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Adoption of artificial intelligence-integrated CRM systems in agile organizations in India

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A R T I C L E I N F O

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A B S T R A C T

Artificial intelligence integrated with customer relationship management (CRM) systems has revolutionized organizations' means of analyzing their huge volumes of customer data. To effectively respond to and manage the opportunities and challenges that arise from this, organizations are developing competencies and processes that evolve their agility, fine-tuning them to the artificial intelligence customer service system (AICS) and wider digitalization setting. In this context, this study identifies the factors impacting the adoption of an AI-integrated CRM system (AICS) in agile organizations as a part of their digitalization strategy. Methodologically, the research builds its theoretical foundation on extant works to develop hypotheses and a corresponding conceptual model. The model is quantitatively validated through a survey across the spectrum of Indian companies, following expert-based pretesting and pilot testing, and subsequently it is statistically tested using the partial least squares structural equation modeling (PLS-SEM) technique. The results, contextualized against the backdrop of organizational agility, identify and elucidate the relationship between stakeholders and perceived value and easiness of AICS, between employee trust and attitude, and the influence of attitude and behavioral intention as key mediators towards AICS adoption. The findings are conclusively transcribed into tangible implications for practice and explicit avenues for future research.

1. Introduction – research background, gap and aim

This research is grounded in three unequivocal premises stemming from contemporary organizational realities and inescapable contextual business precincts. These are the customer-centric nature of business (focus), the increasing dependence of organizational operations on technology (means), and the ever-changing and unpredictable nature of the business environment that demands attitudinal and procedural agility to adapt swiftly and effectively to the changes for competitive advantage (aim). For the purposes of this research, these are practicably and generally transcribed into customer relationship management (CRM), digitalization and artificial intelligence (AI) systems, and applied agility. Thus, this paper studies artificial intelligence-integrated customer relationship management systems, in the context of organizational agility, as the intersection of the three most prominent notions – CRM, digitalization, and AI – of present business theory and practice, and with corresponding value and contribution to knowledge. Accurate analysis of customer data is an important CRM activity. Organizations perform such activities to extract the best information. But since the volume of customer data can be huge, we need to investigate how AI technology could manage and analyze so much data in an accurate and cost-effective way to achieve business success (Gnizy, 2019). Only using AI in a CRM system might suffice in a static business environment. However, since the business environment is ever-changing and unpredictable in nature, organizations should have apt procedural and attitudinal agility to quickly adapt to the changes to gain competitive advantage. Hence, we need to know how the intersection of agility and AICS could fetch competitive advantage for the organizations.

To survive and grow in the contemporary hypercompetitive business environment, organizations need to continuously reinforce their

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practices, processes, products, and services (Abu Ghazaleh and Zabadi, 2020; Loukis et al., 2020; Vrontis et al., 2017a; Werder and Maedche, 2018; Chatterjee et al., 2021). Towards this, organizations need to develop the competencies that will utilize all available opportunities and swiftly respond to changes in an unpredictable environment (; Zerbino et al., 2018; Ferraris et al., 2019). This ability, conceptualized as an organization's 'agility', is considered to be a critical success factor across industries, regions, and organizational types (Carmeli and Dothan, 2017; Rialti et al., 2019; Teece et al., 2016). One crucial element of the agility aspiration is the organizational aptitude to gather, analyze, interpret, and use mass customer data in the context of customer relationship management (CRM) (Chatterjee et al., 2020b; Nguyen and Mutum, 2012; San-Martína et al., 2016; Skare and Soriano, 2020). The sheer volume of this data, nonetheless, is an inherent obstacle to its full and/or proper utilization and is increasingly overcome with the help of digital technologies known as artificial intelligence (AI) (Eriksson et al., 2020; Stone et al., 2020). Particular to CRM, AI technologies have evolved into specific AI-integrated CRM systems (AICS), which allow better customer data analysis, with ease and at a lower cost (Chatterjee et al., 2019; Ferraris et al., 2017; Gnizy, 2019; Wen and Chen, 2010).

