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Assessing the Implementation of AI Integrated CRM System for B2C Relationship Management: Integrating Contingency Theory and Dynamic Capability View Theory

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Abstract
Customer relationship management (CRM) is a strategic approach to manage an organization's interaction with current and potential customers. Artificial Intelligence (AI) can analyze huge volume of data without human intervention. The integration of AI with existing legacy CRM system in the business to customer (B2C) relationship makes sense given the massive potential for growth of AI integrated CRM system. Failure to plan AI-CRM technology implementation in an organization could lead some to success and others to failure. The Contingency theory states that it is not possible for organizations to take decisions without a contingency plan and the optimal course of action depends on the internal and external circumstances. The Dynamic Capability View theory emphasizes the organizational ability to react adequately in a timely manner to any external changes and combines multiple capabilities of the organization, including organizational CRM and AI capabilities. Against this background, the purpose of this study is to examine the success and failure of implementation of AI integrated CRM system in an organization from B2C perspective using Contingency theory and Dynamic Capability View theory. The study finds that information quality, system fit, and organizational fit significantly and positively impact the implementation of AI-CRM for B2C relationship management. Also, there is a moderating impact of technology turbulence on both acceptance and failure of AI-CRM capability in the organization.

Keywords AI-CRM · B2C · Success and failure · Contingency theory · Dynamic capability view

1 Introduction

Organizations consider Customer Relationship Management (CRM) as an effective and useful tool to understand their customers. The CRM tool helps organizations "by identifying a company's best customers and maximizing the value from them by satisfying and retaining them" (Kennedy, 2006, p.58). CRM enables achieving high customer satisfaction and improves the performance of organizations (Graca et al., 2015; Nguyen & Mutum, 2012). The capability of CRM can be best assessed to what extent the CRM tool could accurately analyze the huge volume of customers' data (Li & Nguyen, 2016). However, it is difficult to analyze such huge volume of customers' data with only human efforts. In this light, the application of Information and Communication Technology (ICT) is expected to overcome this issue. More specifically, the use of ICT in this respect also includes applications of Artificial Intelligence (AI) technology (Josiassen et al., 2014; Wang & Feng, 2012). This explains the rationale

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to study AI integrated CRM system for B2C relationship management (San-Martína et al., 2016). Consequent upon growing number of transactions, the volume of data of the customers is increasing rapidly. The increase of volume of customer data helps the organizations to better understand their customers since the data possess more information of the customers. This data is of multifarious types (Powell et al., 2018). It is a fact that the organizations need to work more for extracting information since most of the data is unstructured (Chatterjee et al., 2020). It is a challenging task to understand the unstructured data. The AI tools can convert unstructured data to structured data. Then machine learning algorithms can detect the patterns of such data and can provide important insights beneficial for businesses. Thus, AI technology can provide scalable solution to the organizations enabling them to handle and analyze large volume of customers' data rapidly (Chatterjee et al., 2019). Hence, in the changed business scenario, there is a necessity for applying AI integrated CRM system to embolden the relationships between organizations and the customers (Alam et al., 2021; Wikner, 2018). According to Salesforce.com, the use of AI in CRM (AI-CRM) will boost global business revenue to USD 1.1 trillion by 2021. A recent survey by IDC found that 28% of all respondents say their organizations have already started using AI-CRM and an additional 41% plan to adopt AI-CRM in the next two years. Thus, the potential for growth for AI integrated with existing legacy CRM system is huge.

AI integrated CRM system is helpful for automated decision-making and enhances the overall performance of organizations by improving B2C relationship (Peters et al., 2012; Cortez & Johnston, 2020). The principal issue of B2C relationship management is how much information-transfer between the organizations and customers is taking place (Michaelidou et al., 2011). AI integrated CRM systems are expected to perform automated routine tasks and support an organization to appropriately customize, prioritize, and segment the collected customers' data to improve the performance of an organization (Gotteland et al., 2020) by improving the relationship between the organizations and their potential customers. AI technology is still considered as a relatively new technology and its integration with CRM tool is likely to bring technological turbulence (Mier et al., 2020; Song et al., 2005).

The effective implementation of AI integrated CRM system enables overcoming the adverse impacts of technological turbulence. But if technological turbulence creates an adverse behavior, there might be a total failure to fetch profitable results by such integration, i.e. of AI with CRM in organizations (Tian et al., 2010). However, not many studies in extant literature exist that examine the acceptance and failure of implementation of AI-CRM in B2C relationship management. In this context, this study investigates the acceptance and failure for the implementation of AI-CRM system in organizations as well as how the moderating effects of technology turbulence could impact acceptance and failure towards implementation of AI-CRM system in organizations. The aim of this study is to address the following research questions (RQs).

RQ1: How do the organizational characteristics affect the success or failure for implementing AI integrated CRM system in B2C relationship management?
RQ2: Whether there is any moderating impact of technology turbulence for success and failure of implementation of AI integrated CRM system in the organizations?

For understanding the RQs, a few theoretical streams have been integrated. The conception of AI integrated CRM system in B2C context is rested in the contingency theory and dynamic capability view (DCV) theory. The contingency theory has been extended by investigating how the contingency plan coalesces with several abilities to produce best results by implementing AI integrated CRM system in organization in the B2C context. This study also used DCV theory and integrated this theory with contingency theory since either of these theories is perceived not to have been able to interpret the entire end to end scenario under the boundary condition of technology turbulence. Basing on the 326 survey responses, it has been possible to empirically validate the nomological model by the identification of the components and the consequential effects of AI integrated CRM system in B2C context.

The remaining parts of the article are organized as follows. Section 2 presents literature review followed by the discussions on theoretical background and development of conceptual model in section 3. Thereafter, section 4 describes research methodology. Then section 5 details the description of data analysis and results. Next, in section 6, theoretical contributions, practical implications, and limitations with future scope of research are described. The article ends with a brief conclusion in section 7.

2 Literature Review

B2C marketing is related to the business model where an organization markets its products or services to an individual customer (Balaji et al., 2016). The steps for gaining loyalty of the customers contain development of cordial relationships with the customers. The effectiveness of the CRM depends on the ability of the organizations. It is also a fact that loyal customers help to derive more benefits to the organizations than the non-loyal customers (Reichheld

