It has been highlighted in this study that employee experience and the information processing system in the B2B context are improved by implementation of effective AI-CRM (H2b and H2c), which has received support from other studies (Lacka et al., 2020; Pillai et al., 2020). From this study, it is seen that organizational performance is improved by the quality of B2B engagements, employee experience, and the information processing system (H3a, H3b, and H3c), which has been supplemented by several other studies (e.g. Auh & Menguc, 2019; Duan et al., 2019; Pillai et al., 2021). This study has revealed that organizational performance positively

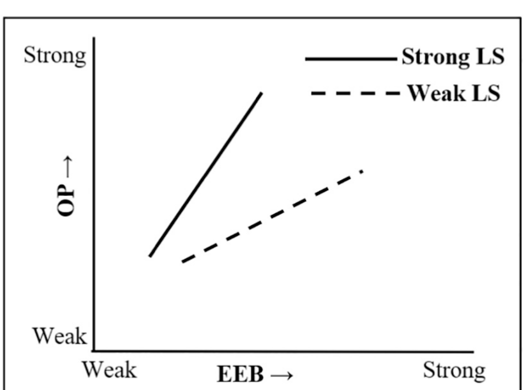

Fig. 4. Effects of LS on H3b.

impacts the competitive advantage of the organizations (H4). This hypothesis, H4, is also supported by some prior studies (Kreye & Perumovic, 2020; Shyam & Sharma, 2018; Zhang et al., 2021). These studies highlighted that AI and machine learning (ML) would help the organizations to increase their sales, which will provide them impetus to be able to compete with their counterparts in the hypersensitive market. Finally, our study has shown that for exhibiting better performance, leadership support has a major moderating effect on the firm performance in the B2B context using an AI-CRM system (Gupta et al., 2019; Mikalef & Gupta, 2021).

5.1. Theoretical contributions

This study has provided several theoretical contributions. In this context, it is pertinent to mention that numerous benefits are provided by the RBV to organizations to contribute to their marketing theory and practice. However, RBV is found to be lacking in explaining how institutional factors such as norms, implementational process quality, individuals'/employees' capabilities and expertise, organizational overall abilities and know how, legitimacy, and societal as well as environmental demands impact organization performance (Auh & Menguc, 2009). Thus, to interpret the organizational performance from every aspect, it is essential to integrate RBV and institutional theory.

At this juncture and in the light of this argument, this study has combined institutional theory and RBV to integrate how different factors could impact implementation of AI-CRM in a B2B context and how such implementation could eventually improve competitive advantage predicted by an organization's performance working in the B2B context. By such presumption, the theoretical model has been proposed, and it could achieve a high predictive power (76%). By integrating institutional theory and RBV, this study could simultaneously consider normative and economic rationality in decision making, scientifically analyse the acceptability and availability of resources, and effectively legitimize and optimize resource choice.

There are studies where institutional theory was used in a B2B context relating to the improvement of co-creation activities (Massi et al., 2020). However, this theory has been used for ensuring safety of shipping companies' adoption of IT (Glave, Joerss, & Saxon, 2014; Lebbadi et al., 2015). AI and its implications for developing marketing knowledge in a B2B context have also been explained by institutional theory in another study (Paschen et al., 2019). But no studies have used institutional theory to interpret the institutional factors impacting implementation of AI-CRM in B2B relationship management. Wu et al. (2005) used RBV theory to explain supply chain management in organizations. This idea has been adapted in the current research, and this has been extended further into how B2B engagement, experience of employees, and implementational processing could manage to best use the internal and external resources of the organizations working in a B2B context.

This study mainly deals with implementation and adoption of AI-CRM in the B2B context in organizations. Rather than using standard technology adoption models, this research has integrated institutional theory and the RBV with context-specific determinants yielding high predictive power. Moreover, this study has analysed a rival model considering direct impacts of IAB on OP and has shown that the proposed research model considering the effects of three mediating variables and a moderator LS is more efficient than the alternative rival model. This concept has provided a distinctive contribution to the extant literature. Several studies highlighted that lack of adequate knowledge of leadership of organizations as to how and where to apply AI technology has created impediments to realizing the potential application areas of AI that could improve B2B relationships (Farrokhi et al., 2020; Fountaine et al., 2018; Ransbotham et al., 2018;). Hence, the leadership should be acquainted properly with the potential usage of AI-CRM to improve B2B relationships. In this context, it is to be noted that the support of the leadership would be helpful for improving B2B relationships in the context of AI-CRM applications. From such a perspective, this study has considered the moderating effects of leadership support that help the organizations to capture the opportunities of AI-CRM to improve B2B relationships for better performance gain.

