Journal of Business Research 153 (2022) 46–58

Contents lists available at ScienceDirect

Journal of Business Research

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

Digital transformation of organization using AI-CRM: From microfoundational perspective with leadership support

Sheshadri Chatterjee [a,*], Ranjan Chaudhuri [b], Demetris Vrontis [c], Fauzia Jabeen [d]

[a] *Indian Institute of Technology Kharagpur, West Bengal, India*
[b] *Indian Institute of Management Ranchi, Ranchi 834 008, Jharkhand, India*
[c] *School of Business, University of Nicosia, Cyprus*
[d] *College of Business, Abu Dhabi University, Abu Dhabi, United Arab Emirates*

A R T I C L E I N F O

Keywords:
Digital transformation
AI-CRM
Microfoundation
Leadership support
Resistance to change
Perceived risk

A B S T R A C T

Business firms are increasingly innovating their traditional business model to a technology-enabled digitalized model for their sustainability in the competitive market. Firms have already felt the necessity to embark on a digital transformation journey to sustain themselves. However, specific capabilities at the microfoundation level are needed for successfully exploiting this paradigm shift towards digital transformation. In the digital transformation journey, specific digital skills and capabilities at the microfoundational level are essential to achieve success. The psychological foundations of the employees should be aligned in favor of digitalization to successfully gain competitive advantage. Not many studies are available to understand individual capabilities and skills at the microfoundational level. In this background, the aim of this study is to investigate the role of individual capability at the microfoundational level, including the leadership role along with technology capability like an AI-enabled CRM system, towards digitalization. With the help of RBV theory and status quo bias theory, a theoretical model has been developed which was later validated using SEM technique with data of 341 respondents from different industries. The study finds that there is a significant influence of individuals' skills and capabilities to embrace the digital transformation journey.

1. Introduction

Business firms have already realized the essentiality to take part in the present trend of digital transformation journey to be competitive in this rapid changing global business environment (Li, 2018). This paradigm shift has dramatically changed the business style, activities, and has made the firms learn how to successfully capture values and opportunities (Mithas, Tafti, & Mitchell, 2013; Hopp, Antons, Kaminski, & Oliver Salge, 2018). Various technologies like artificial intelligence (AI), blockchain, social media, and so on have brought a drastic change in the business process. There has been a dramatic shift how the employees update the customer relationship management (CRM) tool in their firms in real time so that performance of the firms can be improved, and they can remain competitive (Bresciani, Ferraris, & Del Giudice, 2018; Gunasekaran et al., 2017; Wamba, Gunasekaran, Dubey, & Ngai, 2018; Bertello, Ferraris, Bresciani, & De Bernardi, 2020). However, it is essential to develop the individual characteristics, skills, and key capabilities to master this revolution of digital transformation. Thus, the global consulting firms are found to be hugely relying on the importance of the human skills responsible to harness the benefits of digital transformation. Very little is known about the critical role and contribution at the individual level in this digital transformation journey (Barney & Felin, 2013). It is not clear how the firms could use the individuals to extract best potentials of digital transformation and how the individuals' psychological foundation and characteristics could be congenial with this digital transformation philosophy (Zimmermann, Hill, Birkinshaw, & Jaeckel, 2020; Picone, De Massis, Tang, & Piccolo, 2021). In such scenario, it will not be exaggeration to observe that change management abilities of the firms are needed for digital transformation to relish the boon of the contribution of modern technology like AI. For this, overhauling of the human resource management abilities of the firms is necessary (Benson, Johnson, & Kuchinke, 2002; Sousa & Rocha, 2019). Digital transformation in the business firms is essential to achieve competitive advantage. It is essential to weigh and assess the

* Corresponding author.
E-mail addresses: sheshadri.academic@gmail.com (S. Chatterjee), ranjan.chaudhuri@iimranchi.ac.in (R. Chaudhuri), vrontis.d@unic.ac.cy (D. Vrontis), fauzia.jabeen@adu.ac.ae (F. Jabeen).

https://doi.org/10.1016/j.jbusres.2022.08.019
Received 5 January 2022; Received in revised form 3 August 2022; Accepted 8 August 2022
Available online 13 August 2022
0148-2963/

antecedents concerns with innovative response behaviors of the individual employees who are the pillars for ensuring success by using digital technologies (Goepel, Hölzle, & zu Knyphausen-Aufseß, D., 2012; Dhir, Pallesen, Torsheim, & Andreassen, 2016). In this context, the role of the individual managers and the leadership of the firms for bringing a wave of digital culture in the business firms is crucial which is expected to motivate the employees to adopt digital culture (Singh & Hess, 2017). The business firms are needed to change the style and process by overcoming the existing routine rigidities (Clauss, Abebe, Tangpong, & Hock, 2019; Belyaeva, Shams, Santoro, & Grandhi, 2020). Hence, it is construed as a great challenge how to enhance the skills, and abilities of the individual employees to smoothly adopt digital technologies in the business firms (Haefner, Wincent, Parida, & Gassmann, 2020; Mas & Gómez, 2021). The present study has contributed that the employees' intention to use a AI-CRM system in their organizations will help the organizations to actually use the digital technologies towards achieving competitive advantage under the moderating influence of the leadership support. In this perspective, it is pertinent to mention here that the extant literature is scant to provide pragmatic guidelines and insights what specific technology will be helpful towards such digital transformation, how individual characteristics, skills, and capabilities could master such digital transformation by successfully using AI-CRM technology and how the business firms could achieve competitive advantage by being a part of such digital transformation journey. Thus, it has become evident that digital transformation needs superior abilities for change management, and digital transformation is needed for the development of HRM (Human Resource Management) practices (Sousa & Rocha, 2019). It implies that it is necessary to realize why digitalization is not merely a technological issue but a strategy where the human dimension plays a critical role (Tabrizi, Lam, Girard, & Irvin, 2019). However, empirical evidence suggests that employees who feel uncertain and that their workload has increased might reject the new digital strategies (Yeow, Soh, & Hansen, 2018). Nevertheless, the extant literature is found scant in investigating the managerial role for digital transformation as well as the part that organization leadership plays in stimulating a digital culture in their companies. In this context, the aim of this study is to address the following research questions (RQs).

RQ1: If individual capability at the microfoundational level could influence the digital transformation journey of the business firms?
RQ2: How technology like AI-CRM can influence the digital transformation of organizations?
RQ3: Whether there is any moderating effect of leadership support at the microfoundational level to influence the digitization process of the business firms?

To answer the research questions, some theoretical streams have been integrated. Digital transformation is perceived to help the firms to gain competitive advantage. In this study, digital transformation is ensured by using AI-CRM tool along with the individual capability at the microfoundational level. The individuals will have the motivation to use the digital technology and resources if they can accrue the capability which has the roots in resource-based view (RBV) theory (Barney, 1991). Also, the leadership ability can overcome the initial resistance offered by the employees for such change which is in consonance with status quo bias theory (Samuelson & Zeckhauser, 1988). These two theories could interpret how different factors could impact the digital transformation journey of the business firms. In this context, a theoretical model has been developed conceptually and has been validated statistically. The findings of this study contribute that individual capability at the microfoundational level influences the digital transformation journey of the business firms. Moreover, the study also confirms that digital technology like AI-CRM ensures the digital transformation of the firm. Finally, the study documented that there is a significant moderating effect of leadership support at the microfoundational level which impacts the digitization process of the business firms to ensure competitive advantage.

The remainder of the manuscript is arranged as follows. Section 2 presents the literature review followed by discussions on the theoretical underpinning as well as the hypotheses development in section 3. Thereafter, in section 4, the research methodology has been detailed, which is followed by the analysis of data, with results in section 5. Next, in section 6, the authors discuss the results of this study along with theoretical and practical contributions. At the end, in subsection 6.3, the authors discuss the limitations of this study along with future scope of research.

2. Literature review

In the business context, digital transformation has focused on changing the existing conventional business model (von Leipzig et al., 2017) whereas Li (2018) interpreted digital transformation is the new ways of doing the business. Again, other studies have documented emerging technological factors which could drive digital transformation. Nadeem et al. (2018) explained digital transformation by interlinking it with firms' structural changes, cross-functional integration (digital business strategy), as well as talent, skill, expertise, operational ability of the individuals responsible to ensure such paradigm shift (microfoundation). In the industrial marketing segment, applications of AI are well acknowledged as one of the important digital technologies. It helps to improve the CRM technology which is expected to ensure competitive advantages to the business firms (Dwivedi et al., 2019; de Jong, de Ruyter, Keeling, Polyakova, & Ringberg, 2021; Mustak, Salminen, Plé, & Wirtz, 2021; Vlačić, Corbo, Costa e Silva, & Dabić, 2021; Samuel, Kashyap, Samuel, & Pelaez, 2022). Digital technology like AI helps to accurately analyze huge volumes of customers' data quickly which can improve the CRM activities of the firms (Kabra, Ramesh, Akhtar, & Dash, 2017; Sharma, Al-Badi, Rana, & Al-Azizi, 2018; Dimitropoulos, Koronios, Thrassou, & Vrontis, 2020). Thus, digital transformation and digitalization are found to have been developing exponentially (Hess, Matt, Benlian, & Wiesböck, 2016; Scuotto, Santoro, Bresciani, & Del Giudice, 2017; Ferraris et al., 2021; Li et al., 2022). Applications of digital technology like AI, internet of things, social media networks, blockchains, bigdata analytics and so on are found to have changed the business model of the firms and has enhanced the performance of the firms (Alberti-Alhtaybat, Al-Htaybat, & Hutaibat, 2019; Enkel, Bogers, & Chesbrough, 2020; Harel, Schwartz, & Kaufmann, 2021; Bresciani et al., 2021a, 2021b). Studies have demonstrated that big data analytics and usage of social media in digital marketing improve performance of the firms (Ferraris, Mazzoleni, Devalle, & Couturier, 2018; Song, Xia, & Vrontis, 2022). Knowledge management abilities, managerial understanding, and networking capabilities help a business firm to derive business benefits through the process of digital innovation (Muninger, Hammedi, & Mahr, 2019; Hizir, 2022). To ensure digital transformation in a successful way, the employees of the firms should adopt digital culture with the help of digital leadership capability (El Sawy, Kræmmergaard, Amsinck, & Vinther, 2016; Bresciani et al., 2021a, 2021b; Rialti, Marrucci, Zollo, & Ciappei, 2022). Besides, in the context of relationship management of the firms with the customers, necessity is there to strengthen the firms' CRM activities and it can be achieved by the integration of AI with the existing CRM system of the firms (Graca, Barry, & Doney, 2015). Integration of AI with the legacy CRM system helps in the process of offering personalized services to the customers, and segmentation of the customers on a real-time basis (Graca et al., 2015). There are several advantages of digitalization by using AI-CRM (Mithas, Jones, & Mitchell, 2002; Nguyen, Chatterjee, Ghosh, & Chaudhuri, 2019, Margiono, 2021). However, there are also challenges while adopting AI integrated CRM system in the firms. Employees' resistance to change to use AI-CRM technology, other risk factors including technological uncertainty, privacy issues, security concerns and so on could demotivate the intention of the employees to use AI-CRM technology to its full potentials (Kim & Kankanhalli, 2009; Nicolle, Fleming, Bach, Driver, & Dolan, 2011; REF2020). For such digital transformation in the firms, the role of leadership is critical that can help the employees to be motivated to use digital technologies to overcome their feelings of uncertainty (Kim, Lee, & Rha, 2017). The skill, expertise, and capabilities of the leadership will help to dissuade the employees from offering initial resistance to use various digital technologies in the firms (Zhang, Gao, Zhang, & Lu, 2020). While the global consulting firms and practitioners could realize the importance of individual capability for ensuring digitization in the firms, little is known how such individuals' capability at the microfoundational level could be managed effectively by the leadership of the firms in terms of the individuals' psychological foundations (Picone et al., 2021). It was observed that the extant literature of digital transformation, digital strategy, as well as digitalization in an exponential pace, has been enriched during the last few years (Bertello et al., 2020). Studies have also unveiled how applications of AI, IoT, Blockchain, and so on could revolutionize the business processes of organizations. Other studies have demonstrated that applying these modern technologies has considerable impacts on internationalization (Bertello et al., 2020), business activities, and eventually on business performance of the organizations (Gunasekaran et al., 2017).