& Teal, 1996). The huge volume of data of customers are needed to be analyzed without much human assistance by using AI integrated CRM system (Ferraris et al., 2017; Gorla et al., 2010). In the context of B2C relationship, CRM system analyses huge volume of customers' data that would help the organizations to prioritize, customize, and segment such data (Alshawi et al., 2011; Lacka et al., 2020). AI is supposed to complement the CRM activities (Nelson et al., 2005; Verma & Verma, 2013; Xu et al., 2013). To analyze data with the CRM system, AI technology assists organizations toward automated decision making in an accurate, time and cost-effective manner that enhances the organization's performance (Assimakopoulos et al., 2015). Technologies are undergoing changes in a rapid way. The organizations must be able to cope up with such rapid change of technology (Alam et al., 2021). For adopting updated processes and practices of the organization consequent upon introduction of new technology like AI-CRM, the organizations are likely to face some teething issues which are conceptualized as technology turbulence (Ullah et al., 2020). For example, the emergence of the new technology, such as AI and its integration with CRM, may create technology turbulence (Santos et al., 2020). The implementation of any technology in an organization is usually within the domain of Contingency Theory (Ginzberg, 1980; Otley, 1980; Vroom & Jago, 1995) which posits that the nature of design, system, organization, and its user characteristics play an important role that affects the implementation of technology in an organization (Daradkeh, 2019). Besides, it has been observed that adoption of a new technology in an organization depends on the capacity of the existing system and system fit that includes to what extent the prevailing system of the organization can adjust with the innovation (Halabi et al., 2017; Peng et al., 2018). To use a new system where features are changing continuously, the organization must have the ability to assimilate such technology in a dynamic environment that is in conformity with the dynamic capability view (DCV) theory (Helfat & Peteraf, 2009). Studies have demonstrated that there is a consistent link between user characteristics and the results of implementation of a new system in an organization (McKenney & Keen, 1974). Studies have documented that whether the implementation of a new technology in an organization will be successful or not depends on the characteristics of the organization. These characteristics include four important components, which include the structure of an organization, existing technology, the tasks the organizations are to perform and the performance ability of the employees (Leavitt, 1964). Studies have suggested that the success or failure to implement a technology in an organization depends on many factors, such as design characteristics, system characteristics, quality of information, and so on (Sivarajah et al., 2019). Different organizations are uncertain regarding the extent of success following the adoption of the AI-CTM technology (Gao et al., 2012). This is mainly due to deficient quality of data to be analyzed by AI and the design-making ability of an organization (Kaufmann et al., 2009). It has been observed that the users' abilities would affect the quality of information to be procured, system characteristics as well as readiness of the organization towards implementation of a new technology (Powell et al., 2018). Studies have been conducted to investigate the potentials of AI implementation in organizations, but none investigated the factors responsible for achieving success or incurring failure to implement a new system like AI integrated CRM system in an organization (Chatterjee et al., 2020) especially, in the context of B2C relationship management. Several studies are there where the studies investigated the potentials of applications of AI in organizations (Akter et al., 2020; Chatterjee et al., 2020; Rana et al., 2021). But no extant literature investigated how AI integrated CRM system in organizations could result in success and failure of AI-CRM system implementation. To fill up this gap, this study has taken a holistic attempt.

3 Theoretical Background and Development of Conceptual Model

3.1 Theoretical Background

From the review of literature, it has been observed that for implementation of AI-CRM system for B2C relationship management, the best way is to depend on common characteristics of the concerned organization and its employees. This implies that by following one best way, it is not possible to successfully implement a new technology in an organization. This concept is supplemented by Contingency Theory (Ginzberg, 1980; Otley, 1980; Vroom & Jago, 1995). Contingency Theory has developed an idea that, to succeed in implementing a technology, different organizations are needed to adopt different strategies (Kast & Rosenzweig, 1979; Lawrence & Lorsch, 1986). The adoption process must be situation specific. The Contingency theory highlights that system performance as well as organizational performance help to assess the extent of success of design and implementation of a new system in an organization (Otley, 1980). Based on large scale empirical studies, the contingency approach is fundamentally based on two salient central findings. The first finding includes the concept that there is not one best way to achieve success for implementation of a technology in an organization. Secondly, each method adopted by an organization to implement a technology should not be considered equally productive for other organizations (Galbraith, 1973). Thus, the main theme of Contingency theory is that there are several ways for successful implementation of a technology which are contingent upon a specific and effective number of common specialties of the employees of the organizations and the organizational abilities. The Contingency theory highlights that the organization must consider the situation and environment before choosing a method to implement a specific technology in that organization. The Contingency theory has projected a framework covering some specific areas that include system design, planning, system implementation, user involvement and ability, performance level, and the internet facilities (Reinartz et al., 2004). Following the framework (Fig. 1) articulated by Ginzberg (1980),our study examines the implementation of AI-CRM for B2C relationship management in an organization.

It is observed that mere implementation of a technology in an organization cannot fetch the expected results. There is need to ensure the full-scale assimilation of that technology. The full-scale assimilation includes how the concerned organization could effectively change the operations and methods for full assimilation of the technology in response to the dynamic changes of the situation. This concept is in line with Dynamic Capability View (DCV) theory (Helfat & Peteraf, 2009). The dynamic capability is meant "as ability to integrate, build, and reconfigure internal and external resources / competencies to address and possibly shape rapidly changing business environments" (Teece, 2012, p.1395). The dynamic abilities can be understood by the three dimensions as suggested by Teece (2014). These three dimensions are sensing, seizing, and reconfiguring abilities. Ability to identify congenial opportunities which can address the needs of the customers in the dynamic markets is the sensing ability. Seizing ability is conceptualized as the ability of the organizations for aptly mobilizing the resources to satisfy the customers by meeting their needs in the changing market conditions. An organization possesses many valuable resources. But for performing a specific task, organizations need to recombine a specific number of resources to successfully complete the tasks. This ability is known as reconfiguring ability (Fainshmidt et al., 2016).

The executives of organizations are supposed to respond and react to the continuously changing external environment and are supposed to act according to the changing situations in order to ensure sustained competitive performance. If organizations do not respond to the dynamic situation they would not be able to assess what are the present demand. By knowing this, the organizations are required to adjust their AI-CRM system to satisfy the needs and demands of the customers and employees in the dynamic environment of organizations. This is the main theme of DCV theory and is the main reasons why even after the implementation of a technology an organization fails to succeed, and another organization succeeds. Thus, in the context of implementation of AI-CRM in the B2C context, the organizations are needed to consider the situation and environment for choosing the appropriate method of implementation which corroborates contingency theory. In this way, the AI-CRM technology can be adopted. Now, to use the AI-CRM technology, the sensing, seizing, and reconfiguring abilities will help the organizations to use and apply the AI-CRM technology in the organizations to fetch best results. Hence, for adoption and use of AI-CRM technology in the organizations, the concepts of both contingency theory and DCV theory are needed.

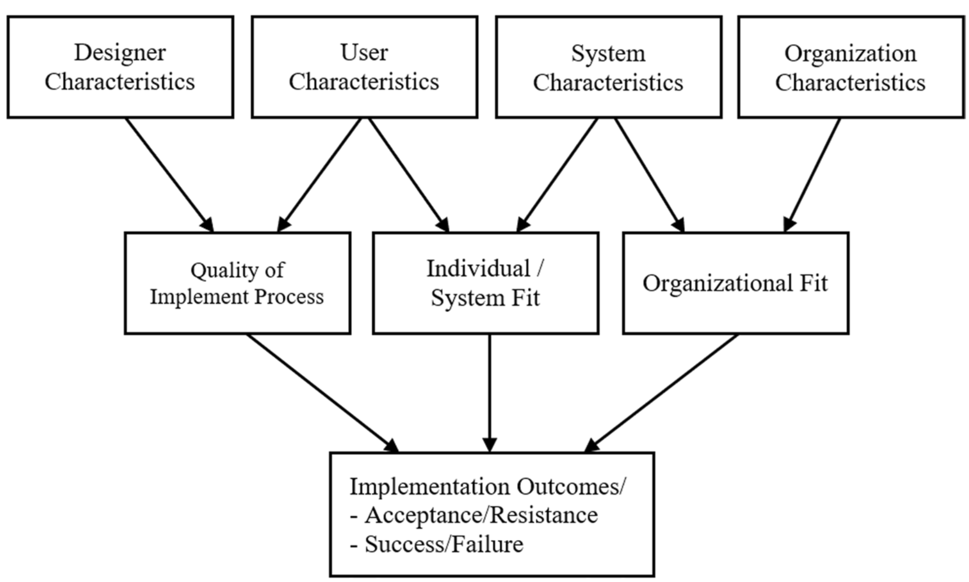


Fig. 1 General model of information system implementation. Source: Ginzberg (1980)

3.2 Hypotheses Development and Conceptual Model

Based on the literature review and theories, we have identified the factors that impact the implementation of AI-CRM for B2C relationship management. We will explain these variables and would try to develop a conceptual model.