5.2. Implications for practice

This study has highlighted how CRM integrated with AI in the context of B2B relationship management could improve organization performance. Integration of AI with CRM for analysing the available data from internal and external sources is an effective way to improve organization performance. This study has highlighted that AI-CRM implementation is expected to enhance the relationship among the collaborative organizations. The study also reveals that implementation of AI-CRM in a B2B context eventually improves organization performance, triggering competitive advantage. Hence, the organizations' top management needs to allocate sufficient funds to support integration of CRM with AI.

The study reveals that close collaboration enhancing B2B engagement, experience of the employees, and the information processing system impact organization performance, being prompted indirectly by effective AI-CRM implementation. As such, an organization's top management needs to ensure proper training is delivered to their employees involved in B2B relationship management so that the employees' engagement with AI-CRM usage may be increased and their experience is developed to motivate them to use the new system. Besides, managers need to be careful to ensure that the system developers and designers develop the system in such a way that the information processing takes place smoothly. This study has shown that leadership support moderates the impact of organization performance, which implies that an organization's top management working in a B2B context should actively help the employees to acquire sufficient knowledge to use AI-CRM in an effective way.

The organization's leadership needs to be in contact with employees to listen to their difficulties in using the system and to help them to improve their individual capabilities and enhance their expertise. The top management should also focus their attention on the fact that the organization's overall competencies are improved to sustain the new system.

5.3. Limitations and future research directions

Like any other studies, this research also has some limitations. The results of this study have been obtained by analysing the replies of respondents from India. Hence, the results may be considered not to necessarily reflect what is happening internationally. This point may be investigated by future researchers. Again, analysis has been carried out considering the responses of 349 usable respondents. It cannot portray a general representation. Our study has considered different features of organizations such as organization size, age, and type that impact organization performance. However, the analysis would have been better had this study considered other features of organizations such as financial status, corporate culture, and risk-taking capability. Future researchers may investigate this issue. The results of our study depend on the analysis of replies of managers of manufacturing and service organizations. Consideration of other types of organizations might have yielded more generalized results. The predictive power of the proposed model is 78%. Future research may consider other boundary conditions such as risk-related issues to examine if such considerations may strengthen the proposed model.

6. Conclusion

This study integrated institutional theory and the RBV and developed a model showing how successful implementation of AI-CRM in B2B relationship management could impact organizations' performance and ultimately their competitive advantage. The proposed model is observed to have possessed high internal consistency and reliability, having better predictive power. Identification of institutional factors impacting effective implementation of AI-CRM in organizations in a B2B context supported by institutional theory has provided better impetus towards pedagogical as well as instructional usage of AI-CRM. This study has been able to successfully extract the outputs of RBV theory highlighting essentialities of absorption of VIRN data by the organizations to facilitate achieving better organization performance to trigger competitive advantage. This study is expected to offer values to the organizations' top management to ensure competitive advantage prompted by successful organization performance.

Appendix A. Research instrument

Item	Source	Statements	Response [SD][D][N][A][SA]
QIP1	Ginzberg, 1980; Marquis et al., 2016; Massi et al., 2020; Scott, 1995; Wallin & Fuglsang, 2017; Zand & Sorensen, 1975	Quality is important for implementation of AI_CRM solution for B2B relationship management.	[1][2][3][4][5]
QIP2		Regular testing of the AI-CRM system is important to examine its appropriateness.	[1][2][3][4][5]
QIP3		Quality AI-CRM implementation for B2B relationship management helps improving the satisfaction level of employees.	[1][2][3][4][5]
QIP4		Incremental improvement of the AI-CRM is essential to enhance its features and functionalities.	[1][2][3][4][5]
QIP5		Quality implementation of AI-CRM is essential to extract its full potentials.	[1][2][3][4][5]
IF1	Ginzberg, 1980; McKenney & Keen, 1974; Nadler & Tushman, 1977;	Employees need to be trained appropriately on AI-CRM functionalities.	[1][2][3][4][5]
IF2		Individual should have the appropriate learning attitude.	[1][2][3][4][5]
IF3		Individual needs to demonstrate the willingness to adopt AI-CRM technology for B2B relationship management.	[1][2][3][4][5]
OF1	Ginzberg, 1980; Leavitt, 1964; Nadler & Tushman, 1977	Organization should have appropriate strategy in place to fit AI-CRM for B2B relationship management.	[1][2][3][4][5]
OF2		Organization must have appropriate data set for effective implementation of AI-CRM for B2B relationship management.	[1][2][3][4][5]
OF3		The organizations should be able to fit AI-CRM into its overall technology eco-system.	[1][2][3][4][5]
OF4		Organization should follow a pilot approach to implement AI-CRM which would help to know if the system is really fit for the organization.	[1][2][3][4][5]
IAB1	Barney, 1991; Chatterjee et al., 2019a; Johnston & Cortez, 2018; Lacka et al., 2020; Saura et al., 2019; Scott, 2008; Wu et al., 2005	Adequate investment and resources are required to successfully implement AI-CRM for B2B relationship management.	[1][2][3][4][5]
IAB2		Implementing AI-CRM required appropriate planning.	[1][2][3][4][5]