Agility and AICS are inherently associated through the latter's facilitation of sensing and responding to threats and opportunities effectively, efficiently, and sincerely (Chan et al., 2019; Vrontis et al., 2017b). Organizational agility helps organizations address the challenges and utilize the opportunities in such situations where traditional foresight demands to be upgraded and updated with modern technology like AICS (Bag et al., 2020; Vecchiato, 2015; Sreenivasulu and Chatterjee, 2019; Chatterjee, 2020). However, an organization should use AICS in an agile manner in order to achieve benefits quickly, otherwise, any benefits could be delayed. More agile organizations might enjoy the same benefits sooner (Campanella et al., 2020). To quickly harness the full business potentials of an AI-integrated CRM system, the organization should be agile by appropriately sensing and responding to the dynamic needs of the markets (Nazir and Pinsonneault, 2012; Santoro et al., 2019). In this context, adaptability, innovativeness, and resilience are necessary competencies to achieve organizational agility and, in parallel, to best utilize AICS itself (Holbeche, 2018; S.M.R. Shams et al., 2020). The agility of an organization helps better utilize AICS by simultaneously exploiting the new practices and resources, while exploring existing resources and practices (Jagtap and Duong, 2019; Sambamurthy et al., 2007). It also assists in developing organizational ambidexterity (another relevant competency) (Akhtar et al., 2018; Chebbi et al., 2015).

The extant literature, in the context of establishing the beneficial link between agility and AICS (Jagtap and Duong, 2019; Osei et al., 2019), has not been systematic or exhaustive, but has dealt with the topic in a fragmented way. The nature of the relationship, as well as its optimization, emerging from the intersection of agility and AICS has remained underexplored. To fill this gap, this research *aims* to identify the factors impacting the adoption of an AI-integrated CRM system (AICS) in agile organizations, as a part of their digitalization strategy, with the following *objectives*.

1 To identify the factors impacting the adoption of an AI-integrated CRM system (AICS) in the digitalized agile organizations.
2 To examine the mediator role of attitude and behavioral intention for the successful adoption of an AI-integrated CRM system (AICS) in digitalized agile organizations.
3 To understand how trust impacts on both users' attitude and the adoption of an AI-integrated CRM system (AICS) in digitalized agile organizations.

Methodologically and *structurally*, the research subsequently builds its theoretical foundation on extant works to develop its hypotheses and a corresponding conceptual model. The latter is then quantitatively validated through a survey, across the spectrum of Indian companies, following qualitative expert-based pretesting and pilot testing, and finally it is statistically tested using the partial least squares structural equation modeling (PLS-SEM) technique. The results, contextualized against the backdrop of organizational agility, identify and elucidate the relationship between stakeholders and the perceived value and easiness of AICS, between employee trust and attitude, and the influence of attitude and behavioral intention as key mediators towards AICS adoption. The findings are ultimately transcribed into tangible implications for practice and explicit avenues for future research.

2. Theoretical foundations and contextualization

This study has relied on the technology acceptance model (Davis et al., 1989) as the basis for predicting the adoption of an AI-integrated CRM system. There are three rationales for using this model. The statistical power of this model for elucidating attitude and intention to use AI-integrated CRM systems in organizations is found to be either equal to or better than the other competing theories (Lin, 2007). This model possesses more statistical power than the expectation-disconfirmation theory (Premkumara and Bhattacherjee, 2008), and it is less expensive (Lin, 2007). Its procedures have minimal costs, and it permits a comparatively small sample size for statistical validation (Luo et al., 2010). Hence, the two core constructs of this model – perceived usefulness and perceived ease of use – have been identified as exogenous variables in this study. In the context of the adoption of new technology like an AI-integrated CRM system, the extrinsic-intrinsic dichotomy is measured by these two variables (Van der Heijden, 2004), which influence attitude, or the extent to which a user is unfavorably or favorably inclined to act (Ahn and Back, 2018; Chong, 2013; Fishbein and Ajzen, 1975). Moreover, consideration of these two exogenous factors has been successfully used by subsequent theories, like DTPB (Taylor and Todd, 1995) and TAM2, (Venkatesh and Davis, 2000), wherein it has been observed that perceived usefulness is prompted by the subjective norm of job relevance, and results in demonstrability. CRM activities involve analyzing customer data to understand their needs. Since the volume of data is huge, it is difficult for humans to accurately analyze it. AI in this context functions in a quicker, cost-effective, and accurate way without human intervention.