3.2.1 Design Characteristics (DC)

From the knowledge of contingency theory, we have observed that if the data and algorithm are not compatible, that is, if the design is not appropriate, it will cause problems to improve the quality of information (Ginzberg, 1980; Otley, 1980; Vroom & Jago, 1995). The AI technology will work to the desired level in the context of AI-CRM activities in organizations if there is availability of cheap and powerful cloud computing system, if there exists smarter data model, and if there is scope for uninterrupted access of unlimited volume of data (Alshare & Lane, 2011). The organization must have these designs to ensure better results to enhance the quality of output information (AlShibly, 2014). It has been observed that most of the successful CRM applications in organizations are supported with upgraded AI algorithms and applications like "Dynamics 365 for customer insights", "Salesforce.com" and so on. This type of design helps an organization to make accurate predictions through automated analysis of customer data. But this application of auto-analysis of customer data leads the organization to enhance the quality of data so gathered since the design would effectively work if it can get scope to analyze quality data (Awasthi & Sangle, 2013). These inputs lead to formulate the following hypothesis.

H1: Design Characteristics (DC) of the AI integrated CRM system positively impacts Information Quality (IQ).

3.2.2 User Characteristics (UC)

From Contingency theory, we know that the successful implementation of a system in an organization is instrumental to implement any innovative process. When an organization proceeds to implement a new technology in the organization, the characteristics of the employees concerning their belief and trust factors along with their capability level play an important role. The employees are required to possess the appropriate knowledge and skills on the new technology to be implemented. The employees must not have any doubt and uncertainty to use the technology because such perception might impede the employees to use the new system (Jarvenpaa et al., 2000). If the users are not knowledgeable and do not have the required skills, it will be difficult for them to extract and absorb appropriate information necessary for the organizations (Karunagaran et al., 2019). Besides, the individuals' know-how will help to improve the system of the organizations conducive to implement a new system (Alsharari et al., 2020). These arguments lead to formulate the following hypotheses.

H2a: There is a positive correlation between User Characteristics (UC) and Information Quality (IQ).
H2b: There is a positive correlation between User Characteristics (UC) and System Fit (SF).

3.2.3 System Characteristics (SC)

The System Characteristics (SC) is associated with the complexity and compatibility of the technology to be implemented in the organization. In the dynamic knowledge-intensive industry, system characteristics are manifested through the compatibility of the technology. It is perceived to play an important role in the context if the existing system fits with the technology to be implemented. Besides, the organizations must have the ability to assimilate the new system. Technological intellectual capital of an organization justifies the system characteristics (Wonglimpiyarat, 2005) of that organization. Besides, when the employees of an organization have a belief that existing system might help the employees to learn and use the new system, there does not exist any constraint for implementation of that new system (Cagliano et al., 2019). With these inputs, the following hypotheses are formulated.

H3a: System Characteristics (SC) is positively corelated with System Fit (SF).
H3b: System Characteristics (SC) is positively corelated with Organizational Fit (OF).

3.2.4 Organization Characteristic (OC)

The specialties of organizations are instrumental for successful implementation of a new system in that organization. The infrastructural constraint of that organization should not constrain the implementation of a new system. The organizations must not have any organizational complexity for the smooth implementation of the new system (Sonnenwald et al., 2001). The organizational capability will help the organization to implement a new system in an easier way. The capacity of an organization is associated with availability of congenial technological as well as environmental infrastructure to help the organization to smoothen the new system (Halabi et al., 2017). The organizations must be otherwise ready to facilitate the deployment of a new system in the organization. The organizations must also have the infrastructural abilities to assimilate the new system to be implemented which is perceived to keep the existing system of the organization conducive to assimilate the applications of the new system. These inputs lead us to develop the following hypothesis.

H4: Organization Characteristic (OC) positively impacts Organizational Fit (OF) for implementing AI-CRM system in the organizations for B2C relationship management.

3.2.5 Information Quality (IQ)

The quality of information is associated with extent the information collected by the organization. This could derive effective benefits for the AI-driven CRM activities and analyse information that is beneficial for an organization. The information gathered must have some value, it should be inimitable, rare and non-substitutable (Lin et al., 2020). The organization collects various information of the customers from different sources. This information (data) is fed to the system for effective analysis by the AI-CRM system to arrive at a correct decision that selects the future course of action of the organization. The quality of data will help the organization to know the potential customers more systematically by "identifying a company's best customers and maximizing the value from them by satisfying and retaining them" (Kennedy, 2006, p.58). Practically, CRM system can capture 360-degree information of customers' data (Chalmeta, 2006). This also emphasizes that how information quality is important. The quality of information of customers' data include knowledge acquisition regarding social activities of the customers, campaign-response history, customers' contact details, customers' purchase history, online activities of the customers, ticket information after sale, and so forth (Chatterjee et al., 2019; Hillebrand et al., 2011). These inputs lead to construe that quality of information helps successful implementation of AI-CRM system to improve B2C relationship. With this knowledge, the following hypothesis is developed.

H5: Information Quality (IQ) positively and significantly impacts the Implementation of AI-CRM for B2C Relationship Management (IARM).

3.2.6 System Fit (SF)

An organization must be compatible to adapt a system that is otherwise construed as system fit (Peng et al., 2018). Compatibility is defined as "the degree to which an innovation is perceived as consistent with the existing values, past experience, and needs of the potential adopters" (Rogers, 2003, p.240). The system fit can be conceptualized as the extent to which the successful assimilation and integration of a new system would fit with the existing infrastructure of the organization (Halabi et al., 2017; Peng et al., 2018). It is observed that if the existing system in an organization fits with the innovative technology, the organization does not face any impediment to implement that innovative technology (Parveen & Sulaiman, 2008). This concept is in conformity with the theme of contingency theory (Vroom & Jago, 1995). All these inputs help us to develop the following hypothesis (H6).

H6: System Fit (SF) positively and significantly impacts the Implementation of AI-CRM for B2C Relationship Management (IARM).

3.2.7 Organizational Fit (OF)

The technological competence of an organization can be conceptualized as an organizational fit which is ascertained by the intersection of organization characteristics and system characteristics as is envisaged in General model of Information System Implementation model (Ginzberg, 1980). From the perspective of implementation of an innovative technology in an organization, the organizational fit is characterized by four salient components. These four components are the existing structure of the organization, the tasks needed to be done by the organization, the technology, which is scheduled to be employed, and the performance of the employees (Leavitt, 1964). Another study recommended by addition of more components of organizational fit (Nadler & Tushman, 1977; Tushman & Nadler, 1978). With all these discussions, it may be perceived that organizational fit can ensure better outcomes through implementation of a new technology in an organization. These ideas lead to prescribing the following hypothesis.

H7: Organizational Fit (OF) positively and significantly impacts the Implementation of AI-CRM for B2C Relationship Management (IARM).