(continued on next page)

(*continued*)

Item	Source	Statements	Response [SD][D][N][A][SA]
IAB3		I believe that employees are more satisfied post AI-CRM implementation in our firm.	[1][2][3][4][5]
IAB4		I think that Information processing is much faster post AI-CRM implementation.	[1][2][3][4][5]
IAB5		AI-CRM has helped improving the B2B engagement process in our organization.	[1][2][3][4][5]
BE1	Auh & Menguc, 2009; Barney, 1991; Lin et al., 2020; Cortez & Johnston, 2019; Wernerfelt, 1984	AI CRM provides effective recommendations which help us to develop close B2B engagement.	[1][2][3][4][5]
BE2		I believe that leadership plays an important role to make the employees realizing the value of AI-CRM solution for B2B relationship management.	[1][2][3][4][5]
BE3		I believe AI-CRM implementation for B2B relationship management is a significant milestone to develop better B2B engagement.	[1][2][3][4][5]
EEB1	Lin et al., 2020; Cortez & Johnston, 2019; Wernerfelt, 1984	I found AI-CRM provides superior experience than traditional CRM.	[1][2][3][4][5]
EEB2		I think employees require less time to perform their job using AI-CRM solution.	[1][2][3][4][5]
EEB3		I believe employees like to use AI-CRM over traditional CRM for B2B relationship management.	[1][2][3][4][5]
EEB4		I believe that leadership support is important at the initial stage of post AI-CRM implementation for reinforcement.	[1][2][3][4][5]
BIP1	Johnston & Cortez, 2018; Lacka et al., 2020	Information processing power of AI-CRM is higher than the traditional CRM.	[1][2][3][4][5]
BIP2		Post AI-CRM implementation, B2B contact management has become easier and faster.	[1][2][3][4][5]
BIP3		We can close a deal faster post AI-CRM implementation for B2B relationship management.	[1][2][3][4][5]
BIP4		We can place order to our partners or get orders from our partners much faster using AI-CRM.	[1][2][3][4][5]
BIP5		AI-CRM helps us by providing quick recommendations which were absent in traditional CRM technology.	[1][2][3][4][5]
OP1	Keramati et al., 2010; Kreye & Perunovic, 2020; Li et al., 2006	I believe that successful implementation of AI-CRM will help the organization to improve its operational efficiency.	[1][2][3][4][5]
OP2		I think AI-CRM helps in quick decision making which helps the organization to improve its operational performance.	[1][2][3][4][5]
OP3		I believe that after AI-CRM implementation we can handle more queries from our customers and partners.	[1][2][3][4][5]
OP4		I believe implementation of AI-CRM for B2B relationship management has helped our firm to improve reputation.	[1][2][3][4][5]
COA1	Rogers, 1983, 1985; Sin et al., 2005	I think that successful implementation of AI-CRM will help an organization to win over its competitor which has not yet implemented AI-CRM for B2B relationship management.	[1][2][3][4][5]
COA2		AI-CRM is a part of our overall competitive strategy.	[1][2][3][4][5]
COA3		I believe that AI-CRM for B2B relationship management has helped our firm to increase market share.	[1][2][3][4][5]

Appendix B. Loadings and Cross-loadings - Loadings and cross-loadings have been estimated. It is seen that cross-loadings are all less than the corresponding loadings which confirm discriminant validity. The estimations are shown in the following table

Table B1
Loadings and cross-loadings.