3. Theoretical underpinning and development of hypotheses

3.1. Theoretical underpinning

The present study has taken a holistic attempt for recognizing the importance of initiating digital transformation journey for remaining competitive in the global market (Li, 2018). In this vein, this study proceeds to identify some salient factors which could impact the individuals' capabilities at the microfoundational level for using digital technologies like AI integrated CRM system. For achieving this, the individuals are needed to develop such capabilities for utilizing different valuable, rare, inimitable, and non-substitutable resources to eventually achieve competitive advantage. In this context, the present study has taken help of resource-based view (RBV) theory with its extension (Barney, 1991). RBV is considered a managerial framework for determining the strategic measures of a firm, which the firm can exploit to achieve sustainable competitive advantage. In RBV theory, managerial attention is principally focused on the firm's internal resources, especially the individual capabilities at the microfoundational level, to accurately identify their competencies, assets, and resources that the firm can utilize to gain superior competitive advantage.

The RBV theory suggests that firms are expected to develop firm-specific core competencies at the microfoundational level which helps the firms to outperform their competitors by doing things in a better way (Prahalad & Hamel, 1990). The extended form of RBV helps to extract data from several sources for information which is appropriate in the dynamic market (Gunasekaran et al., 2017). The theory highlights that to achieve better competitive advantage by using digital technologies like AI-CRM technology, the individuals at the microfoundational level need to identify the opportunities to develop the reconfiguring capabilities (Fainshmidt, Pezeshkan, Frazier, Nair, & Markowski, 2016). In this perspective, the employees of the firms need to learn how to easily handle the technological operations. It is argued that along with these abilities, the employees of the firms must possess relationship satisfaction capability, personalized service ability, and real time business analytics capability to attract, retain, and enhance the number of customers. For this, the individuals at the microfoundational levels of the firms must be able to acquire valuable, rare, inimitable, and non-substitutable data, which is the core theme of RBV theory.

The firms in this digital era are trying to develop their business model ecosystem using disruptive technology. But the issue of resistance to change to use a new technology has caused delays, budget overruns, and even total failures in implementing the new model using disruptive technology (Vrhovec, Hovelja, Vavpotic, & Krisper, 2015). Such resistance to change from the employees can be interpreted by status quo bias (SQB) theory (Samuelson & Zeckhauser, 1988). This theory posits that individuals normally will prefer not to switch at all unless they will have the possibility of enjoying benefits from the changes that outweigh the risks. However, there are some factors that cause employees to resist change and to maintain the status quo. These factors include transaction cost, fear of retrenchment, inability to learn new technology, psychological commitment, as well as regret avoidance (Nicolle et al., 2011; Gal & Rucker, 2018). SQB theory posits that individuals have the tendency not to be involved in any change and, in this context, concept of inertia emerges. Individuals cannot predict how they will gain when they initially start to use a new technology, and as such they resist the change (Bostrom & Ord, 2006; Reisch & Zhao, 2017).

Thus, to overcome the inertia, which impedes employees' intention to use the technology, the role of leadership support is perceived to be critical (Liu, 2015; Li & Sun, 2015). The leadership of the firm must motivate the employees to be aligned to use the new technology. In the present study, the leadership of the firms should influence the employees to use AI-CRM ecosystem-based applications and business model, which is perceived to impact the firms' competitiveness (Zhang et al., 2020). Thus, resistance to change is considered to impede employees from using AI-CRM applications in the absence of appropriate support by the firms' leadership teams.

3.2. Development of hypotheses

From the inputs of the literature review and the theoretical underpinning, it has been possible to identify the determinants impacting firms' intention to use an AI-CRM-enabled business model. In this section, the determinants will be explained, and the hypotheses will be formulated to develop a theoretical model.

3.2.1. Relationship satisfaction (RS)

Previously, most of the firms had felt uncertain about the effectiveness and productivity of their CRM programs and had considered such CRM-related programs as burdens on their marketing budgets (Hassan, Nawaz, Lashari, & Zafar, 2015; Piccolo, Chaudhuri, & Vrontis, 2021). But with the rapid development of ICT and due to rapid change of marketing dynamics, firms have realized the importance of understanding customer needs and have been trying to tailor their product and service offerings commensurate with customers' needs in a sustainable competitive manner that they expect will yield considerable incremental sharable value (Thrassou, Chatterjee, Chaudhuri, Vrontis, & Ghosh, 2021). Since digitalization is booming among businesses, firms could realize the effectiveness of initiating digital transformation journey by using AI-CRM tool which is expected to help integrate firms' entire supply chain to create customer value at every step by either increasing benefits for the customers or by lowering costs of products or services to ensure customers have better relationship satisfaction (Anderson, Fornell, & Mazvancheryl, 2004; Chatterjee, 2019a).

Customers' relationship satisfaction can be achieved through seamless coordination with the customers in the context of meeting their needs by quickly responding to customers' touch functions and addressing their pain points (Mithas et al., 2002). Customers with increased satisfaction will return to the firm again and again for its products and services (Westbrook & Oliver, 1991; Tamilmani, Rana, & Sharma, 2021). The relationship satisfaction is perceived to impact the intention of the individuals working at the microfoundational level of the firms to use digital technology like AI integrated CRM system in a more efficient manner. Accordingly, it is hypothesized as follows.

H1a: Relationship satisfaction (RS) positively impacts the intention to use an AI-CRM-enabled business model (AIBM) to improve the digitalization process of the firms.

3.2.2. Personalized services ability (PS)

It has been observed that, prior to the initiation of firms' digitalization process, consumption of information and its distribution had taken place through limited channels. Big brands had been visible to a large population through advertisements in the print media (Balakrishnan & Dwivedi, 2021). After seeing such advertisements, customers picked up items of their choice, but the items were not prepared to customers' choice of features (Thrassou et al., 2021). With the advancement of new technologies, the customer relationship concept has undergone a considerable change (Chaudhuri, Vrontis, Thrassou, & Ghosh, 2021). Firms have now realized that poor quality customer service may impact their profitability and competitive advantages (Zhang et al., 2020).

Better personalized customer services have become unique selling propositions of the firms. Personalization of services now plays a critical role in attracting more customers and maintaining relationships with them (Borges, Laurindo, Spínola, Gonçalves, & Mattos, 2021; Dwivedi, Chatterjee, & Rana, 2021). Personalization is conceptualized as refining the products or services for an individual customer by analyzing the data concerning that particular person (Nguyen et al., 2019). The concept of a firm providing personalized service, in the context of using digital technology like AI-CRM ecosystem-based business model, has scope to attract and retain customers, since they can order items or services according to their specific needs and choice when using an online platform. The firms also analyzing such data can deliver the items or services according to the customers' specific choice (Thrassou et al., 2021). Such personalized service ability is considered as one of the VRIN capabilities of the employees of the firms, in conformity with RBV theory (Barney, 1991). Personalized service ability needs to serve strong, automated platform-based services to the customers that meet their specific needs, thus enhancing the customers' loyalty (Chatterjee, Ghosh, & Chaudhuri, 2020; Balakrishnan & Dwivedi, 2021). Accordingly, it is hypothesized as follows.

H1b: Personalized service ability (PS) by the employees of the firms positively impacts the intention to use an AI-CRM-enabled business model (AIBM) to improve the digitalization process of the firms.

3.2.3. Real time analytics capability (RA)

Real time analytics is used for describing those technologies which help to facilitate automated decision-making (Nguyen et al., 2019). It is observed that sometimes practitioners use CRM analytics and real time analytics interchangeably. However, there are differences between these two. Automated decision-making can be accomplished by real time analytics, whereas CRM analytics refers to business intelligence which can analyze data to provide effective and managerial insights that help to better understand potential customers (Chatterjee, 2019a; Chaudhuri et al., 2021). Real time analytics capability is considered as a specific ability of the individuals at the microfoundational level which brings value, and this capability is rare in terms of RBV theory (Barney, 1991). Through real time analytics, employees of the firms can quickly process an incoming customer request against structured, predefined business rules or data algorithms to determine the best course of action to be taken to satisfy potential customers' requests (Dwivedi et al., 2020; Basile, Chatterjee, Chaudhuri, & Vrontis, 2021). This technique is deemed to be useful for the firms, but they need to have an appropriate application of digital technology like AI-enabled CRM ecosystem for this type of analytics. Accordingly, the following hypothesis is proposed.

H1c: A firm's real time analytics capability (RA) positively impacts its intention to use an AI-CRM-enabled business model (AIBM) to improve the digitalization process of the firms.

3.2.4. Resistance to change (RC)

As the success of using a new technology mainly depends on the users, the extant literature appears to have investigated the issue of resistance to change from the users' perspective (Kim & Kankanhalli, 2009). Markus (1983) argued that the prospect of the threat of loss explains that resistance to change depends on firms' internal factors, poor user experience, bad system design, as well as flaws in design features. From the cost-benefit perspective, Joshi (1991) concluded that users resist change because of perceived inequity. Lack of leadership support also is considered as a major reason that instigates the user to resist accepting change (Aga, Noorderhaven, & Vallejo, 2016; Shao, Feng, & Hu, 2016; Chatterjee et al., 2020).

Resistance to change by the employees of firms, in the context of adopting of a digital technology like AI-CRM ecosystem, can be explained by SQB theory (Samuelson & Zeckhauser, 1988). The employees resist changes because they have an inherent tendency to maintain the status quo (Nicolle et al., 2011). Besides, other causes that also provoke employees to adhere to the existing legacy system include regret avoidance, psychological constraints, and fear of learning new things (Gal & Rucker, 2018). Individuals prefer to have no change that disturbs the status quo unless it is confirmed that the benefits outweigh the risks (Zhang et al., 2020). Accordingly, it is hypothesized as follows.

H2a: Resistance to change (RC) by the employees of a firm negatively impacts their intention to use an AI-CRM-enabled business model (AIBM).