Another independent factor, trust, has been considered in this study to prompt attitude and adoption (DeConick, 2010; Nelson et al., 2020; Ferraris et al., 2018). Trust is construed to be more than that which occurs in the relationship of reliability (Chatterjee et al., 2020a), and to be a predictor of attitude and adoption (Dehghanpouri et al., 2020; Kelton et al., 2008; Rialti et al., 2019; Zerbino et al., 2018). However, in developing the model, we also consider that success in utilizing the full potential of AICS also rests on organizational ambidexterity with exploration and exploitation (Bodwell and Chermack, 2010, James et al., 2017; Chebbi et al., 2017; Santoro et al., 2019). This study has considered perceived usefulness, perceived ease of use, and trust to be three exogenous variables triggering attitude and intention and acting as endogenous mediating variables impacting adoption of AICS in organizations.

2.1. CRM and digitalization

In the historical sense, AI is considered to be a computer program, operating on its own, without human help (Turing, 1956). In the contemporary business paradigm, organizations are required to deal with and analyze a huge volume of consumer data that will provide an effective mechanism of CRM. AICS undertakes this task much more efficiently and effectively than humans, and without human intervention (Fotiadis and Vassiliadis, 2017). This requires agile, ambidextrous organizational philosophy and practice (Campanella et al., 2020; Vrontis et al., 2017a; Verma and Verma, 2013) to ensure prompt and proper responses to changes, and to balance between exploration and exploitation (Chatterjee et al., 2020b).

2.2. AI-integrated CRM system in digitalized organizations

AI is being used in many organizations to improve their existing CRM system. Google has already harnessed AI to predict accurately what is being searched and to autocomplete the search field. In the context of attracting customers, Amazon products are being tailored with the help of an AI algorithm. From the perspective of CRM, all organizations need to store and analyze customer data to understand their needs. As analyzing huge amounts of customer data is difficult for humans, organizations use AI (Awastha and Single, 2012; Chatterjee et al., 2020c) with their CRM digitalized platform to understand customers' needs, likes, and dislikes. These digitalized organizations can also harness the best potential of AI-CRM system for improving innovation, growth rate, and performance (Ferreira and Franco, 2019; Schultz et al., 2012).

2.3. Adopting an AI-integrated CRM system

The literature provides many adoption models, but concerning the adoption of an AI-integrated CRM system, it is difficult to identify one standard model. In using AI-CRM technology, factors like compatibility, simplicity, and self-efficacy are considered important (Shams, 2019). However, studies reveal that perceived ease of use *includes* these three vital attributes, which prompt individuals to adopt modern technology like AI (Chatterjee et al., 2020b; Gupta et al., 2017, 2018; Yi et al., 2009). Other studies have shown that perceived ease of use is a vital predictor of perceived usefulness (Chen et al., 2015; Kar and Chatterjee, 2015). Hence, it becomes clear that, for an AI-integrated CRM system to be adopted, perceived usefulness and perceived ease of use are very important factors. These two factors have been considered in some adoption models, including the decomposed theory of planned behavior (Taylor and Todd, 1995) and technology acceptance model 2 (TAM2) (Venkatesh and Davis, 2000). TAM2 has highlighted that perceived usefulness is triggered by other important factors like job relevance, subjective norms, and results in demonstrability. Hence, by considering perceived usefulness and perceived ease of use, we are including six vital factors. Again, when an organization adopts a new system, users always exhibit a sense of uncertainty regarding the outcomes (Dwivedi et al., 2017; Susanto and Goodwin, 2011). To ease employees' sense of uncertainty, they need to be able to trust the use of this modern technology. As such, trust is also considered another independent variable prompting attitude and adoption (Chong, 2013; Kelton et al., 2008; Komodromos et al., 2019). Users' attitudes impact their intentions to behave accordingly, which eventually prompts them to actually use the technology (Dwivedi et al., 2017; Hung et al., 2013; Lu et al., 2010). Besides, the research reveals that considering behavioral intention includes considering social characteristics like behavioral control, complexity, and social involvement (Gibbons et al., 2004; Komodromos et al., 2019). Hence, this study has used perceived usefulness, perceived ease of use, and trust as independent factors mediating through an organization's employees' attitude and behavioral intention to trigger adoption of an AI-CRM system.