3.2.8 Implementation of AI-CRM for B2C Relationship Management (IARM)

AI technology can work by learning from a large volume of existing data. “For successful implementation of AI applications, business needs to adopt a better data ecosystem with data governance, use cases with business values, analytic tools and technologies, workflow integration, and an ambidextrous organization culture” (Akter et al., 2020). Thus, in the organizations, AI technology could be helpful and supportive for taking accurate and timely decision by the employees of the organizations using organization’s AI-CRM system (Chatterjee et al., 2019). It has been mentioned that the quality along with organizational capabilities are instrumental to impact the outcomes of implementation of AI-CRM for B2C context. It has also been highlighted that the various issues including abilities of the employees of organizations, capability of the organizations, resource collection abilities, and other factors help in successful implementation of a new system, like AI-CRM in an organization to improve the B2C relationship (Wu, 2011). In this way, if it is possible to appropriately implement AI-CRM for B2C relationship management, it is perceived that the organizations would not hesitate towards using AI-CRM system. Accordingly, it is hypothesized as follows.

H8: Appropriate implementation of AI-CRM for B2C relationship management (IARM) will lead to AI-CRM acceptance (ACA) in the organizations.

It has been observed that, even after the adoption of technology by an organization, the management of the organization suffers from the feelings of uncertainty to achieve desired success (Gao et al., 2012). This mostly occurs owing to lack of design making approach as well as defective information processing system (Kaufmann et al., 2009). This may invite eventual failure. To plug this, it is necessary for the concerned organizations to emphasize the procedural rationality (Dean Jr & Sharfman, 1996). Thus, to achieve success after implementing a new technology in an organization the top management of the organization is needed to focus on procedural rationality that includes competitive threat Dean Jr & Sharfman, 1993), organization type and size of the organization (Elbanna & Child, 2007), and so on. If the input data quality is poor, even by applications of AI, incorrect decisions may be reached (Ghasemaghaei, 2019; Rana et al., 2021). It has been observed that “AI-driven systems and models will stop functioning when being fed wrong and malformed data. Furthermore, the speed they can run at is bound to diminish when they have to ingest a large amount of data. These problems will, at best, slow the entire system down and, at worst, bring it to its knees”. (Tse et al., 2020, p.3). Thus, inappropriate implementation of AI-CRM in B2C relationship management is perceived to result in unsuccess in AI-CRM adoption in organizations. Accordingly, it is hypothesized as follows.

H9: Inappropriate implementation of AI-CRM for B2C relationship management (IARM) will lead to AI-CRM failure (ACF) in the organizations.

3.2.9 Moderating Effects of Technology Turbulence (TT)

The technological uncertainty and the accelerated change of technology are simultaneously conceptualized as Technology Turbulence (TT) (Song et al., 2005). Since the technology is undergoing a rapid change, organizations are needed to manage and adjust such change in an effective way for success. An organization is perceived to face several issues when the organization adopts an incremental transformation of the existing technology or to implement a new technology. This concept is related with the sense of technology turbulence (Ullah et al., 2020). In this study, regarding the implementation of a new technology, like AI-CRM in B2C context, turbulence is concerned with a concept of this new technology (Santos et al., 2020). Upgradation to a new technology or introduction of a new technology may bring in reorientation of business relation between organizations and customers since it affects the relationship in a new shape (Powell et al., 2018). Technology turbulence is such a concept that it inhibits an organization to enjoy the color of success even after implementation of a new technology like AI-CRM in B2C relationship management. To overcome this constraint, the employees must be trained properly so that they do not face any unwanted and unexpected inconvenience in using that new system. In this perspective, technology turbulence is perceived to help or inhibit the prospect of implementation of a new system in an organization. These inputs help us to prescribe the following hypotheses.

H10a: Technology Turbulence (TT) acts as a moderating variable between the relationship of Implementation of AI-CRM for B2C Relationship Management (IARM) and AI-CRM Acceptance (ACA).
H10b: Technology Turbulence (TT) acts as a moderating variable between the relationship of Implementation of AI-CRM for B2C Relationship Management (IARM) and AI-CRM Failure (ACF).

These inputs support developing a conceptual model shown in Fig. 2.

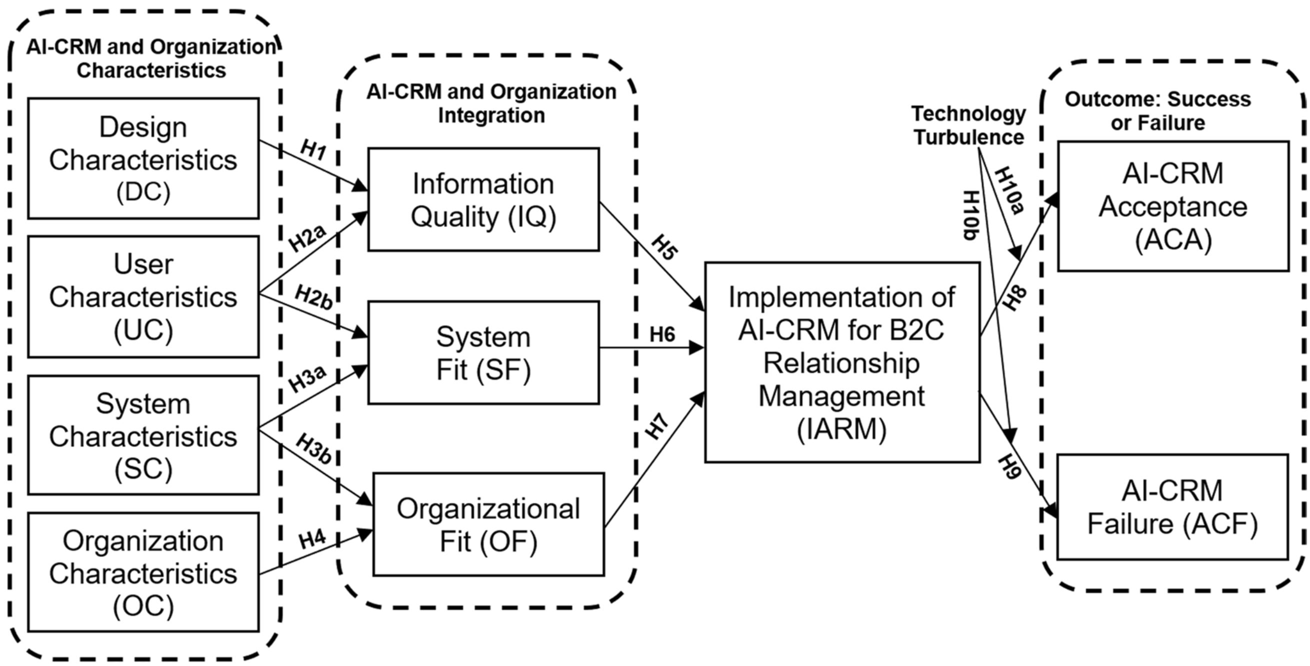


Fig. 2 The conceptual model

4 Research Methodology

The hypotheses are to be tested and the conceptual model developed (Fig. 1) is to be statistically validated by our exploratory study. In this context, the Partial Least Square (PLS) – Structural Equation Modelling (SEM) technique has been preferred because this technique yields better results to analyze an exploratory study and it does not impose any sample restriction (Hair et al., 2019). The PLS-SEM technique is preferred for many reasons. It is a powerful multivariate analysis technique, and it does not require data to be normally distributed. It can analyze a complex hierarchical model in a simple way (Akter et al., 2017). The technique requires the quantification of responses of potential respondents with a standard scale. We have used a 5-point Likert scale.