3.2.5. Perceived risk (PR)

Perceived risk (PR) mainly comprises technology risk and security risk (Rana, Dwivedi, & Akter, 2022). A business firm's success is adversely affected by technical failure (Khaksar, Khosla, Singaraju, & Slade, 2019). Applications of digital technology like AI-CRM needs to be adopted by the individual employees of the firms at the microfoundational level with appropriate precaution. Modern digital technology like AI-CRM can take decision on its own. But if the underline AI algorithm is biased then it can take wrong decision which could invite risks for the employees for taking inappropriate decision based on inappropriate recommendations of AI-CRM application (Yeoh, 2019). The nature and characteristics of technology risks undergo continuous change with the arrival of industry 4.0, but, if these are not applied appropriately, they could impact a firm's competitive edge (Nguyen et al., 2019). Firms need to adopt risk management mechanisms that address the risks, as observed in a survey conducted by KPMG (2017). Security risk includes information security risk that concerns the vulnerabilities related with firms' processes and practices in using various sophisticated information systems (Kuo, Shihping, & Yen-Chun, 2010). A firm can create a security risk if it lacks a proper contingency plan, as without such plan, a firm can hardly address any risks that might occur (Post & Kagan, 2006). Thus, perceived risk could impact the employees of the firms for not adopting modern digital technology like AI-CRM to its full potential. This perceived risk could also negatively impact the lower adoption of digital technology by the employees which may negatively impact the competitiveness of the firms. Accordingly, it is hypothesized as follows.

H2b: Perceived risk (PR) negatively impacts on employees' intention to use AI-CRM enabled business model (AIBM).

3.2.6. Intention to use AI-CRM enabled business model (AIBM)

Intention is considered a motivational factor that influences an individual to exhibit a specific behavior (Dwivedi et al., 2020; Chatterjee, 2019b). Whenever an individual's intention is seen to be stronger towards a behavior, it is likely that the individual would perform that specific behavior (Borges et al., 2021). Behavioral intention of the employees of a firm is manifested through the behavior of the employees of that firm. Intention of employees of a firm to use digitally empowered AI-CRM ecosystem-enabled business model is considered as an important determinant to comprehend the actions of the employees to intend to use the model (Scott & Christian, 2012; Wu, Cheng, & Ai, 2018). Intention of an individual is exhibited through two categories, which are favorable intention and unfavorable intention (Thrassou et al., 2021). Favorable intention motivates the individuals to perform the concerned

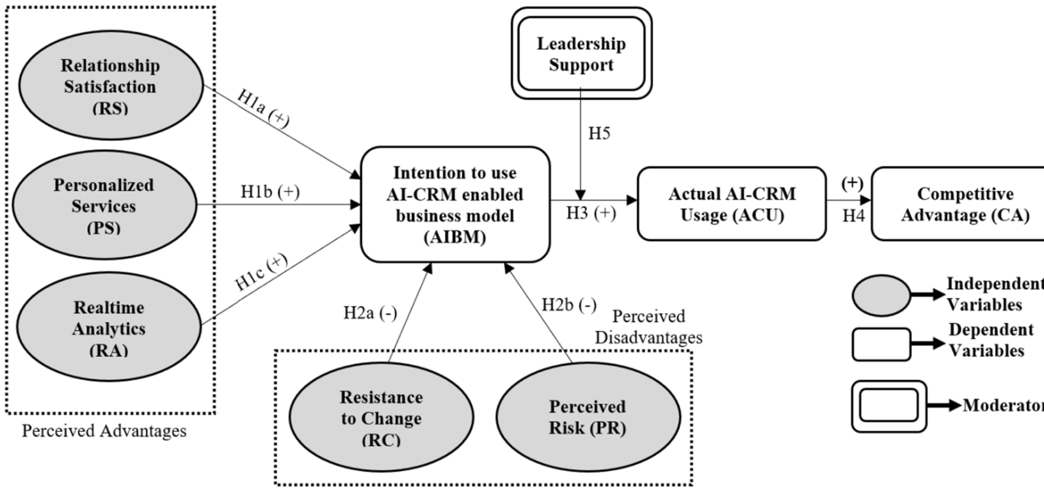


Fig. 1. The conceptual model.

action (Baker & Crompton, 2000; Chatterjee, 2015). If employees contemplate that using AI-CRM ecosystem-based business model would benefit them as well as their firms, then they would intend to use the AI-CRM ecosystem-based applications for their firms' betterment and to improve their own performance (Chen & Chen, 2010).

By improving relationship satisfaction, personalized service ability, and real time analytics capability, the leadership of the firms can enhance their employees' perceptions or the advantages in using AI-CRM. But employees' resistance to change and their perceptions of risks create disadvantages in using the AI-CRM in the firms. The leadership team should encourage the employees to use new technology to get all the benefits of that technology, which could eventually help them to overcome their attitude about change and to use the new technology. Accordingly, it is hypothesized as follows.

H3: Intention to use an AI-CRM-enabled business model (AIBM) positively impacts actual AI-CRM usage (ACU) in the firm.

3.2.7. Actual AI-CRM usage (ACU) and competitive advantage (CA)

Studies have unveiled that digital transformation has invited revolutionary change in the business practices of the firms (Bertello et al., 2020). In such context, use of digital technology like AI-CRM could benefit the firms with the appropriate applications of AI algorithms. Appropriate usage of firms' complementary resources, which are valuable, rare, inimitable, and non-substitutable, will derive the best benefits for the firms when they use AI-CRM (Borges et al., 2021; Balakrishnan & Dwivedi, 2021). In such cases, the firms will outperform their counterparts in making accurate and quick decisions (Grover, Kar, & Dwivedi, 2020; Dwivedi et al., 2020). This concept is in conformity with RBV theory (Barney, 1991).

In the new business landscape, firms have become customer centric and are always engaged in collecting customer data to understand customers' actual needs (Stein, Smith, & Lancioni, 2013; Chatterjee et al., 2020). But manually analyzing such huge volumes of data is difficult and sometimes impossible. That is why the usage of AI integrated with CRM is essential (Nguyen et al., 2019). In this way, it is perceived that the firms will be able to increase their market share. Accordingly, it is hypothesized as follows.

H4: Actual AI-CRM usage (ACU) positively impacts the competitive advantage (CA) of a firm.

3.2.8. Moderating effects of leadership support (LS)

In a variable relationship between two constructs, a third variable may influence the relationship by accelerating the relationship, retarding the relationship, or even, in some cases, by altering the direction of the relationship. This third variable is called the "moderating variable". It is a common experience that whenever a firm tries to implement a new system or a new technology, expecting to gain more competitive advantage, its employees are found to exhibit implicit and explicit behaviors to resist such change (Kim & Kankanhalli, 2009; Rialti, Zollo, Ferraris, & Alon, 2019). The reasons for their resistance are threat perception, uncertainty, fear of job insecurity, learning inability, and so on (Kim et al., 2017). This idea is commensurate with SQB theory (Samuelson & Zeckhauser, 1988). Studies have demonstrated that such a situation can be resolved by the active support of leadership (Zhang et al., 2020). Other studies also subscribe a similar view that leadership support can act as a favorable factor to help reduce employees' resistance and can ensure successful implementation and adoption of the new system in the firm (Shao et al., 2016). Leadership captures the behavior which "asserts absolute authority and control over subordinates and demands unquestionable obedience" (Cheng, Chou, Wu, Huang, & Farh, 2004, p. 89). In changing employees' attitudes, it appears that leadership support plays a crucial role (Schepers, Wetzels, & De Ruyter, 2005; Chatterjee et al., 2020). Strong leadership support is perceived to help transform the intention of the employees in favor of using digital technology like AI-CRM in the firms. In this context, the following hypothesis is formulated.

H5: Leadership support (LS) moderates the relationship between intention to use AI-CRM enabled business model (ACBM) and actual AI-CRM usage (ACU).

With all these discussions, a theoretical model is proposed conceptually which is shown in Fig. 1.

4. Research methodology

For hypotheses testing and for validating the proposed theoretical model, the partial least squares (PLS) – structural equation modeling (SEM) technique was preferred, as it can analyze an exploratory study like this (Peng & Lai, 2012). This technique helps to analyze a complex model in a simple way (Vinzi, Trinchera, & Amato, 2010; Akter, Fosso Wamba, & Dewan, 2017). The PLS-SEM technique gives liberty to analyze such data which are not normally distributed, though that is not permitted in the covariance-based SEM approach (Rigdon, Sarstedt, & Ringle, 2017; Kock & Hadaya, 2018; Akram, Saeed, Bresciani, Rehman, & Ferraris, 2022). Moreover, this technique does not provide any restriction in the sample size (Willaby, Costa, Burns, MacCann, & Roberts, 2015; Hair, Sarstedt, Ringle, & Gudergan, 2018). A survey is conducted to collect feedback from the respondents against a set of structured questions (questionnaire). The feedback is quantified using a standard scale, and in this study, a 5-point Likert scale was used. The 5-point Likert scale was preferred because it is simple to use and the respondents can be neutral by choosing the "neither disagree nor agree" option.

4.1. Measurement instrument

With the help of existing validated scale, knowledge of the constructs and the literature review, and inputs from the theories, a set of questions (questionnaire) were prepared. Questions were written in the form of statements with five options for each question in terms of the 5-point Likert scale and anchored as "strongly disagree" (SD), marked as 1, to "strongly agree" (SA), marked as 5.

The questions so prepared were rectified through a step-by-step correction procedure as enumerated by Carpenter (2018). The questions were pretested, and from the outcomes of the pretest, the wordings of some questions and some of the formats of the questions were corrected. After that, a pilot test was conducted, and the feedback of the pilot test helped the authors to fine tune the wordings and readability of the questions. Also, opinions of experts were taken, which helped to improve the readability and comprehensiveness of the questions. The experts have adequate knowledge in the domain of this study. All these rectification processes were undertaken to confirm that the questions are easily understood by the respondents. This would not only enhance the response rate, but it would also improve the quality of responses. In this way, 35 instruments were prepared.

4.2. Collection of data

To target the respondents from different industries, a list of firms was procured from the Bombay Stock Exchange (BSE), India. Initially, from the list, 50 firms were selected at random. On verification, it appeared that, out of these 50 firms, only 26 have introduced AI-CRM model, though only at the incubation stage, and some other firms were almost ready to implement the AI-CRM ecosystem-based business model. Top executives of these 26 firms were contacted by telephone or emails to request them to allow their employees to participate in this survey. The top executives of these 26 firms were appraised that the aim of this study is purely academic, and it was also intimated to them that the anonymity and confidentiality of the participants in the survey would be strictly preserved. However, the authors' attempts to target the respondents in this way were not very encouraging, since the top executives were found highly reluctant to respond to the authors' requests. However, after a long persuasion, top executives of 19 firms were pleased to allow their employees of different ranks to participate in the survey.