2.4. AI-integrated CRM system in the agility context

Studies transpire that the essential part played by CRM is to make an organization customer-centric, which needs customers' habits to be analyzed (Graca et al., 2015; Kar and Chatterjee, 2018; Sreenivasulu and Chatterjee, 2019). The organization therefore requires an effective mechanism to help generate and meaningfully execute ideas (Kizgin et al., 2019; Vrontis et al., 2017b; West, 2002). This organization must exhibit its operational and strategic agility for analyzing the habits of customers (Benner and Tushman, 2003; Giacomarra et al., 2019; Holdeche, 2018). The organization will be able to utilize the potentials of the explorative and exploitative concept (Galati et al., 2017; Kanti et al., 2019a; R. Shams et al., 2020) in analyzing the habits of customers, provided the organization is agile (Kanti et al., 2019b; Rana et al., 2020). Studies reveal that CRM activities need to analyze customers' likes and dislikes by synthetizing huge amounts of customer data. Therefore, AI is necessary to synthesize huge amounts of data accurately and quickly without human help (Chatterjee et al., 2020b; Majumdar et al., 2019; Mustafa et al., 2019; Real et al., 2006). The use of CRM together with AI can analyze the customers' data accurately without human intervention, thus helping organizations to reach the customers quickly (Akhtar et al., 2018; Lee et al., 2007; Raisch and Birkinshaw, 2008). However, if AICS is not used in an agile manner, the organization will delay receiving benefits compared to other organizations and will not enjoy a competitive advantage (Campanella et al., 2020; Chebbi et al., 2015). In this context, the organization needs to be agile by sensing and responding accurately and quickly to reap the full potential of AICS (Overby et al., 2006; Santoro et al., 2019). The organization needs to exhibit its agility by aptly changing the environmental dynamics, processes, and practices (Aburub, 2015; Sambamurthy et al., 2007). The agility of the organization reflects the ability of the organization to respond by changing its knowledge, digital process, and design capital accordingly to make best use of its AICS (Kaulio et al., 2017).

3. Developing and conceptualizing hypotheses

Combining the findings of the background theoretical research of specific extant conceptions based on TAM2 (Venkatesh and Davis, 2000), perceived usefulness (PU) and perceived ease of use (PEU), along with the factor of trust (Themistocleous, 2019) are construed as key determinants for organizations to adopt AICS. We have also, thus, confirmed that PU and PEU impact directly or indirectly on behavioral intention (BI) (Tan and Teo, 2000), and that PU has a direct impact on intention (Szajna, 1996; Wu and Wang, 2005). PU itself is interpreted as indicating the degree to which a user believes that using a particular technology or system would effectively enhance job performance (Al-Gahtani, 2001; Davis, 1993; Seddon, 1997). PU is perceived to indirectly influence intention, mediated through organizations' attitude (ATT), in adopting AICS (Ramayah and Jantan, 2004; Ramayah et al., 2005). Stemming from the above, we develop the following hypotheses.

H1a. Perceived usefulness (PU) positively impacts the behavioral intention (BI) of users towards using AI-integrated CRM systems (AICS) in organizations.

H1b. Perceived usefulness (PU) has a positive impact on attitude (ATT) of the employees of organizations towards using AI-integrated CRM systems (AICS) in organizations.

Moreover, research has revealed that PEU affects PU (Chen et al., 2001; Szajana, 1996). PEU is interpreted as the degree to which a user does not find it complex to learn, realize, and operate a system. It is explained as the extent to which the use of technology is effortless (Davis, 1989; Rogers, 1962). PEU also indirectly affects intention, mediating through ATT (Ramayah et al., 2005). Therefore, the following hypotheses are developed.

H2a. Perceived ease of use (PEU) has a positive influence over attitude (ATT) of employees of organizations to use AICS.

H2b. Perceived ease of use (PEU) has a positive influence over perceived usefulness (PU) in using AICS in organizations.