Item	QIP	IF	OF	IAB	BE	EEB	BIP	OP	COA
QIP1	**0.90**	0.17	0.18	0.29	0.28	0.11	0.33	0.17	0.28
QIP2	**0.95**	0.18	0.19	0.32	0.37	0.17	0.37	0.19	0.37
QIP3	**0.85**	0.29	0.26	0.17	0.33	0.32	0.32	0.21	0.33
QIP4	**0.85**	0.27	0.33	0.24	0.34	0.33	0.17	0.23	0.32
QIP5	**0.90**	0.17	0.17	0.18	0.11	0.18	0.11	0.26	0.11
IF1	0.15	**0.94**	0.19	0.26	0.17	0.19	0.13	0.27	0.14
IF2	0.17	**0.92**	0.32	0.22	0.26	0.21	0.29	0.18	0.17
IF3	0.31	**0.87**	0.13	0.31	0.32	0.23	0.34	0.29	0.31
OF1	0.22	0.21	**0.88**	0.17	0.19	0.17	0.19	0.17	0.29
OF2	0.36	0.28	**0.93**	0.29	0.21	0.33	0.31	0.16	0.27
OF3	0.17	0.15	**0.94**	0.35	0.18	0.18	0.17	0.13	0.33
OF4	0.29	0.12	**0.86**	0.19	0.24	0.31	0.32	0.31	0.39
IAB1	0.32	0.31	0.33	**0.87**	0.32	0.32	0.18	0.17	0.31
IAB2	0.17	0.17	0.19	**0.89**	0.19	0.33	0.32	0.32	0.17
IAB3	0.19	0.18	0.32	**0.90**	0.18	0.34	0.16	0.15	0.16
IAB4	0.28	0.29	0.18	**0.95**	0.31	0.17	0.15	0.37	0.19
IAB5	0.26	0.27	0.34	**0.90**	0.33	0.29	0.31	0.11	0.31
BE1	0.26	0.36	0.17	0.28	**0.95**	0.33	0.18	0.29	0.37
BE2	0.33	0.18	0.32	0.21	**0.95**	0.17	0.38	0.32	0.34
BE3	0.31	0.34	0.18	0.31	**0.90**	0.18	0.26	0.11	0.33
EEB1	0.17	0.17	0.16	0.34	0.12	**0.96**	0.22	0.34	0.17
EEB2	0.20	0.32	0.29	0.21	0.24	**0.94**	0.24	0.16	0.19
EEB3	0.29	0.11	0.33	0.26	0.31	**0.87**	0.32	0.22	0.22
EEB4	0.33	0.27	0.19	0.17	0.19	**0.89**	0.11	0.26	0.17
BIP1	0.19	0.28	0.18	0.19	0.29	0.22	**0.84**	0.29	0.28
BIP2	0.21	0.33	0.32	0.30	0.33	0.33	**0.86**	0.33	0.33

(*continued on next page*)

Table B1 (*continued*)

Item	QIP	IF	OF	IAB	BE	EEB	BIP	OP	COA
BIP3	0.24	0.17	0.34	0.11	0.34	0.34	**0.89**	0.17	0.32
BIP4	0.26	0.26	0.19	0.12	0.17	0.31	**0.96**	0.18	0.11
BIP5	0.30	0.31	0.20	0.11	0.19	0.17	**0.95**	0.13	0.17
OP1	0.31	0.32	0.17	0.19	0.26	0.28	0.17	**0.90**	0.18
OP2	0.19	0.34	0.31	0.34	0.32	0.11	0.33	**0.94**	0.37
OP3	0.27	0.19	0.33	0.12	0.33	0.34	0.32	**0.95**	0.33
OP4	0.29	0.28	0.29	0.17	0.18	0.33	0.12	**0.85**	0.19
COA1	0.17	0.17	0.18	0.27	0.11	0.33	0.11	0.32	**0.85**
COA2	0.31	0.32	0.11	0.29	0.17	0.37	0.17	0.34	**0.96**
COA3	0.19	0.11	0.27	0.18	0.32	0.19	0.38	0.17	**0.90**

Note: The loadings have been shown in bold.

Appendix C. Rival or alternative model

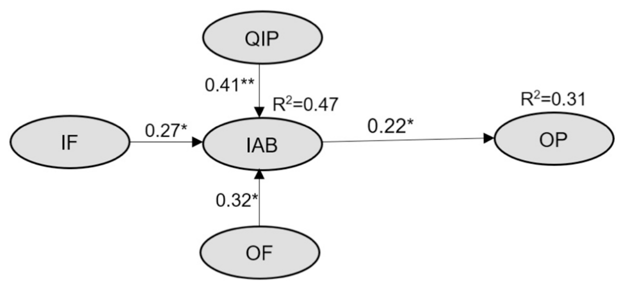

Fig. C1. Rival or alternative model.
[IF: Individual Fit; QIP: Quality of Implementation Process; OF: Organization Fit; IAB: Implementation of AI-CRM for B2B relationship management; OP: Organizational Performance].

A rival model has been proposed considering how IAB prompted by QIP, IF, and OF could directly impact OP. The arguments behind discussion concerning the rival model include how IAB could impact in a direct way without consideration of the mediating variables BE, EEB, and BIP as well as the effects of moderator LS, which have been taken into account in the original model shown in Fig. 1. This study showed that though the impacts of predictors of IAB remain invariant in both the models (proposed model and rival model), the path coefficient concerning the linkage IAB➔OP in the rival model appears to be 0.22 with level of significance $*p < 0.05$ whereas the path coefficients considering the endogenous three variables are all greater than 0.22 having levels of significance $***p < 0.001$ for each when considered from either side. Besides, the predictive power of the proposed model (Fig. 2) is 76% whereas the predictive power of the rival model is 31%. This leads to the inference that there are considerable effects of the mediating variables BE, EEB, and BIP towards the impacts on OP connecting IAB to OP, and the effects of LS as moderator has also considerable contributions on OP. Had that not been so, the predictive power of the proposed model (Fig. 2) would not have been as high as 76%.

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