The top executives of these 19 firms provided details of a few contact people to whom subsequent communications were made. The contact persons procured details of 711 employees. All of them were contacted and were appraised by emails about the purpose of this study. The authors provided them with a response sheet that contained 35 instruments with five options for each instrument. Each respondent needed to put one tick mark out of five options against each question, since the quantification of the responses has been done on a 5-point Likert scale. Guidelines on how to fill in the response sheet were also provided with each response sheet. All these 711 prospective participants were given three months to respond (December 2020 to February 2021). Within the stipulated time, out of 711 potential respondents, responses from 353 respondents were obtained. The response rate was 49.6 %. Here the non-response bias test was performed following the guidelines as provided by Armstrong and Overton (1977). The chi-square test and independent *t*-test were conducted by analyzing the inputs of the first and the last 100 respondents. No appreciable difference in the results could be detected. This confirms that non-response bias did not pose a major concern in this study. On scrutiny, out of these 353 responses, 12 responses were found incomplete which could not be considered. The statistical analysis was done using 341 responses against 35 instruments. It is worth mentioning here that the ratio of the number of items and the number of respondents should lie between 1:4 to 1:10 (Deb & Lomo-David, 2014). The demographic information of 341 respondents is provided in Table 1.

Table 1
Demographic information (N = 341).

Particulars	Category	Number	Percentage (%)
Firm type	Manufacturing firm	6	31.6
	Service firm	13	66.4
Working position	Senior manager	117	34.3
	Midlevel manager	169	49.6
	Junior manager	55	16.1

Table 2
Measurement properties.

Constructs / Items	LF	AVE	CR	α	t-values
RS		0.78	0.83	0.89	
RS1	0.87				21.12
RS2	0.85				26.17
RS3	0.94				29.01
RS4	0.87				27.11
PS		0.80	0.85	0.91	
PS1	0.95				28.31
PS2	0.90				38.24
PS3	0.89				28.11
PS4	0.96				17.06
RA		0.76	0.82	0.88	
RA1	0.85				31.11
RA2	0.89				30.86
RA3	0.88				37.17
RC		0.88	0.91	0.94	
RC1	0.92				29.11
RC2	0.90				18.87
RC3	0.97				19.11
RC4	0.96				36.22
PR		0.80	0.84	0.91	
PR1	0.96				28.17
PR2	0.93				24.11
PR3	0.85				38.07
PR4	0.89				39.31
AIBH		0.84	0.89	0.95	
AIBH1	0.91				32.27
AIBH2	0.95				36.17
AIBH3	0.96				39.29
AIBH4	0.90				37.11
AIBH5	0.94				30.24
AIBH6	0.85				19.91
ACU		0.88	0.90	0.94	
ACU1	0.97				30.62
ACU2	0.95				22.48
ACU3	0.94				27.18
ACU4	0.92				31.11
ACU5	0.90				24.19
CA		0.87	0.92	0.97	
CA1	0.95				27.11
CA2	0.90				29.37
CA3	0.94				36.41
CA4	0.89				34.18
CA5	0.96				36.31

5. Analysis of data and results

5.1. Measurement properties and discriminant validity test

To verify convergent validity, the loading factor (LF) of each item has been assessed. To examine the validity, reliability, and internal consistency, average variance extracted (AVE), composite reliability (CR), and

Table 3
Discriminant validity test (Fornell & Larcker criteria).

Constructs	RS	PS	RA	RC	PR	AIBM	ACU	CA	AVE
RS	0.88								0.78
PS	0.17	0.89							0.80
RA	0.22	0.37	0.87						0.76
RC	0.26	0.23	0.36	0.94					0.88
PR	0.19	0.32	0.24	0.33	0.89				0.80
AIBM	0.17	0.19	0.23	0.17	0.32	0.92			0.84
ACU	0.31	0.29	0.31	0.22	0.34	0.24	0.94		0.88
CA	0.26	0.21	0.36	0.38	0.21	0.39	0.22	0.93	0.87

Table 3A
Discriminant validity test (HTMT test).

Constructs	RS	PS	RA	RC	PR	AIBM	ACU	CA
RS								
PS	0.26							
RA	0.29	0.39						
RC	0.32	0.37	0.41					
PR	0.19	0.31	0.44	0.30				
AIBM	0.43	0.17	0.27	0.34	0.32			
ACU	0.30	0.22	0.29	0.17	0.36	0.39		
CA	0.29	0.32	0.33	0.26	0.41	0.28	0.47	

Cronbach's alpha (α) of each construct has been estimated. It is pertinent to mention here that the lowest value of LF should be 0.70 (Chin, 2010) and the lowest value of AVE should be 0.50 (Hair, Hollingsworth, Randolph, & Chong, 2017). The results are found to be within the permissible range. The results are shown in Table 2.

To verify the discriminant validity, all the square roots of the AVEs have been estimated. It has been noted that all the square roots are found to be less than the corresponding bifactor correlation coefficients. It satisfies Fornell and Larcker criteria (Fornell & Larcker, 1981). This confirms discriminant validity. The results are shown in Table 3.

To supplement the Fornell and Larcker criteria (Fornell & Larcker, 1981) that confirms the discriminant validity of the constructs, the Heterotrait-Monotrait (HTMT) test was conducted (Henseler et al., 2014a, 2014b). The results highlight that all the concerned values are$<$0.85 (Voorhees, Brady, Calantone, & Ramirez, 2016), reconfirming discriminant validity. The results are shown in Table 3A.

5.2. Moderator test (multigroup analysis)

To test the effects of the moderator, leadership support (LS), on the linkage AIBM → ACU (H3), the multi group analysis (MGA) process was adopted with the bootstrapping procedure considering 5000 resamples. The effects of the moderator LS on H3 have been tested with two categories of strong LS and weak LS on H3. On verification through MGA, it appears that the p-value difference between the effects of the two categories of the moderator is 0.03. It is known that, if the p-value difference for the effects of two categories of a moderator on a linkage is either$<$0.05 or greater than 0.95, then the effects of the said moderator on the linkage is significant (Hair, Hult, Ringle, & Sarstedt, 2016; Mishra, Maheswarappa, Maity, & Samu, 2018). Since, in this study, the p-value difference is 0.03 ($<$0.05), the effects of the moderator LS on H3 are significant.

5.3. Effect size f^2

To verify if the exogenous constructs make effective contributions to the corresponding endogenous variables, effect size f^2 values of different linkages need to be evaluated. If the range of f^2 is 0.020 to 0.150, it is weak; if it is between 0.150 and 0.350, it is medium; and if it is greater than 0.350, it is large (Cohen, 1988). In the present study, the effect sizes of RS, PS, RA, RC, and PR on AIBM are 0.411 (L), 0.320 (M), 0.399 (L), 0.112 (W), and 0.426 (L), respectively. The effect size of AIBM on ACU is 0.376 (L), whereas the effect size of ACU on CA is 0.419 (L). The results highlight that there is effective contribution of the exogeneous variables on the corresponding endogenous variables since most of the f^2 values are large.

5.4. Common method bias (CMB)

In this study, a survey was conducted to collecting feedback from the respondents and to quantify the data for analysis with a statistical approach. Here, the chance of getting biased replies cannot be overruled. Of course, as a preemptive measure, when preparing the questionnaire, the wordings of the questions and some of the formats of the questions were corrected through a pretest so that the questions could be easily understood by the respondents. Also, at the survey stage, all respondents were assured that their anonymity and confidentiality would be strictly preserved. This was done to ensure the replies would be unbiased.

However, to verify if any biases remained, CMB has been conducted using Harman's Single Factor Test (SFT). The results emerged that it accounts for 31.11 % of the variance, which is less than the recommended highest threshold value of 50 % (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). To reconfirm these findings, a marker-correlation test has also been conducted (Lindell & Whitney, 2001). The difference in correlation between the original and the marker-based model appears to be very small ($\leq$0.06) (Mishra et al., 2018). Hence, it is inferred that the results do not pose any major concern.

5.5. Causality test

Causality is considered as an important aspect that needs to be addressed before performing hypotheses testing (Guide & Jr. & Ketokivi, M., 2015). In terms of suggestions from Kock (2015), non-linear bivariate causality direction ratio (NLBCDR) needs to be estimated. Its acceptable value is considered as $\geq$ 0.7 (Wamba, Gunasekaran, Akter, & Dubey, 2019). On estimating the NLBCDR for each path, the estimates are found to be PR → AIBM (1.002); PS → AIBM (1.000); PA → AIBM (0.989); RC → AIBM (1.001); PR → AIBM (0.999); AIBM → ACU (1.003); and ACU → CA (1.002). These results clearly highlight the support for the existence of reversed hypothesized directions is very weak. Hence, causality should not be considered as a vital issue in the present study.

5.6. Hypotheses testing (SEM)

To test the hypotheses, the blindfolding process has been adopted with the bootstrapping procedure considering 5000 resamples (Mishra et al., 2018). With consideration of omission distance 5, cross-validated redundancy has been measured for the dependent variables. The Stone-Geisser Q^2 positive value (0.074) indicates that the model has due predictive relevance (Stone, 1974; Geisser, 1975).

For assessing overall model fit SRMR (standardized root mean square residual error) has been considered as a standard index. The values came

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

Linkages	Hypotheses	R^2 values / Path coefficients	p-values	Remarks
Effects on AIBM		$R^2 = 0.37$		
By RS	H1a	0.29	$p < 0.001$ (***)	Supported
By PS	H1b	0.32	$p < 0.01$ (**)	Supported
By RA	H1c	0.02	$p > 0.05$ (ns)	Not Supported
By RC	H2a	−0.13	$p < 0.05$ (*)	Supported
By PR	H2b	−0.14	$p < 0.01$ (**)	Supported
Effects on ACU		$R^2 = 0.44$		
By AIBM	H3	0.41	$p < 0.001$ (***)	Supported
Effects on CA		$R^2 = 0.73$		
By ACU	H4	0.32	$p < 0.001$ (***)	Supported
(AIBM → ACU) × LS	H5	0.16	$p < 0.05$ (*)	Supported

out to be 0.068 for PLS and 0.032 for PLSc. Since both values are greater than the recommended highest value of 0.08 (Hu & Bentler, 1998), the model is in order. Here the process, recommended by Henseler et al. (2014a, 2014b), has been followed. This process helps to estimate the path coefficients, R^2 values, and p-values. The results are shown in Table 4.

With all these inputs, the validated model is shown in Fig. 2.

5.7. Results

The present study has formulated eight hypotheses out of which one hypothesis (H5) is concerned with the moderating effects of LS on H3. Out of the remaining seven hypotheses, six hypotheses have been supported by statistical analysis. One hypothesis, RA → AIBM (H3), has not been supported, as the concerned path coefficient is 0.02 with level of non-significance as $p > 0.05$(ns). The results highlight that the impacts of RS and PS on AIBM (H1a and H1b) are positive and significant because the concerned path coefficients are 0.29 and 0.32, respectively, with corresponding levels of significance as $p < 0.01$(**) and $p < 0.01$ (**). The impacts of RC and PR on AIBM (H2a and H2b) are both negative but significant, as the concerned path coefficients are found to be −0.13 and −0.14, respectively, with corresponding levels of significance as $p < 0.05$(*) and $p < 0.01$(**). The results also show that the impact of AIBM on ACU (H3) is significant and positive, as the concerned path coefficient is 0.41 with level of significance $p < 0.001$(***). The results then highlight that the impact of ACU on CA is positive and significant, because the concerned path coefficient is 0.52 with level of significance $p < 0.001$ (***). The effects of the moderator LS on H3 are positive and significant since the concerned path coefficient is 0.16 with level of significance $p < 0.05$(*). So, for as coefficients of determinant are concerned (R^2), the results indicate that RS, PA, RA, RC, and PR could explain AIBM to the tune of 32 % ($R^2 = 0.32$), whereas AIBM could impact ACU to the tune of 44 % ($R^2 = 0.44$), and ACU can explain CA to the extent of 73 % ($R^2 = 0.73$), which is the explanative power of the proposed theoretical model.