PEU includes a sense of compatibility, simplicity, and self-efficiency, as Yi et al. (2009) found. Moreover, another facet for the adoption of AI-integrated CRM in organizations is the attitude of their employees. Attitude includes an individual's feeling positively or negatively about performing a target behavior (Davis et al., 1989; Taylor and Todd, 1995). Studies based on the theory of planned behavior (TPB) highlight that ATT contributes significantly towards intention to adopt an innovation (Ajzen, 1991; Hung et al., 2013; Pavlou and Fygenson, 2006). Again, BI includes an individual's effort to achieve a goal. This effort is strengthened through intention (Ajzen, 1991, 1996), which is significantly influenced by PU (Loewenstein et al., 2001). PU thus influences intention, which acts as a catalyst to reach a goal. Whenever someone uses a new system, that person is uncertain as to whether the system will have the desired results, especially concerning the security and privacy of the system (AI-Gahtani, 2011; Alshibly, 2015; Park et al., 2015). This concern over privacy and security affects the user's trust (Al-Omari and Al-Omari, 2006). Employees' trust (TR) when attempting to use AICS in their organizations is an important determinant of their intention, mediating through ATT (Grewal and Shivani, 2012; Mulero and Adeyeye, 2013). With this input, the following hypothesis is formulated.

H3a. Trust (TR) of employees in using AICS in their organizations has a positive impact on employees' attitude.

Moreover, if employees feel assured that they should not be afraid of security and privacy breaches, they will develop trust in the new system, which the organization can adopt without hesitation (Chen et al., 2015; Gefen et al., 2003). From the perspective, the following hypothesis is developed.

H3b. Trust (TR) of employees towards using AICS in organizations positively influences the adoption of AI-integrated CRM systems (AICS) in organizations.

The users believe they will perform better with the technology if they can trust it (Schaupp and Carter, 2010). This leads us to construe that the users will gain trust and become more assured, and then they will perceive that the technology will improve their job performances (Hung et al., 2006; Susanto and Goodwin, 2011). From this consideration, the following hypothesis is formulated.

H3c. An employee's trust (TR) towards the use of AICS has a positive impact on the PU of the AICS in organizations.

A search of various adoption theories highlights that ATT is considered a useful factor for measuring BI to adopt an innovation (Ajzen, 1991; Fishbein and Ajzen, 1975; Taylor and Todd, 1995). ATT towards a behavior is interpreted as the level at which an individual expresses a positive or negative appraisal of behavior (Hung et al., 2013). In other words, ATT concerning behavior is normally observed to effectively and precisely predict one's BI (Lu et al., 2010). Again, BI is explained as behavior which acts as a positive catalyst to achieve the goal, and intention is considered the effort planned to achieve the goal (Ajzen, 1991). In different studies that conceptualize the factor which affects BI, it is seen ATT acts as a critical factor (Hung et al., 2009; Pavlou and Fygenson, 2006). From this standpoint, the following hypothesis is formulated.

H4. Employees' attitude (ATT) towards using AICS positively influences their behavioral intention (BI) to use AICS in the organization.

The above discussion makes it clear that if an organization's employees feel that using a system would be useful, they would intend to use the system. It can be said that their BI would influence them as to whether they adopt a system or not (Loewenstein et al., 2001; Orbell and Sheeran, 2000). With this consideration, the following hypothesis is developed.

H5. Employees' behavioral intention (BI) towards using AICS positively impacts the adoption of the AI-integrated CRM system (AICS) in the organization.

The conceptual model of these hypotheses is shown in Fig. 1.

The conceptual model, as shown in Fig. 1, is to be validated and the hypotheses are to be tested with the help of statistical methodology (Straub et al., 2004).