4.1 Measurement Instrument

With the knowledge of the extant literature and drawing on the Contingency and DCV theory, we prepared 33 questions in the form of statements. We prepared questions to understand the attitude of the respondents towards AI-CRM implementation in organizations with a view to improving B2C relationship management. These questions were prepared in a manner that the potential respondents did not face any difficulties understanding the questions (Mellahi & Harris, 2016). To rectify the recital of the questions for enhancing their readabilities and comprehensiveness, we consulted five experts with expertise in the domain of this study. We also prepared a response sheet to be provided to the respondents. The response sheet contained 5 options for each question, namely Strongly Disagree (SD) marking as 1 to Strongly Agree (SA) marking as 5. Each respondent was scheduled to put tick mark in one option out of the 5 options for each of the questions. The questions were tested with 11 managers of some organizations where AI-CRM was implemented and where the organizations function in B2C context. This pre-test was done to weigh the actual difficulties felt by them in responding against those 33 questions. Along with the response sheet, guideline was provided to explain how to fill up the sheet to enhance the response rate (Chidlow et al., 2015). By this way of continuous as well as methodological scale development approach, the questions were fine-tuned. The details of the instruments along with their sources are provided in the appendix.

4.2 Data Collection

To targeting potential respondents, we collected the list of organizations to contact from the Bombay Stock Exchange, Mumbai, India. On scrutiny from the list of the organizations, it has been ascertained that 41 organizations are using AI integrated CRM system in their various departments. By contacting the top executives of these organizations over telephone we could ascertain that out of these 41 organizations, only 29 organizations work in B2C context using AI-CRM or contemplate to use AI-CRM shortly. We requested the top executives of 29 organizations to allow their employees to participate in the survey but cooperation was not forthcoming. We apprised the executives that the aim of our study is purely academic and assured that we will keep the identities of the respondents confidential. However, after such persuasion, only executives of 17 organizations agreed to allow their employees of different ranks to participate in this survey. From these 17 organizations, we contacted 692 managers at different levels of hierarchy. These 692 managers of different ranks were provided the questionnaire with other documents. These 692 potential respondents were requested to respond in the response sheet within two months (January–February 2019). During this period of two months, we requested each of them at least two times by emails to expediate the response within scheduled time. Eventually, within the stipulated time, we received 344 responses. The response rate was 49.7%. We scrutinized the 344 responses and found 18 incomplete responses which were not considered. We had 326 usable responses for the 33 questions which was within the allowable range (Deb & David, 2014). With 326 replies, we conducted PLS-SEM analysis. The details of the demographic information are shown in Table 1.

5 Data Analysis with Results

5.1 Measurement Properties and Test of Discriminant Validity

For assessing the convergent validity of each item, we estimated the Loading Factor (LF) of each item. For assessing the validity, consistency, reliability and multicollinearity defects, we estimated the Average Variance Extracted (AVE), Cronbach's alpha (α), Composite Reliability (CR), and Variance Inflation Factor (VIF) of each construct. It was ascertained that all the parameters were within the permissible range. The results are shown in Table 2.

The square roots of all the AVEs were greater than the corresponding bi-factor correlation coefficients and satisfied the Fornell and Larcker criteria (Fornell & Larcker, 1981) which confirmed the discriminant validity. The results are shown in Table 3.

5.2 Moderator Analysis (Multi Group Analysis)

In our study, we considered technology turbulence (TT) as a moderating variable that impacted the relationships between H8 and H9. This moderator TT has been categorized as High TT and Low TT. To estimate the effects of TT as moderator on these two relationships covering H8 and H9, we have performed Multi Group Analysis (MGA) by accelerated and bias corelated bootstrapping procedure by considering 5000 subsamples. Through this procedure we could assess the p value differences for the effects of the two categories of the moderator on H8 and H9. The results showed that the estimated values of p value differences were 0.02 and 0.04, both being less than 0.05 (Hair Jr et al., 2016). It highlights that the effects of the moderator TT on these two linkages are significant.

5.3 Common Method Variance (CMV)

While validating the model by PLS-SEM technique, we analyzed the responses of the participants of the survey. Hence our results are based on self-reported data and as such, there is possibility of bias in the data. Though as a preemptive measure, we assured the potential respondents that their anonymity and confidentiality will be preserved to ensure unbiased responses, we have also performed CMV to become sure that the data is unbiased. For this, we performed the first factor test of Harman and found that the first factor emerged for 41.03% of variance which is less than the threshold highest value of 50% (Podsakoff et al., 2003). Since scholars opined that the Harman's SFT is not to that extent robust (Ketokivi & Schroeder, 2004), marker variable technique (Hossain et al., 2020; Lindell & Whitney, 2001) has been applied. The results clearly show that difference between the original as well as CMV based correlations were small (≤0.06) (Mishra et al., 2018). Hence, CMV could not distort the results and the prediction of the present study.

Table 1 Demographic Information (N = 326)

Particulars	Category	Number of organizations / respondents	Percentage (%)
Type of Industry	Service	4	23.5
	Manufacturing	13	76.5
Employee Profile	Junior Manager	93	28.5
	Mid-level Manager	154	47.3
	Senior Manager	79	24.2

Table 2 Measurement properties

Constructs / Items	LF	α	CR	AVE	VIF	t-value	No. of Items
DC	`	0.89	0.85	0.82	4.8		3
DC1	0.87					26.81	
DC2	0.96					29.02	
DC3	0.89					27.11	
UC		0.93	0.90	0.87	4.3		3
UC1	0.95					29.07	
UC2	0.90					31.31	
UC3	0.95					36.73	
SC		0.88	0.87	0.82	3.9		3
SC1	0.85					37.04	
SC2	0.90					31.06	
SC3	0.96					19.17	
OC		0.89	0.87	0.84	4.1		3
OC1	0.88					29.71	
OC2	0.96					32.24	
OC3	0.91					36.77	
IQ		0.89	0.86	0.83	3.7		3
IQ1	0.94					27.02	
IQ2	0.92					29.44	
IQ3	0.87					36.12	
SF		0.94	0.92	0.88	4.6		3
SF1	0.95					36.06	
SF2	0.90					27.11	
SF3	0.97					26.04	
OF		0.91	0.87	0.84	3.5		3
OF1	0.87					33.06	
OF2	0.93					30.11	
OF3	0.95					36.72	
IARM		0.89	0.87	0.85	4.2		4
IARM1	0.88					29.48	
IARM2	0.97					33.17	
IARM3	0.86					36.16	
IARM4	0.98					19.09	
ACA		0.94	0.92	0.90	3.8		4
ACA1	0.95					19.77	
ACA2	0.87					32.46	
ACA3	0.90					27.11	
ACA4	0.89					38.27	
ACF		0.91	0.87	0.84	3.9		4
ACF1	0.86					36.11	
ACF2	0.93					37.92	
ACF3	0.89					34.81	
ACF4	0.96					30.88	

5.4 Hypotheses Testing with SEM

With the help of structural model and analysis, the hypotheses have been tested (Hair et al., 2012). Using SmartPLS3 software, we performed bias corelated and accelerated bootstrapping procedure by considering 5000 iterations of subsamples, estimated the path coefficients of the several linkages and the corresponding level of significance by computing probability values (p values) for ensuring stability of the results. Here we created the subsamples by random observations depending on the original data sets. The results are shown in Table 4.