6. Discussion

In the changed dynamic and complex business scenario, firms are facing challenges to compete with their counterparts for meeting the customers' dynamic needs. In this context, the firms are intending to introduce new digital technology enabled business models with the help of industry 4.0 technologies. In this context, the present study has identified some determinants which facilitate or impede firms' intention to use an AI-CRM ecosystem-based business model with consideration of the moderating effects of leadership support to impact the relationship between intention and actual use of AI-CRM ecosystem-based business models in the firms. The present research study has hypothesized that relationship satisfaction impacts positively the intention of the firm to use an AI-CRM applications-oriented business model (H1a). This hypothesis has received support from a study by Nguyen and Waring (2013) that discussed contributions of CRM to SMEs. The present study has demonstrated that, by developing the individual abilities of the employees, the aim of achieving better results through digital transformation could be realized. This study has also highlighted that if the organizations can successfully implement their CRM activities with the help of AI technology, their digitalization process will be more effective and they will gain better competitive advantage. The present study has documented that active leadership support would facilitate the relationship between actual use of AI-CRM and gaining competitive advantage for the organizations. In this way, the present study has addressed the research questions stated in the introduction. The present study has highlighted that the role of microfoundations, that is, the role of individual stakeholders of the organizations, is found to be critical in articulating digital strategies as well as the process of digital transformation journey.

The present study has hypothesized that personalization ability positively and significantly impacts their intention to use AI-enabled CRM ecosystem-based business models, which has also received

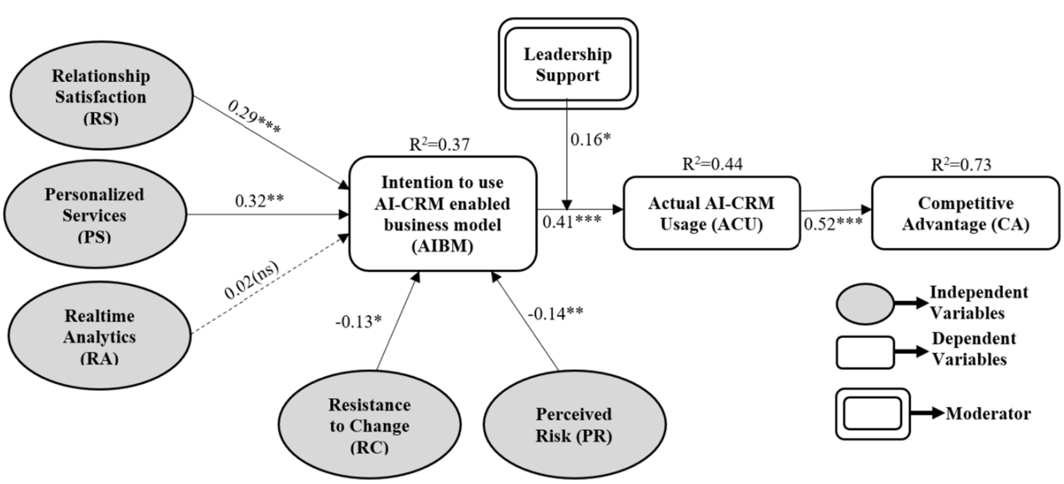


Fig. 2. Validated model (SEM).

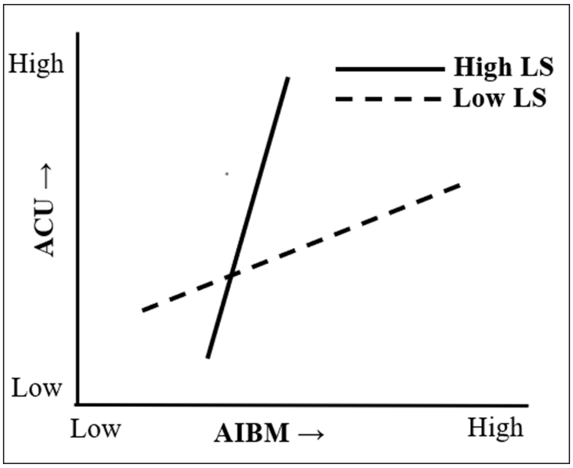


Fig. 3. Effects of moderator LS on H3.

support from another study by Sandström, Edvardsson, Kristensson, and Magnusson (2008). The present study has highlighted that the impact of real time analytics capability on firms' intention to use an AI-CRM model was not supported (H1c). This is presumably because employees do not trust the power of AI-CRM technology to process so much data and respond quickly and accurately to meet the needs of the customers. Based on the input of those employees of the firms, it is possible that such results have been arrived at.

This research study has shown that the risk factors impede the firms' intention to adopt AI-CRM based business models (H2b), which has received support from another study (Rana et al., 2022). This study also hypothesized that employees' resistance to change negatively and significantly impacts their intention to use AI-CRM model (H2a), which is supported by SQB theory, which highlights individuals always resist to change the way they currently function (Samuelson & Zeckhauser, 1988).

The present research study highlights that the actual use of AI-CRM models in firms will help them to gain competitive advantage (H4). This has been supplemented by another study (Mikalef & Gupta, 2021) which investigated how AI could impact on firms' creativity and performance. The present study has developed a rival model by not considering the moderating effects of leadership support and the mediating effects of ACU. The study has demonstrated that the proposed theoretical model is superior to the rival model. The details are discussed in the Appendix.

The present study has hypothesized that impact of leadership support has a moderating impact on the relationship between intention to use AI-CRM business model and actual use of AI-CRM (H3 and H5). This concept has duly been supported by a study by Zhang et al. (2020) that discussed how leadership support helps employees overcome their resistance to change and to use a new technology. Thus, this model is deemed to be helpful for the business community to understand which factors to nurture so that they can ensure their firm's transformation to adopt a new ecosystem-based business model that uses disruptive technology, such as AI-CRM ecosystem-based applications.

The effects of the strong LS and weak LS on the linkage H3 (AIBM → ACU) are explained here through graphical presentation in Fig. 3.

With the increase of AIBM, the rate of increase of ACU is more from the effects of strong LS compared to the effects of weak LS on H3, because the gradient of the continuous line, representing the effect of strong LS, is more than the gradient of the dotted line, representing the effects of weak LS.

6.1. Theoretical contribution

Digitalization has brought in huge beneficial impacts to the firms. The present study has demonstrated how such exponential growth in the context of digital transformation could ensure better competitive advantage to a firm duly supported by the leadership of the firms. No other studies could simultaneously analyze the issue of digitalization and the impact of individual ability at the microfoundational level on the competitiveness of the firms.

This study has used RBV theory to explain the capabilities which help a firm to use an AI-CRM-enabled business model. In this context, the present study has extended the application of RBV theory to interpret how firms must transform their existing business model to an AI-CRM ecosystem-based business model that uses disruptive technology to address customer needs, which are ever-evolving. In terms of RBV, resources of a firm represent factors which a firm either owns or controls and transforms into final products or services. Nevertheless, not all the resources that a firm owns or controls have the potential to improve firm performance. The proponents of RBV are of the opinion that resources which are simultaneously valuable, rare, inimitable, and non-substitutable (VRIN) can help improve the performance of a firm compared to its counterparts. The RBV has an intra-firm focus in explaining how a firm could perform better than others by properly deploying its firm-specific resources. Therefore, through RBV theory, the study interpreted how relational capability could help a firm to intend to use an AI-CRM-enabled business model. The authors argued that relationship development capability is needed to be considered as a VRIN capability, as enjoined in the RBV theory. This is claimed to be a unique theoretical contribution of this study.

With the help of SQB theory, this study also shows how employees' resistance to change could be removed by the effective support of the firm's leadership team. The study's inclusion of the contribution of leadership support is deemed to have strengthened the explanative power of the study's proposed theoretical model. This is also claimed as a theoretical contribution of the present study.

A study by Rafiki, Hidayat, Razzaq, and D. (2019) investigated the contributions of CRM to organizational performance of telecommunication companies in Kuwait, and they confirmed that CRM activities provide essential dividends to organizational performance. This idea has been extended in the present study by highlighting that advanced CRM abilities (AI-embedded CRM) could help the firms to gain more competitive advantage, even in a dynamic business environment. A study by Zhang et al. (2020) has highlighted that, in implementing an information system project in China, support of leadership dominantly mitigated user resistance to change. This idea has been extended in the present study, and it is seen that employees' resistance to use an ecosystem-based AI-CRM business model can be considerably reduced by the firm's leadership support through emotional incentivization the unwilling employees.

6.2. Implication to practice

This study has many practical implications. The results of this study show that relationship satisfaction and personalization ability positively and significantly impact intention to use an AI-enabled CRM business model (H1a and H1b). This implies that, for ensuring positive intention of the employees at the microfoundational level to use an ecosystem-based AI-CRM business model in the firms, the managers must encourage the employees to use AI-CRM business applications, which will ensure improved relationships between potential customers and the firms. Managers must attempt to enhance the personalized services facility offered to customers of the firms. For this, the managers must have regular coaching conversations with employees to make them fully realize that the firm's success lies on superior relationship management with customers to make them more satisfied, and that is why the employees at the microfoundational level should learn and adopt AI-enabled CRM business applications.

With such coaching conversations, the employees should be highly motivated to meet the customer-specific needs and offer better service to the customers. The employees should realize that the ability to use

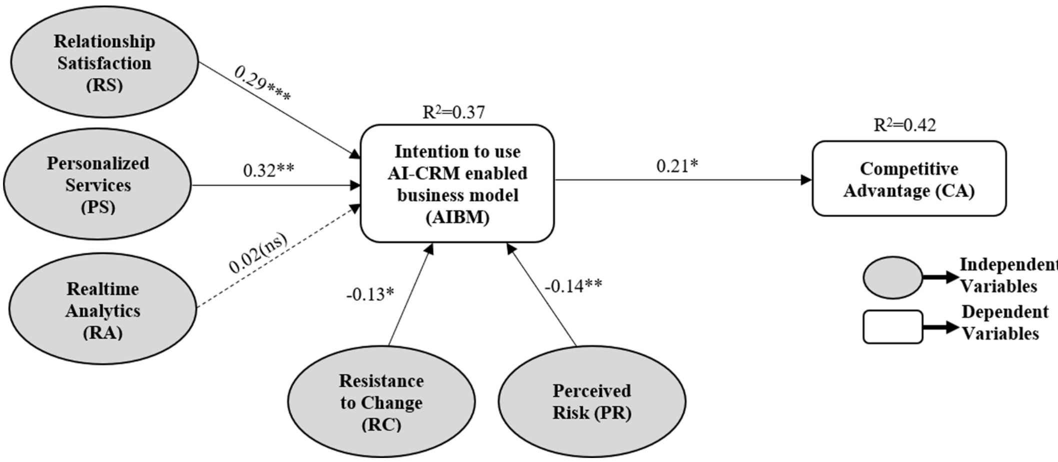


Fig. 4. Rival model.