4. Research methodology and results

4.1. Participants and procedure

With the help of the conception of constructs as well as available theories, 42 measurement items were prepared for the survey to validate the conceptual model with the partial least squares structural equation modeling (PLS-SEM) technique. Since the conceptual model indicates that the number of independent variables is greater than the number of dependent variables, to validate the conceptual model and hypotheses testing, PLS-SEM analysis was adopted (Abdi, 2010; Wold, 2001). The PLS-SEM approach yields better results in analyzing an exploratory study like this (Hair et al., 2019). Besides, this technique does not requ3ire any sample restriction in the survey (Willaby et al., 2015). This technique is applicable to data which do not have a normal distribution. The CB-SEM technique cannot analyze these kind of data (Ringle et al., 2012). The questionnaire was framed following standard guidelines. The prospective respondents were informed that the aim of this study is purely academic. We focused attention on the point that there must not be any leading and complex questions in the questionnaire. Attention was also given to see that the potential respondents did not have any problems understanding the questions. All these attempts were taken to increase the response rate (Chidlow et al., 2015). The layout of the questionnaire was in order and no leading or ambiguous questions were set. The questionnaire was prepared according to the scale development procedure (Carpenter, 2018). The items were prepared in the form of statements, and the respondents were asked to reply with tick marks. A 5-point Likert scale was used, ranging from *Strongly Disagree* (SD) to

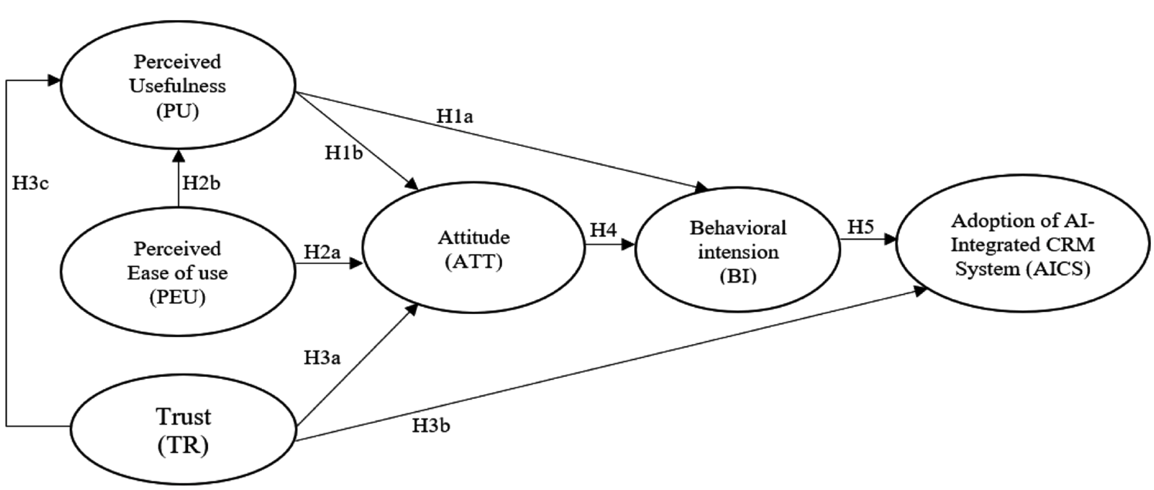

Fig. 1. Conceptual model of organizations adopting AICS.

Strongly Agree (SA).

The questionnaire was given to seven experts for their opinion, who opined that, out of 42 items, nine had readability issues, and they were eliminated from consideration. The number of usable items was 33. The questionnaire items are shown in Appendix A1. It is worth mentioning that four of the experts came from industries and had more than 15 years of experience in the domain of CRM as well as AI. We also chose three academic experts who have more than ten years of experience in the allied field. The step-by-step architecture to prepare the questionnaire is shown in Fig. 2.

The respondents came from two multinational companies (MNCs) working in India, five large Indian organizations, and 11 small and medium enterprises (SMEs) who have reported attempting to adopt an AI-integrated CRM system in their respective organizations. The two MNCs are manufacturing organizations. Out of five large Indian organizations, two are in manufacturing and the remaining three are service organizations. The 11 SMEs were various kinds of companies. The sales and marketing executives and employees of these organizations were contacted. We asked the employees for their consent to complete the questionnaire and assured them that their identities would not be disclosed. Eventually, 396 employees were selected to provide feedback via email. After one month, 357 responses were obtained. Out of 397 responses, 357 replies were obtained. The response rate was 90.15%. Given this high response rate, it was not perceived essential to perform a non-response bias test (Armstrong and Overton, 1977). The responses were examined by the seven experts, who noted that, out of 357 responses, 31 responses were incomplete and were therefore rejected. Hence, there were 326 usable responses. The number of items and respondent ratio should lie between 1:4 to 1:10 (Deb and David, 2014; Hinkin, 1995). As such, the responses are within standard acceptable limits. The number of responses by type of organization are shown in Table 1.