Table 3 Discriminant validity test (Fornell and Larcker criteria)

Construct	DC	UC	SC	OC	IQ	SF	OF	IARM	ACA	ACF	AVE
DC	0.90										0.82
UC	0.17	0.93									0.87
SC	0.22	0.26	0.90								0.82
OC	0.29	0.32	0.26	0.92							0.84
IQ	0.36**	0.34	0.38***	0.25	0.91						0.83
SF	0.34	0.30	0.29	0.21	0.33	0.94					0.88
OF	0.35	0.28**	0.27	0.34	0.34*	0.28	0.92				0.84
IARM	0.19*	0.25	0.30**	0.29	0.30	0.19*	0.33	0.92			0.85
ACA	0.27	0.19*	0.33	0.30*	0.26	0.26	0.27*	0.32*	0.95		0.90
ACF	0.26***	0.24	0.22	0.26**	0.20*	0.34	0.29	0.30**	0.36	0.92	0.84

$p < 0.05$ (*); $p < 0.01$(**); $p < 0.001$(***)

Table 4 Results of hypotheses testing

Paths	Hypotheses	Path coefficients	p-values	Remarks
DC → IQ	H1	0.17	P < 0.05(*)	Supported
UC → IQ	H2a	0.29	P < 0.01(**)	Supported
UC → SF	H2b	0.31	P < 0.05(*)	Supported
SC → SF	H3a	0.19	P < 0.001(***)	Supported
SC → OF	H3b	0.23	P < 0.05(*)	Supported
OC → OF	H4	0.36	P < 0.001(***)	Supported
IQ → IARM	H5	0.24	P < 0.001(***)	Supported
SF → IARM	H6	0.32	P < 0.01(**)	Supported
OF→IARM	H7	0.27	P < 0.001(***)	Supported
IARM→ACA	H8	0.15	P < 0.05(*)	Supported
IARM→ACF	H9	0.29	P < 0.001(***)	Supported
(IARM→ACA) × TT	H10a	0.23	P < 0.05(*)	Supported
(IARM→ACF) × TT	H10b	0.34	P < 0.01(**)	Supported

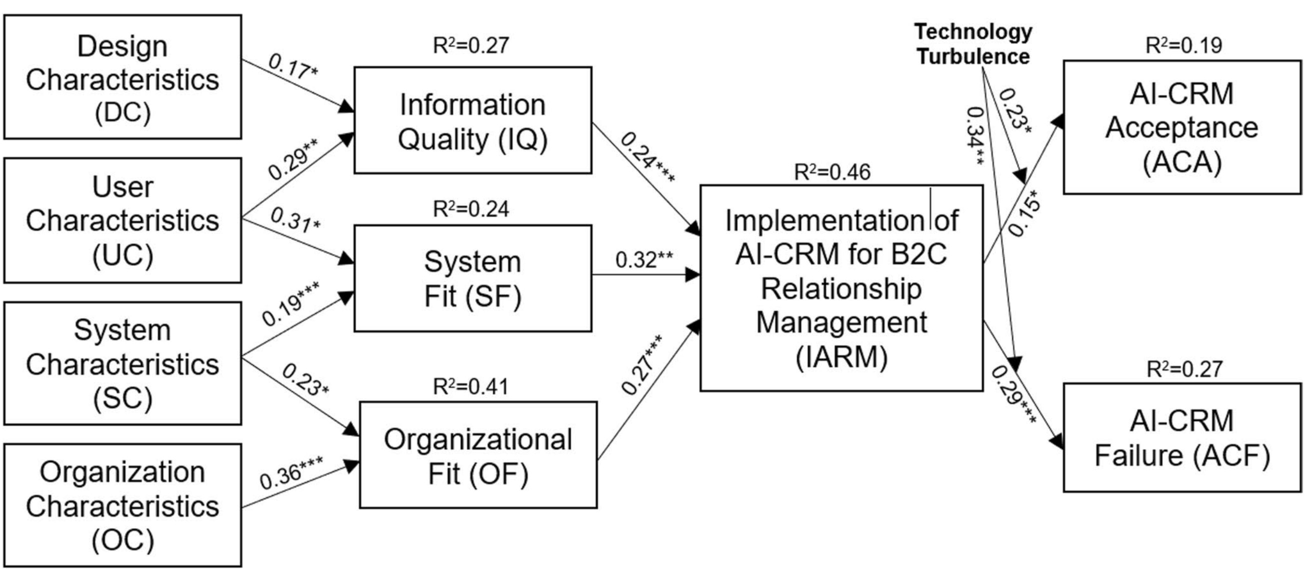
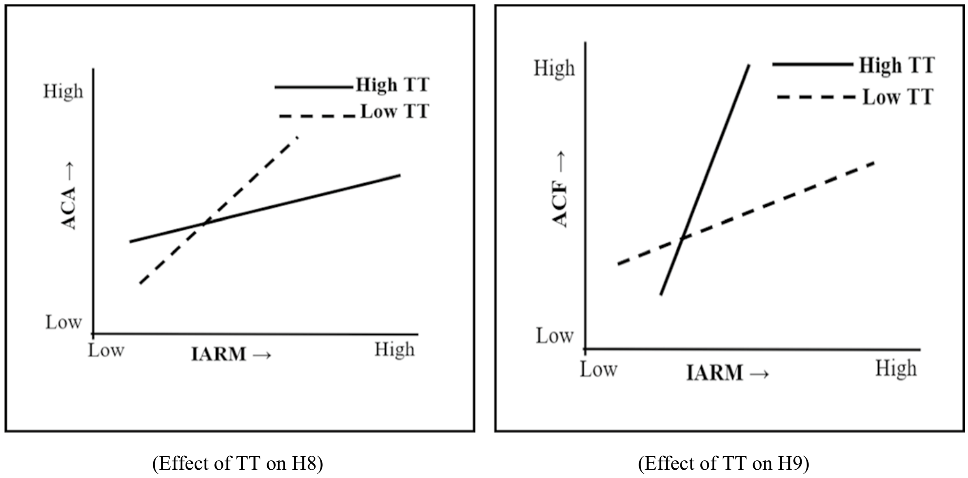


Fig. 3 Structural model

Fig. 4 Effects of the moderator TT on H8 and H9



After validating the results by hypotheses testing, the structural model is shown in Fig. 3.

5.5 Results and Discussions

The results highlight that the four independent exogenous variables, i.e. DC, UC, SC and OC, significantly impact IARM through three endogenous mediating variables, which are IQ, SF, and OF. The results show that DC impacts IQ with path coefficient 0.17 with level of significance $p < 0.05$ (H1). UC impacts IQ and SF significantly as the concerned path coefficients are 0.29 and 0.31 respectively with levels of significance $p < 0.01$(**) and $p < 0.05$(*) respectively. SC impacts SF and OF significantly with path coefficients 0.19 and 0.23 respectively with significance levels $p < 0.001$(***) and $p < 0.05$(*) respectively (H3a, H3b). OC impacts OF significantly since the concerned path coefficient is 0.36 with level of significance $p < 0.001$(***) (H4). The results also highlight that IQ, SF, and OF simultaneously impact IARM and among these impacts, the impact of SF on IARM is maximum as the concerned path coefficient is the highest among the three linkages and this is 0.32 with level of significance $p < 0.01$(**) (H6). The construct IARM impacts ACA and ACF (H8 and H9) significantly since the path coefficients are 0.15 and 0.29, respectively with levels of significance $p < 0.05$(*) and $p < 0.001$(***). respectively. The effects of the moderator TT on the two linkages IARM→ACA and IARM→ACF are found significant as the impacts of moderator TT on these two linkages bear path coefficients 0.23 and 0.34 with levels of significance $p < 0.05$(*) and $p < 0.01$(**) respectively.