AI–enabled business applications will help them to acquire prompt and accurate decision-making power to answer any urgent customer queries, which in turn would satisfy the customers' needs and expectations. Since AI-CRM helps to advise employees, they will be able to quickly connect with the customers using different means such as emails, social media, mobile telephony, and so on, provided the employees are able to use AI-CRM enabled business applications in an efficient manner. For this, the managers must arrange to impart periodic training to the employees on how to best use different AI enabled solutions.

Besides, to ensure customers get personalized services, the managers must be watchful to see what the actual customer needs are. If necessary, the managers should advise the product or service team to further customize the product or services to meet the customers' expectations, which will enhance the overall customer experience and will make them loyal to the firm.

The study has demonstrated that real-time analytics capability has an insignificant impact on the intention of the firms to use an AI-enabled CRM business model (H1c). But theoretically, real time analytics capability of a firm should positively impact the intention to use AI-CRM. This result of this study has been reached presumably due to the distrust employees have in the capability of AI-CRM technology to provide accurate, real time, and actionable information. To improve the trust level of the individual employees regarding the real-time analytics capability of AI-CRM technology, the role of managers is crucial. The immediate managers of the employees should hold regular meetings with employees to keep them appraised about success stories regarding the capability and contribution of real-time analytics ability of the AI-CRM technology. Such success stories will help to improve employees' mindset regarding the power of AI-CRM real time analytics capability.

Since it is a fact that whenever any new technology is introduced in a firm, the employees initially lack trust and perceive the new technology as a risk to their jobs, thus resisting to use the new system (H2a, H2b). Here, the role of leadership is critical (H5). The leadership must emotionally incentivize the employees so that they do not become reluctant to use the system. Leadership should incentivize the employees to adopt AI-CRM ecosystem-based business models for all the business applications. This will also encourage and motivate the employees to actual use the AI-CRM-based business applications (H3), which will, in turn, improve the competitiveness of the firms (H4). All these measures will help the firm to sustain competitive advantage. Thus, the leadership support is critical to fully use and adopt the AI-CRM ecosystem-based business model and applications for the firm to remain competitive in the market.

6.3. Limitations with future scope of research

The present study is based on data which are cross sectional in nature. This yields defects of endogeneity and affects the causality of relationships between different constructs. This is one of the defects of this study. It is suggested that future researchers should conduct a longitudinal study with econometric analysis to remove this defect. The present study did not discuss a rival model, which could be compared with the proposed theoretical model to assess the superiority of the proposed theoretical model. Future researchers may investigate this.

This research study has arrived at the findings based on the inputs of 341 respondents from different industries. The sample size is not adequate to conduct a robust analysis and is also inadequate to project the entire spectrum of industries. It is suggested that future researchers consider inputs from more respondents of various industries so that the results do not suffer from the lack of generalizability. The explanative power of the model is 73 %. It is suggested that future researchers may consider other boundary conditions to examine if, by including other boundary conditions, the explanative power of the proposed model could be improved.

In the survey, the respondents were selected from India. Hence the result of the study is India-specific. It may not yield similar results if the study is conducted in other countries where the businesses operate using a different ecosystem. So, this study lacks generalizability. It is suggested that future researchers should collect data from respondents all over the globe and from different industries. Diversification of respondents will make the findings more robust and generalizable.

Again, feedback was also taken from those firms where the usage of AI-CRM based business model was at the initial stage. In a few of the firms, the usage of an AI-CRM ecosystem-based business model was at the conceptual stage. Hence, feedback was obtained from respondents who were non-adopters of AI-CRM ecosystem-based business model. Therefore, proper cautions must be taken when the results of this study are applied to firms that have fully adopted an AI-CRM ecosystem-based business model and where the ecosystem is well developed and matured.

CRediT authorship contribution statement

Sheshadri Chatterjee: Project administration, Methodology, Conceptualization, Writing – original draft. **Ranjan Chaudhuri:** Methodology, Formal analysis, Data curation. **Demetris Vrontis:** Supervision, Conceptualization. **Fauzia Jabeen:** Resources, Investigation, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix:. Rival model

An alternative, or rival, model has been developed by not considering the moderating effects of leadership support or the mediating effects of actual AI-CRM usage (ACU). The rival model is shown in Fig. 4.

The analytical study of the rival model has highlighted that the impacts of RS, PS, RA, RC, and PR on AIBM have remained unaltered. But the impacts of AIBM on the goal CA have been reduced to a great extent, since the concerned path coefficient is as low as 0.21 with a level of significance at $p < 0.05(*)$. The explanative power of the rival model has also become 42 % ($R^2 = 0.42$), whereas the explanative power of the proposed theoretical model is 73 % ($R^2 = 0.73$) (Fig. 2). This reveals that the inclusion of ACU to mediate between AIBM and CA is important, and that we need to consider the effects of the moderating variable leadership support on the linkage AIBM → ACU. Hence, by comparing the rival model with the proposed theoretical model (Fig. 2), the superiority and effectiveness of the proposed theoretical model is highlighted (Li et al., 2022).

References

Aga, D. A., Noorderhaven, N., & Vallejo, B. (2016). Transformational leadership and project success: The mediating role of team building. *International Journal of Project Management, 34*(5), 806–818.

Akram, K., Saeed, A., Bresciani, S., Rehman, S. U., & Ferraris, A. (2022). Factors affecting environmental performance during the Covid-19 period in the leather industry: A moderated-mediation approach. *Journal of Competitiveness, 14*(1), 5–22.

Akter, S., Fosso Wamba, S., & Dewan, S. (2017). Why PLS-SEM is suitable for complex modelling? An empirical illustration in big data analytics quality. *Production Planning & Control, 28*(11/12), 1011–1021.

Alberti-Alhtaybat, L. V., Al-Htaybat, K., & Hutaibat, K. (2019). A knowledge management and sharing business model for dealing with disruption: The case of Aramex. *Journal of Business Research, 94*, 400–407.

Anderson, E. W., Fornell, C., & Mazvancheryl, S. K. (2004). Customer satisfaction and shareholder value. *Journal of Marketing, 68*(4), 172–185.

Armstrong, J. S., & Overton, T. S. (1977). Estimating nonresponse bias in mail surveys. *Journal of Marketing Research, 14*(3), 396–402.

Baker, D. A., & Crompton, J. L. (2000). Quality, satisfaction, and behavioral intentions. *Annals of Tourism Research, 27*(3), 785–804.

Balakrishnan, J., & Dwivedi, Y. K. (2021). Role of cognitive absorption in building user trust and experience. *Psychology & Marketing, 38*(4), 643–668.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99–120.

Barney, J. A. Y., & Felin, T. (2013). What are microfoundations? *Academy of Management Perspectives, 27*(2), 138–155.

Basile, G., Chatterjee, S., Chaudhuri, R., & Vrontis, D. (2021). Digital transformation and entrepreneurship process in SMEs of India: A moderating role of adoption of AI-CRM capability and strategic planning. *Journal of Strategy and Management, In Press.*. https://doi.org/10.1108/JSMA-02-2021-0049

Belyaeva, Z., Shams, S. M. R., Santoro, G., & Grandhi, B. (2020). Unpacking stakeholder relationship management in the public and private sectors: The comparative insights. *EuroMed Journal of Business, 15*(3), 269–281.

Benson, A. D., Johnson, S. D., & Kuchinke, K. P. (2002). The use of technology in the digital workplace: A framework for human resource development. *Advances in Developing Human Resources, 4*(4), 392–404.

Bertello, A., Ferraris, A., Bresciani, S., & De Bernardi, P. (2020). Big data analytics (BDA) and degree of internationalization: The interplay between governance of BDA infrastructure and BDA capabilities. *Journal of Management and Governance, 25*, 1035–1055.

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*, 102225.

Bostrom, N., & Ord, T. (2006). The reversal test: Eliminating status quo bias in applied ethics. *Ethics, 116*(4), 656–679.

Bresciani, S., Ciampi, F., Meli, F., & Ferraris, A. (2021a). Using big data for co-innovation processes: Mapping the field of data-driven innovation, proposing theoretical developments, and providing a research agenda. *International Journal of Information Management, 60*, 102347.

Bresciani, S., Ferraris, A., & Del Giudice, M. (2018). The management of organizational ambidexterity through alliances in a new context of analysis: Internet of Things (IoT) smart city projects. *Technological Forecasting and Social Change, 136*, 331–338.

Bresciani, S., Huarng, K. H., Malhotra, A., & Ferraris, A. (2021a). Digital transformation as a springboard for product, process, and business model innovation. *Journal of Business Research, 128*(2), 204–210.

Carpenter, S. (2018). Ten steps in scale development and reporting: A guide for researchers. *Communication Methods and Measures, 12*(1), 25–44.

Chatterjee, S. (2015). Security and privacy issues in E-Commerce: A proposed guidelines to mitigate the risk. *IEEE International Advance Computing Conference (IACC), 393–396*. https://doi.org/10.1109/IADCC.2015.7154737

Chatterjee, S. (2019a). Is data privacy a fundamental right in India? An analysis and recommendations from policy and legal perspective. *International Journal of Law and Management, 61*(1), 170–190.

Chatterjee, S. (2019b). Impact of AI regulation on intention to use robots: From citizens and government perspective. *International Journal of Intelligent Unmanned Systems, 8*(2), 97–114.

Chatterjee, S., Ghosh, S. K., & Chaudhuri, R. (2020). Adoption of ubiquitous customer relationship management (uCRM) in enterprise: Leadership support and technological competence as moderators. *Journal of Relationship Marketing, 19*(2), 75–92.

Chaudhuri, R., Vrontis, D., Thrassou, A., & Ghosh, S. K. (2021). Adoption of artificial intelligence-integrated CRM systems in agile organizations in India. *Technological Forecasting and Social Change., 168*, 120783.

Chen, C. F., & Chen, F. S. (2010). Experience quality, perceived value, satisfaction and behavioral intentions for heritage tourists. *Tourism Management, 31*(1), 29–35.

Cheng, B. S., Chou, L. F., Wu, T. Y., Huang, M. P., & Farh, J. L. (2004). Paternalistic leadership and subordinate responses: Establishing a leadership model in Chinese organizations. *Asian Journal of Social Psychology, 7*(1), 89–117.

Chin, W. W. (2010). How to write up and report PLS analyses. In W. W. Chin (Ed.), *Handbook of partial least squares* (pp. 655–690). Berlin, Heidelberg: Springer.