4.2. Construct reliability test

To assess if the identified constructs are consistent, the Cronbach's alpha of each construct (construct reliability test) was estimated. The lowest acceptable value of Cronbach's alpha is 0.6 (Hair et al., 1998). The estimation of Cronbach's alpha is shown in Table 2, where it is seen that each construct's Cronbach's alpha value is more than 0.6, confirming that the constructs are reliable.

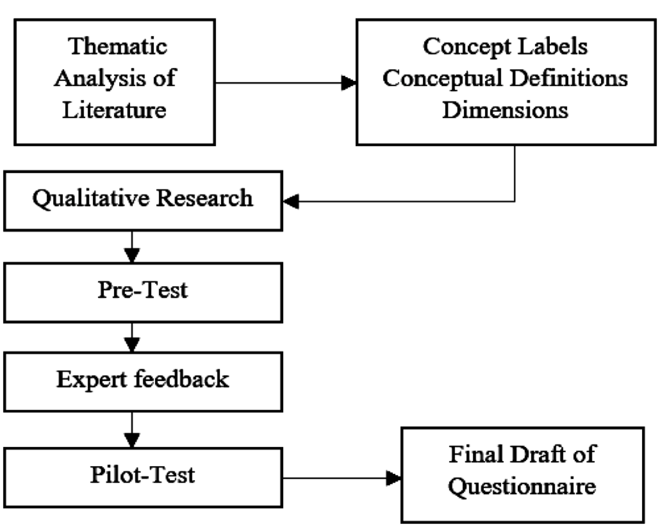

Fig. 2. Steps to prepare a questionnaire.
Source: Carpenter 2018 (p. 25)

Table 1
Type of organization and useful responses.

Organization type	Number of organizations	Employees involved
Multinational companies (MNCs)	2	63
Large Indian organizations	5	120
Small and medium enterprises (SMEs)	11	143

Table 2
Estimation of Cronbach's alpha.

Construct	Value of Cronbach's alpha	Item no.
Perceived usefulness (PU)	0.903	6
Perceived ease of use (PEU)	0.892	6
Trust (TR)	0.911	5
Attitude (ATT)	0.907	6
Behavioral intension (BI)	0.896	5
AI-integrated CRM system (AICS)	0.867	5

4.3. Test of multicollinearity

For the application of regression analysis, it is important to note that the inner meanings of the identified constructs should not be close to each other. To ensure this, it is necessary to estimate the variance inflation factor (VIF) of each construct (James, 2017). If the VIF value of each construct lies between 3.3 to 5 (Kock and Lynn, 2012), it is said that the constructs do not suffer from the multicollinearity defect. The results show that the values of VIF lie between acceptable range, confirming the positive result of the multicollinearity test (Table 3).

4.4. Computation of LF, AVE, CR, and MSV

To test if the identified items are reliable, the loading factor (LF) of each is computed. The lowest acceptable value of LF is 0.707 (Borroso et al., 2010). To satisfy the convergent validity test, the average variance extracted (AVE) of each construct is estimated (Fornell and Larcker, 1981). The lowest acceptable value of AVE is 0.5 (Hair et al., 2006). To test the composite reliability, the construct reliability (CR) is measured for each construct (Straub et al., 2004). Its lowest acceptable value is 0.6 (Urbach and Ahlemann, 2010). The reliability of the constructs is also confirmed through measuring the maximum shared variance (MSV) of each construct. This should be less than the corresponding value of AVE. (Fornell and Larcker, 1981). The results are shown in Table 4, where it is seen that all the estimates are within an acceptable range.

The estimated lowest values of LF, AVE, and CR are 0.809, 0.799, and 0.807, respectively. These are more than their acceptable lowest values. Moreover, each value of MSV is less than its corresponding AVE. The results, as such, establish that the items are appropriate, and the constructs are reliable and consistent.