So far as the coefficients of determination (R^2) are concerned, it appears that DC and UC can explain IQ to the tune of 27%, SF can be explained by UC and SC to the extent of 24% whereas OF can be explained by OC to the tune of 41%. IQ, SF, and OF can explain IARM to the tune of 46%. Again, IARM can explain ACA and ACF respectively to the extent of 19% and 27%.

The study has used the Contingency theory and DCV theory to develop the model. The study has considered four independent variables which separately or jointly impact the quality and ability of infrastructure, system, and organization which eventually impact implementation of AI-CRM in B2C relationship management (H5, H6, and H7). This study is based on the principal that individual and organizational traits are linked to achieve successful implementation of a system in organization and that is why the study has considered such antecedents which are either organizational or individual specific. This corresponds from H1 to H4. This study has highlighted that implementation of a system cannot always yield better result unless the concerned organization uses the potential of its employees to address the ordeal of assimilation stages (Kast & Rosenzweig, 1979; Otley, 1980). The implementation of any new technology in an organization can be successful if the employees responsible for such implementation can acquire knowledge about the technology to overcome the negative effects of technology turbulence. That is why even after the implementation of a technology, an organization sometimes sustains success and some other incur failure (H8 and H9).

Now we shall discuss the effects of technology turbulence as moderator on the two linkages, namely H8 and H9 graphically by dividing technology turbulence in two categories which are High Technology Turbulence (High TT) and Low Technology Turbulence (Low TT). The effects are shown through graphical representation by two graphs collectively marked as Fig. 4.

So far as the effects of TT on H8 are concerned, it appears that with an increase of appropriate implementation of AI-CRM in organizations, the rate of increase of acceptance of

AI-CRM will be higher for the effects of Low TT compared to the effects of High TT on the linkage H8. This is because the gradient of the dotted line which represents the effects of Low TT is higher than the gradient of the continuous line representing High TT.

Again, in terms of the effects of the moderator TT on the linkage H9, it appears that for inappropriate implementation of AI-CRM in organizations the rate of AI-CRM implementation failure will be higher for the effects of High TT than the effects of Low TT. This is because the continuous line representing the effects of High TT has greater gradient than the dotted line representing the effects of the Low TT.

6 Implications of the Study

6.1 Theoretical Contributions

This study makes several theoretical contributions to extant literature on how the implementation of a new technology in an organization could lead to success and sometimes to failure. Our study investigates how the implementation of AI-CRM in organizations for B2C relationship management can be successful and how in some circumstances the implementation could lead to failure. In this respect, our study may be considered as a unique endeavor. Our study has also used the Contingency theory to develop the model for effectively implementing AI-CRM in B2C relationship management. In doing so, our study extended the theoretical lens on the framework of the Contingency theory by importing additional antecedents like 'information quality' as an exogeneous variable. In this manner, we developed a successful model to highlight how the implementation of AI integrated CRM system in B2C relationship management can be ensured which is our unique theoretical contribution. In this study, the contingency theory has been successfully used to interpret how AI-CRM can be implemented in the organizations. The contingency theory is known to have been supported by an abundance of empirical research (Omotosho & Anyigba, 2019; Waters, 2013). This theory has been used in this study since it could widen the understanding by persuading the stakeholders for considering the various impacts of AI integrated CRM system in the B2C relationship management (Peter, 2007). We have also used the DCV theory to interpret that unless the organizations, after implementation of AI-CRM to improve B2C relationship management react and respond to the dynamism of market environment, the organizations may not succeed but rather fail. In this manner this study is provides a new insight into the extant literature.

This study provides empirical support that only contingency theory can hardly explain the adoption and application of AI integrated CRM system in the organizations. This theory helps to interpret how the effective adoption of AI-CRM technology can be ensured in the context of organizational situation and business environment. But for application of AI-CRM technology to get laudable results, the organizations must possess the dynamic capability to assimilate the technology with the sensing, seizing, and reconfiguring abilities which corroborate DCV theory. Thus, this study could successfully integrate these two theories (contingency theory and DCV theory) to explain successful adoption of AI integrated CRM system in the organizations.

In a Karunagaran et al. (2019), through a case study, it has been documented that cloud computing technology could fetch substantive success to both large enterprises as well as SMEs in Germany. This idea has been extended in the present study to demonstrate that several dynamic abilities would help organizations for successful implementation of AI integrated CRM system in the organizations. This is claimed to have added values to the extant literature.

6.2 Practical Implications

Many organizations have implemented technologies to improve their bottom line. But among these organizations, some could not succeed. This study helped organizations to understand the several factors associated with the success and failure of implementation of technology like AI-CRM system in the context of B2C relationship management. Our study has shown that the design characteristics impact information quality (H1). This implies that while implementing AI-CRM in organizations, the system developers and designers need to focus on the design characteristics of AI-CRM tool. This will help to improve the information quality. Further, our study has shown that user characteristic positively and significantly impacts information quality (H2a) and system fit (H2b). This implies that the users (employees of the organizations) of CRM system responsible to manage B2C relationship are needed to be properly trained so they can understand how to use the AI-CRM system effectively. This would help the users to extract maximum benefits using AI-CRM system. Our study highlights that system characteristics positively and significantly impact system fit (H3a) and organizational fit (H3b). This implies that the characteristics of AI-CRM system, including its features and functionalities, are needed to be developed appropriately. It will help the employees of the organizations to use AI-CRM system properly. The system developers should ensure that all the features and functionalities of the newly developed AI-CRM system can be used by the users effectively and easily. The study has highlighted that an organization's characteristics impact organizational fit (H4) which implies that concerned organizations must have a conducive environment for employees to use, adopt, and assimilate the newly developed AI-CRM system. The managers and leaders of the organizations using AI-CRM system for managing B2C relationship must sincerely encourage and incentivize the employees to willingly use the newly implemented AI-CRM systems. The leaders of the organizations should articulate policies and procedures in such a way as these would help the employees to be motivated in using AI-CRM system in B2C context for managing the relationship in an organization. Our study has highlighted that information quality (IQ), system fit (SF), and organizational fit (OF) positively impact the implementation of AI-CRM for B2C relationship management in the organizations (H5, H6, and H7). These imply that the managers should focus their attention on these three predictors of implementation while implementing AI-CRM system in these organizations to manage B2C relationship. Finally, our study has shown that technology turbulence, which acts as a significant moderator, impacts the acceptance and failure of AI-CRM system in organizations (H8, H9). This implies that the leaders, managers, and policy makers must ensure proper business continuity plans while implementing AI-CRM system in organizations to manage B2C relationship. This will help to ensure that technology turbulence should not influence and impede the usage and adoption of AI-CRM by the employees of the organizations and that the employees are trained to use the system effectively.