Clauss, T., Abebe, M., Tangpong, C., & Hock, M. (2019). Strategic agility, business model innovation, and firm performance: An empirical investigation. *IEEE Transactions on Engineering Management, 1–18*. https://doi.org/10.1109/TEM.2019.2910381

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Erlbaum.

de Jong, A., de Ruyter, K., Keeling, D. I., Polyakova, A., & Ringberg, T. (2021). Key trends in business-to-business services marketing strategies: Developing a practice-based research agenda. *Industrial Marketing Management, 93*, 1–9.

Deb, M., & Lomo-David, E. (2014). An empirical examination of customers' adoption of m-banking in India. *Journal of Marketing Intelligence & Planning, 32*(4), 475–494.

Dhir, A., Pallesen, S., Torsheim, T., & Andreassen, C. S. (2016). Do age and gender differences exist in selfie-related behaviours? *Computers in Human Behavior, 63*, 549–555.

Dimitropoulos, P., Koronios, K., Thrassou, A., & Vrontis, D. (2020). Cash holdings, corporate performance and viability of Greek SMEs: Implications for stakeholder relationship management. *EuroMed Journal of Business, 15*(3), 333–348.

Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., & Wang, Y. (2020). Setting the future of digital and social media marketing research: Perspectives and research propositions. *International Journal of Information Management, 102168*. https://doi.org/10.1016/j.ijinfomgt.2020.102168. in press.

Dwivedi, Y. K., Chatterjee, S., & Rana, N. P. (2021). Assessing Consumers' Co-production and Future Participation on Value Co-creation and Business Benefit: An FPCB Model Perspective. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-021-10104-0. in press.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., … Williams, M. D. (2019). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice, and policy. *International Journal of Information Management, 57*, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

El Sawy, O. A., Kræmmergaard, P., Amsinck, H., & Vinther, A. L. (2016). How LEGO built the foundations and enterprise capabilities for digital leadership. *MIS Quarterly Executive, 15*(2), 5–22.

Enkel, E., Bogers, M., & Chesbrough, H. (2020). Exploring open innovation in the digital age: A maturity model and future research directions. *R&D Management, 50*(1), 161–168.

Fainshmidt, S., Pezeshkan, A., Frazier, M., Nair, A., & Markowski, E. (2016). Dynamic capabilities and organizational performance: A meta-analytic evaluation and extension. *Journal of Management Studies., 53*(8), 1348–1380.

Ferraris, A., Degbey, W. Y., Singh, S. K., Bresciani, S., Castellano, S., Fiano, F., & Couturier, J. (2021). Microfoundations of strategic agility in emerging markets: Empirical evidence of Italian MNEs in India. *Journal of World Business, 57*(2), 101272.

Ferraris, A., Mazzoleni, A., Devalle, A., & Couturier, J. (2018). Big data analytics capabilities and knowledge management: Impact on firm performance. *Management Decision, 57*(8), 1923–1936.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50.

Gal, D., & Rucker, D. D. (2018). The loss of loss aversion: Will it loom larger than its gain? *Journal of Consumer Psychology, 28*(3), 497–516.

Geisser, S. (1975). The predictive sample reuse method with applications. *Journal of the American Statistical Association, 70*(350), 320–328.

Goepel, M., Hölzle, K., & zu Knyphausen-Aufseß, D.. (2012). Individuals' innovation response behaviour: A framework of antecedents and opportunities for future research. *Creativity and Innovation Management, 21*(4), 412–426.

Graca, S. S., Barry, J. M., & Doney, P. M. (2015). Performance outcomes of behavioral attributes in buyer supplier relationships. *Journal of Business and Industrial Marketing, 30*(7), 805–816.

Grover, P., Kar, A. K., & Dwivedi, Y. K. (2020). Understanding artificial intelligence adoption in operations management: Insights from the review of academic literature and social media discussions. *Annals of Operations Research*. https://doi.org/10.1007/s10479-020-03683-9. in press.

Guide, V. D. R., & Jr. & Ketokivi, M.. (2015). Notes from the Editors: Redefining some methodological criteria for the journal. *Journal of Operations Management, 37*(1), 5–8.

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B., & Akter, S. (2017). Big data and predictive analytics for supply chain and organizational performance. *Journal of Business Research, 70*, 308–317.

Haefner, N., Wincent, J., Parida, V., & Gassmann, O. (2020). Artificial intelligence and innovation management: A review, framework, and research agenda. *Technological Forecasting and Social Change, 162*, 120392.

Hair, J. F., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems, 117*(3), 442–458.

Hair, J. F., Jr., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling (PLS-SEM)*. London: Sage Publications.

Hair, J. F., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2018). *Advanced Issues in Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Thousand Oaks, CA: Sage Publication.

Harel, R., Schwartz, D., & Kaufmann, D. (2021). Organizational culture processes for promoting innovation in small businesses. *EuroMed Journal of Business, 16*(2), 218–240.

Hassan, R. S., Nawaz, A., Lashari, M. N., & Zafar, F. (2015). Effect of customer relationship management on customer satisfaction. *Procedia Economics and Finance, 23*(1), 563–567.

Henseler, J., Dijkstra, T. K., Sarstedt, M., Ringle, C. M., Diamantopoulos, A., Straub, D. W., & Calantone, R. J. (2014a). Common beliefs and reality about PLS: Comments on Rönkkö and Evermann. *Organizational Research Methods, 17*(2), 182–209.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2014b). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135.

Hess, T., Matt, C., Benlian, A., & Wiesböck, F. (2016). Options for formulating a digital transformation strategy. *MIS Quarterly Executive, 15*(2), 123–139.

Hizir, Z. (2022). Digital transformation: "jobocolypse" or empowerment? *Strategic HR Review, 21*(1), 6–9.

Hopp, C., Antons, D., Kaminski, J., & Oliver Salge, T. (2018). Disruptive innovation: Conceptual foundations, empirical evidence, and research opportunities in the digital age. *Journal of Product Innovation Management, 35*(3), 446–457.

Hu, L., & Bentler, P. M. (1998). Fit indices in covariance structure modeling: Sensitivity to under parameterized model misspecification. *Psychological Methods, 3*(4), 424–453.

Joshi, K. (1991). A model of users' perspective on change: The case of information systems technology implementation. *MIS Quarterly, 15*(2), 229–242.

Kabra, G., Ramesh, A., Akhtar, P., & Dash, M. K. (2017). Understanding behavioural intention to use information technology: Insights from humanitarian practitioners. *Telematics & Informatics, 34*, 1250–1261.

Khaksar, S. M. S., Khosla, R., Singaraju, S., & Slade, B. (2019). Carer's perception on social assistive technology acceptance and adoption: Moderating effects of perceived risks. *Behaviour & Information Technology, 40*(4), 337–360.

Kim, H. J., Lee, J. M., & Rha, J. Y. (2017). Understanding the role of user resistance on mobile learning usage among university students. *Computers and Education, 113*(10), 108–118.

Kim, H. W., & Kankanhalli, A. (2009). Investigating user resistance to information systems implementation: A status quo bias perspective. *MIS Quarterly, 33*(3), 567–582.

Kock, N. (2015), *WarpPLS 5.0 User Manual.* ScriptWarp Systems, Laredo, TX.

Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Information Systems Journal, 28*(1), 227–261.

KPMG (2017). *Disruption is the new norm.* Available at: https://advisory.kpmg.us/articles/ 2017/disruption-new-norm.html?utm_source=itrskmngmntprt1&utm_medium=referral& mid=m-00003093&utm_campaign=c-00049065&cid=c-00049065. (Accessed 12 August 2021).

Kuo, L., Shihping, K. H., & Yen-Chun, J. W. (2010). Operational efficiency integrating the evaluation of environmental investment: The case of Japan. *Management Decision, 48*(10), 1596–1616.

Li, F. (2018). The digital transformation of business models in the creative industries: A holistic framework and emerging trends. *Technovation, 102012*.

Li, W., Liu, Z., Xia, S., Yan, J., Xiong, Y., Sakka, G., & Li, R. Y. (2022). How can emerging-market SMEs domestically benefit from their performance in developed countries? Empirical evidence from China. *Journal of Business Research, 142*, 200–210.

Li, Y., & Sun, J. M. (2015). Traditional Chinese leadership and employee voice behavior: A cross-level examination. *The Leadership Quarterly, 26*(2), 172–189.

Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross-sectional research designs. *Journal of Applied Psychology, 86*(1), 114–121.

Liu, S. (2015). Effects of control on the performance of information systems projects: The moderating role of complexity risk. *Journal of Operations Management, 36*, 46–62.

Margiono, A. (2021). Digital transformation: Setting the pace. *Journal of Business Strategy, 42*(5), 315–322.

Markus, M. L. (1983). Power, politics, and MIS implementation. *Communications of the ACM, 26*(6), 430–444.

Mas, J. M., & Gómez, A. (2021). Social partners in the digital ecosystem: Will business organizations, trade unions and government organizations survive the digital revolution? *Technological Forecasting and Social Change, 162*, 1–17.

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management, 58*(3), 103434.

Mishra, A., Maheswarappa, S. S., Maity, M., & Samu, S. (2018). Adolescent's eWOM intentions: An investigation into the roles of peers, the Internet and gender. *Journal of Business Research, 86*, 394–405.

Mithas, S., Jones, J. L., & Mitchell, W. (2002). Non-contractible factors as determinants of electronic market adoption. *Proceedings of the 23rd International Conference on Information Systems*.

Mithas, S., Tafti, A., & Mitchell, W. (2013). How a firm's competitive environment and digital strategic posture influence digital business strategy. *MIS Quarterly*, 511–536.

Muninger, M. I., Hammedi, W., & Mahr, D. (2019). The value of social media for innovation: A capability perspective. *Journal of Business Research, 95*, 116–127.

Mustak, M., Salminen, J., Plé, L., & Wirtz, J. (2021). Artificial intelligence in marketing: Topic modeling, scientometric analysis, and research agenda. *Journal of Business Research, 124*, 389–404.

Nguyen, B., Chatterjee, S., Ghosh, S., & Chaudhuri, R. (2019). Are CRM systems ready for AI integration? A conceptual framework of organizational readiness for effective AI-CRM integration. *The Bottom Line, 32*(2), 144–157.

Nguyen, T. H., & Waring, T. S. (2013). The adoption of customer relationship management (CRM) technology in SMEs: An empirical study. *Journal of Small Business and Enterprise Development, 20*(4), 824–848.

Nicolle, A., Fleming, S. M., Bach, D. R., Driver, J., & Dolan, R. J. (2011). A regret-induced status quo bias. *Journal of Neuroscience, 31*(9), 3320–3327.

Peng, D. X., & Lai, F. (2012). Using partial least squares in operations management research: A practical guideline and summary of past research. *Journal of Operations Management, 30*(6), 467–480.

Piccolo, R., Chaudhuri, R., & Vrontis, D. (2021). Enterprise social network for knowledge sharing in MNCs: Examining the role of knowledge contributors and knowledge seekers for cross-country collaboration. *Journal of International Management, 27*(1), 100827.

Picone, P. M., De Massis, A., Tang, Y., & Piccolo, R. F. (2021). The psychological foundations of management in family firms: Values, biases, and heuristics. *Family Business Review*. https://doi.org/10.1177/0894486520985630

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903.

Post, G. V., & Kagan, A. (2006). Information security tradeoffs: The user perspective. *EDPACS the EDP audit, control and security newsletter, 34*(3), 1–10.

Prahalad, C. K., & Hamel, G. (1990). The core competence of the corporation. *Harvard Business Review, 68*(3), 79–91.

Rafiki, A., Hidayat, S. E., Razzaq, A. A., & D.. (2019). CRM and organizational performance: A survey on telecommunication companies in Kuwait. *International Journal of Organizational Analysis, 27*(1), 187–205.

Rana, N. P., Dwivedi, Y. K., & Akter, S. (2022). Understanding dark side of artificial intelligence (AI) integrated business analytics: Assessing firm's operational inefficiency and competitiveness. *European Journal of Information Systems, 31*(3), 364–387.

Reisch, L., & Zhao, M. (2017). Behavioural economics, consumer behaviour and consumer policy: State of the art. *Behavioral Public Policy, 1*(2), 190–206.

Rialti, R., Marrucci, A., Zollo, L., & Ciappei, C. (2022). Digital technologies, sustainable open innovation, and shared value creation: Evidence from an Italian agritech business. *British Food Journal, 124*(6), 1838–1856.

Rialti, R., Zollo, L., Ferraris, A., & Alon, I. (2019). Big data analytics capabilities and performance: Evidence from a moderated multi-mediation model. *Technological Forecasting and Social Change, 149*, 119781.

Rigdon, E. E., Sarstedt, M., & Ringle, M. (2017). On comparing results from CB-SEM and PLS-SEM: Five perspectives and five recommendations. *Marketing ZFP, 39*(3), 4–16.

Samuel, J., Kashyap, R., Samuel, Y., & Pelaez, A. (2022). Adaptive cognitive fit: Artificial intelligence augmented management of information facets and representations. *International Journal of Information Management, 65*, 102505.

Samuelson, W., & Zeckhauser, R. (1988). Status quo bias in decision making. *Journal of Risk and Uncertainty, 1*(1), 7–59.

Sandström, S., Edvardsson, B., Kristensson, P., & Magnusson, P. (2008). Value in use through service experience. *Managing Service Quality, 18*(2), 112–126.

Schepers, J. J., Wetzels, M. M., & De Ruyter, J. C. (2005). Leadership styles in technology acceptance: Do followers practice what leaders preach? *Managing Service Quality, 15*(6), 496–508.

Scott, E., & Christian, C. S. (2012). Bias in favor of the status quo. *Social and Personality Psychology Compass, 6*(3), 270–281.

Scuotto, V., Santoro, G., Bresciani, S., & Del Giudice, M. (2017). Shifting intra-and inter-organizational innovation processes towards digital business: An empirical analysis of SMEs. *Creativity and Innovation Management, 26*(3), 247–255.

Shao, Z., Feng, Y., & Hu, Q. (2016). Effectiveness of top management support in enterprise systems success: A contingency perspective of fit between leadership styple and system life cycle. *European Journal of Information Systems, 25*(2), 131–153.

Sharma, S. K., Al-Badi, A., Rana, N. P., & Al-Azizi, L. (2018). Mobile applications in government services (mG-App) from user's perspectives: A predictive modelling approach. *Government Information Quarterly, 35*(4), 557–568.

Singh, A., & Hess, T. (2017). How Chief Digital Officers promote the digital transformation of their companies. *MIS Quarterly Executive, 16*(1), 1–17.

Song, J., Xia, S., & Vrontis, D. (2022). The Source of SMEs' Competitive Performance in COVID-19: Matching Big Data Analytics Capability to Business Models. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-022-10287-0. in press.

Sousa, M. J., & Rocha, Á. (2019). Skills for disruptive digital business. *Journal of Business Research, 94*, 257–263.

Stein, A. D., Smith, M. F., & Lancioni, R. A. (2013). The development and diffusion of customer relationship management (CRM) intelligence in business-to-business environments. *Industrial Marketing Management, 42*(6), 855–861.

Stone, M. (1974). Cross validatory choice and assessment of statistical predictions. *Journal of the Royal Statistical Society, 36*(2), 111–147.

Tabrizi, B., Lam, E., Girard, K., & Irvin, V. (2019). Digital transformation is not about technology Accessed 12 February 2022 *Harvard Business Review* https://hbr.org/2019/03/digital-transformation-is-not-about-technology.

Tamilmani, K., Rana, N. P., & Sharma, A. (2021). The effect of AI-based CRM on organization performance and competitive advantage: An empirical analysis in the B2B context. *Industrial Marketing Management, 97*(8), 205–219.

Thrassou, A., Chatterjee, S., Chaudhuri, R., Vrontis, D., & Ghosh, S. K. (2021). ICT-enabled CRM system adoption: A dual Indian qualitative case study and conceptual framework development. *Journal of Asia Business Studies, 15*(2), 257–277.

Vinzi, V. E., Trinchera, L., & Amato, S. (2010). *Handbook of partial least squares*. Berlin Heidelberg: Springer.

Vlačić, B., Corbo, L., Costa e Silva, S., & Dabić, M. (2021). The evolving role of artificial intelligence in marketing: A review and research agenda. *Journal of Business Research, 128*, 187–203.

von Leipzig, T., Gamp, M., Manz, D., Schöttle, K., Ohlhausen, P., Oosthuizen, G., & von Leipzig, K. (2017). Initialising customer-orientated digital transformation in enterprises. *Procedia Manufacturing, 8*, 517–524.

Voorhees, C. M., Brady, M. K., Calantone, R., & Ramirez, E. (2016). Discriminant validity testing in marketing: An analysis, causes for concern, and proposed remedies. *Journal of the Academy of Marketing Science, 44*, 119–134.

Vrhovec, S. L. R., Hovelja, T., Vavpotic, D., & Krisper, M. (2015). Diagnosing organizational risks in software projects: Stakeholder resistance. *International Journal of Project Management, 33*(6), 1262–1273.

Wamba, S. F., Gunasekaran, A., Dubey, R., & Ngai, E. W. (2018). Big data analytics in operations and supply chain management. *Annals of Operations Research, 270*(1–2), 1–4.

Wamba, S. F., Gunasekaran, A., Akter, S., & Dubey, R. (2019). The performance effects of big data analytics and supply chain ambidexterity: The moderating effect of environmental dynamism. *International Journal of Production Economics, 222*(4), 107498.

Westbrook, R. A., & Oliver, R. L. (1991). The dimensionality of consumption emotion patterns and customer satisfaction. *Journal of Consumer Research, 18*, 84–91.

Willaby, H. W., Costa, D. S. J., Burns, B. D., MacCann, C., & Roberts, R. D. (2015). Testing complex models with small sample sizes: A historical overview and empirical demonstration of what partial least squares (PLS) can offer differential psychology. *Personality and Individual Differences, 84*, 73–78.

Wu, H. C., Cheng, C. C., & Ai, C. H. (2018). A study of experiential quality, experiential value, trust, corporate reputation, experiential satisfaction, and behavioral intentions for cruise tourists: The case of Hong Kong. *Tourism Management, 66*, 200–220.

Yeoh, P. (2019). Artificial intelligence: Accelerator or panacea for financial crime? *Journal of Financial Crime, 26*(2), 634–646.

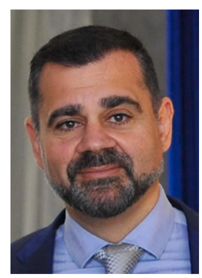
Yeow, A., Soh, C., & Hansen, R. (2018). Aligning with new digital strategy: A dynamic capabilities approach. *The Journal of Strategic Information Systems, 27*(1), 43–58.

Zhang, Y., Gao, P., Zhang, J., & Lu, L. (2020). Effect of authoritarian leadership on user resistance to change: Evidence from IS project implementation in China. *Industrial Management & Data Systems, 120*(10), 1813–1834.

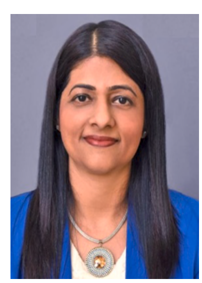
Zimmermann, A., Hill, S. A., Birkinshaw, J., & Jaeckel, M. (2020). Complements or substitutes? A microfoundations perspective on the interplay between drivers of ambidexterity in SMEs. *Long Range Planning, 53*(6), 101927.

Dr. Sheshadri Chatterjee is a post-doctoral research scholar at Indian Institute of Technology, Kharagpur, India. He completed his PhD from Indian Institute of Technology, Delhi, India. He has had work experience in different multinational organizations, such as Microsoft Corporation, Hewlett Packard Company, and IBM. Sheshadri has published research articles in several reputed journals such as Government Information Quarterly, Information Technology & People and Journal of Digital Policy, Regulation and Governance. Sheshadri is also a certified Project Management Professional (PMP) from Project Management Institute (PMI), USA, and completed PRINCE2, OGC, UK and ITIL v3 UK. He can be contacted at: sheshadri.academic@gmail.com.

Dr. Ranjan Chaudhuri is a Professor of Marketing at Indian Institute of Manaement Ranchi, Jharkhand, India. He was a Fulbright Fellow to USA in 2012. Dr. Chaudhuri also served as an Associate Professor at NITIE, Mumbai and Vinod Gupta School of Management, Indian Institute of Technology, Kharagpur, and at the Department of Management Studies, Indian Institute of Technology, Delhi. Dr. Chaudhuri has over 18 years of industrial, teaching and research experience. Dr. Chaudhuri's teaching and research interests are in the areas of Business-to-Business Marketing, Global Marketing and Retail Management.



Demetris Vrontis is a Professor and Executive Dean at the University of Nicosia in Cyprus. He is the Founding Editor and Editor in Chief of the EuroMed Journal of Business and the Associate Editor in Chief of the International Marketing Review. He is also the Founder and President of the EuroMed Research Business Institute (http://emrbi.org). Professor Vrontis has published widely in over 200 refereed journal articles and 40 books in the areas of Business Management, Marketing, Human Resource Management, Innovation and Entrepreneurship. He is a fellow member and certified Chartered Marketer of the Chartered Institute of Marketing and a Chartered Business and Chartered Marketing Consultant. He also serves as a consultant and member of board of directors to a number of international companies. Further details about Professor Vrontis can be found at: http://unic.academia.edu/DemetrisVrontis



Dr. Fauzia Jabeen joined Abu Dhabi University in 2011. She has over 18 years of experience in teaching, consulting, and research and notable academic and industrial experience in the United Arab Emirates. Her teaching and research interests focus on Women's Entrepreneurship and SMEs, Organizational Behavior, Strategic Management, Corporate Social Responsibility, and Emiratization. She was awarded Abu Dhabi University's Distinguished Faculty Award in 2014 and 2015 and the University Teaching Award in 2013, 2014, 2016, and 2017. She holds a PhD in Management from the Dr. A.P.J. Abdul Kalam Technical University in India. Her work has been published in high impact journals, including the International Journal of Hospitality Management, International Journal of Productivity and Performance Management, International Journal of Organizational Analysis, Journal of Small Business and Enterprise Development, Journal of Management Development, Gender in Management, and International Journal of Project Organization and Management.