6.3 Limitations and Future Scope of Research

This study has provided theoretical and practical contributions to the body of literature, yet it suffers from limitations. These would provide impetus to the scholars for further study. While conducting survey to validate the model, we used the sample from India only and have conducted our empirical investigation based on the response. This suggests that our study is deemed to have projected the situation prevailing in India. It is uncertain if the results would be consistent in other countries. Future researchers may consider conducting surveys by using inputs from different countries to provide results that can be generalized. In our study, we relied on the analysis of cross-sectional data. The results of such study could not enlighten the variation of concept and understanding of the respondents with passage of time. Future researchers are needed to focus on the longitudinal dynamics to eliminate this defect. This study has drawn the conclusion based on the inputs derived from individuals (respondents) and this may not be the overall perception of the organizations in implementing AI-CRM for managing B2C relationship. This may be addressed in future work. Though the DCV theory has already attracted attention, it is argued that DCV suffers from context insensitivity which has been noted by Ling-Yee (2007). DCV is not able to identify the conditions when the capabilities of an organization could be most valuable (Dubey et al., 2019). It is suggested that future studies can further explore the optimum conditions under which successful adoption of AI integrated CRM system can be achieved in the organization.

7 Conclusion

Our study has developed the model by principally drawing on the Contingency theory. It envisages that for the implementation of a system in an organization, the course of action to be taken depends on the situation in which such attempt is being taken. In such a scenario, the managers of organizations contemplating to implement AI-CRM for improving the B2C relationship utilizing the contingency approach need to possess appropriate skills and expertise to analyze the various situations (Kast & Rosenzweig, 1979). Our study has extended the Contingency theory with the inclusion of congenial construct to fit with the situation. This modification of the theory has yielded successful results in other study where researchers used another antecedent 'training' to justify the implementation of IS innovation. Our study necessitated inclusion of the construct 'information quality' in the framework of Contingency theory because the introduction of new AI-CRM technology and the model has become successful. Our study has also developed the model that highlights factors that could estimate both the success and failure to implement AI-CRM system in organizations. This model is expected to provide rich dividends for other organizations contemplating to implement modern technologies for managing B2C relationship management.

Appendix

Table 5

Table 5 Summary of questionnaire

Items	Source(s)	Statements	Response [SD][D][N][A][SA]
DC1	Otley, 1980; Ginzberg, 1980	System design plays an important role towards implementing any new AI enabled applications.	[1][2][3][4][5]
DC2	Vroom & Jago, 1995; Alshare & Lane, 2011	I believe that cloud computing helps implementing AI-CRM system in the organizations.	[1][2][3][4][5]
DC3	Awasthi & Sangle, 2013; AlShibly, 2014	AI integrated CRM system can analyze unlimited volume of customer data.	[1][2][3][4][5]
UC1		I believe that successful implementation of a system is instrumental to implement any innovative process.	[1][2][3][4][5]
UC2	Jarvenpaa et al., 2000; Karunagaran et al., 2019	Employee trust on the new application plays an important role towards successful implementation of any AI enabled application.	[1][2][3][4][5]
UC3	Alsharari et al., 2020	Developing the technical skills of the employees is important for successful implementation of AI-CRM system.	[1][2][3][4][5]
SC1		System Characteristics is related to the complexity of the technology.	[1][2][3][4][5]
SC2	Wonglirnpiyarat, 2005	I think that system characteristics is manifested through the compatibility of the technology.	[1][2][3][4][5]
SC3	Cagliano et al., 2019	I believe that organizations must have the ability to assimilate the new system.	[1][2][3][4][5]
OC1	Sonnenwald et al., 2001	Organizations must be able to assimilate new technology for successful implementation of new system.	[1][2][3][4][5]
OC2	Halabi et al., 2017	I believe that specialties of organizations are instrumental for successful implementation of a new system.	[1][2][3][4][5]
OC3		I think that organization infrastructure plays an important role towards implementation of AI-CRM system.	[1][2][3][4][5]
IQ1	Lin et al., 2020; Kennedy, 2006	I believe that maintaining quality of input data to AI-CRM system is necessary for getting effective output.	[1][2][3][4][5]
IQ2	Chalmeta, 2006	Quality customer data should be fed into AI-CRM system for correct decision making.	[1][2][3][4][5]
IQ3	Hillebrand et al., 2011; Chatterjee et al., 2019	For quality of collected data there should be a data governance mechanism in place in the organization.	[1][2][3][4][5]
SF1	Rogers, 2003; Peng et al., 2018	I believe that an organization must be compatible to implement any new system.	[1][2][3][4][5]
SF2	Vroom & Jago, 1995; Halabi et al., 2017;	Implementation of the AI-CRM system is easy if the organization can easily integrate the new system.	[1][2][3][4][5]
SF3	Parveen & Sulaiman, 2008	I believe that if the existing system can fit with the new AI-CRM technology, the organization will not face any implementational hazard.	[1][2][3][4][5]
OF1	Ginzberg, 1980	Technological competence of an organization is important for successful implementation of AI-CRM system.	[1][2][3][4][5]
OF2	Leavitt, 1964	I believe that organizational structure can influence the implementation of AI-CRM system.	[1][2][3][4][5]
OF3	Nadler & Tushman, 1977; Tushman & Nadler, 1978	I think that employees' behavior towards adopting the new system plays a crucial role for successful implementation of AI-CRM system.	[1][2][3][4][5]
IARM1	Chatterjee et al., 2019	I believe that AI-CRM system can help to analyze the customer data faster.	[1][2][3][4][5]
IARM2	Wu, 2011	I believe that AI-CRM system will analyze the customer data without much manual efforts.	[1][2][3][4][5]

Table 5 (continued)

Items	Source(s)	Statements	Response [SD][D][N][A][SA]
IARM3	Gao et al., 2012	AI-CRM system will be helpful for managing multiple customers at a time.	[1][2][3][4][5]
IARM4	Dean Jr & Sharfman, 1996	I believe that the decision-making process will be easier if AI-CRM system is successfully implemented in the organization.	[1][2][3][4][5]
ACA1	Kaufmann et al., 2009	I believe that successful implementation of AI-CRM system will improve the adoption rate.	[1][2][3][4][5]
ACA2	Elbanna & Child, 2007	Skilled system designer is important for successful implementation of AI-CRM system.	[1][2][3][4][5]
ACA3	Chatterjee et al., 2019	There should be an effective data governance policy in place for successful implementation of AI-CRM system.	[1][2][3][4][5]
ACA4	Dean Jr & Sharfman, 1993	I believe that leadership support is crucial for successful implementation of AI-CRM system.	[1][2][3][4][5]
ACF1	Dean Jr & Sharfman, 1996	I believe that without a proper contingency plan, implementation of AI-CRM system could be a failure.	[1][2][3][4][5]
ACF2	Kaufmann et al., 2009	Without any data governance policy, AI-CRM system should not be implemented.	[1][2][3][4][5]
ACF3	Dean Jr & Sharfman, 1993	Inadequate investment in employee training on AI-CRM system could lead to lower-level adoption of the system.	[1][2][3][4][5]
ACF4	Elbanna & Child, 2007	Ineffective sponsorship for implementing AI-CRM system capability could lead to a failure in implementation of the system.	[1][2][3][4][5]

SD Strongly Disagree; *D* Disagree; *N* Neither agree nor disagree; *A* Agree; *SA* Strongly Agree

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