4.5. Discriminant validity test

To ascertain whether the item is closely connected with its construct and weakly related to other constructs, the discriminant validity test

Table 3
Computation of variation inflation factor (VIF).

Construct	Value of VIF
Perceived usefulness (PU)	3.4
Perceived ease of use (PEU)	4.1
Trust (TR)	3.6
Attitude (ATT)	4.5
Behavioral intention (BI)	4.8
AI-integrated CRM system (AICS)	4.9

Table 4
Computation of LF, AVE, CR & MSV.

Construct/Items	LF	AVE	CR	MSV
Perceived usefulness (PU)		0.823	0.829	0.316
PU1	0.946			
PU2	0.892			
PU3	0.877			
PU4	0.899			
PU5	0.901			
PU6	0.926			
Perceived ease of use (PEU)		0.866	0.901	0.350
PEU1	0.944			
PEU2	0.926			
PEU3	0.971			
PEU4	0.979			
PEU5	0.892			
PEU6	0.867			
Trust (TR)		0.799	0.807	0.256
TR1	0.888			
TR2	0.896			
TR3	0.892			
TR4	0.895			
TR5	0.899			
Attitude (ATT)		0.834	0.890	0.261
ATT1	0.896			
ATT2	0.991			
ATT3	0.902			
ATT4	0.943			
ATT5	0.847			
ATT6	0.892			
Behavioral intention (BI)		0.832	0.904	0.272
BI1	0.809			
BI2	0.922			
BI3	0.910			
BI4	0.965			
BI5	0.947			
AI-integrated CRM system (AICS)		0.811	0.896	0.317
AICS1	0.888			
AICS2	0.896			
AICS3	0.892			
AICS4	0.921			
AICS5	0.906			

(Fornell and Larcker, 1981) is conducted. It tests if the square root of each AVE, or average variance (AV), is more than the correlation co-efficient of that construct with other constructs. If so, it is said the discriminant validity test has been established (Gefen and Straub, 2005). The results are shown in Table 5.

It appears that the value of AV (shown in bold in diagonal positions) is greater than the corresponding Pearson correlation coefficients. This confirms the discriminant validity test. This can also be established by computing loading factors of items related to their corresponding construct and cross-loading factors of the item relating to other constructs. If the loading factors are greater than cross loading factors, then discriminant validity is established. The results are shown in Appendix A2.

To supplement the Fornell and Larcker criterion for discriminant validity test, the heterotrait-monotrait test was conducted (Henseler et al., 2014). Results transpire that the values of the constructs are less than 0.85 (Voorhees et al., 2016). This confirms discriminant validity. The results are shown in Table 5A.

Table 5
Discriminant validity test.

	PU	PEU	TR	ATT	BI	AICS	AVE
PU	**0.907**						0.823
PEU	0.492	**0.931**					0.866
TR	0.517	0.580	**0.894**				0.799
ATT	0.494	0.501	0.506	**0.913**			0.834
BI	0.531	0.592	0.471	0.511	**0.912**		0.832
AICS	0.563	0.478	0.503	0.506	0.522	**0.901**	0.811

Table 5A
Discriminant Validity test (HTMT criteria).

Constructs	PU	PEU	TR	ATT	BI	AICS
PU						
PEU	0.34					
TR	0.36	0.41				
ATT	0.45	0.30	0.42			
BI	0.29	0.38	0.32	0.29		
AICS	0.51	0.44	0.19	0.31	0.28	

4.6. Structural equation modeling (SEM)

SEM assesses the relationship among the latent variables. It is needed to confirm whether the structure is in order and to test if it has been able to represent the underlying data accurately. The results of SEM are shown in Table 6. The results show that the estimates are all within acceptable range confirming the accuracy of the model.

All the values of fit indices and the value of RMSE are found to be within the acceptable range. It confirms that the proposed model is in order. It has been able to represent the underlying data accurately.

4.7. Common method bias

It is necessary to identify if the data set is free from common method bias. To achieve this, Harman's single factor test is conducted using the six endogenous and exogenous factors in this study with the scale items (Harman, 1976). The results show that it could explain 47.3% of the variance, which is below the highest cut off value of 50%, as recommended by Podsakoff et al. (2003). Hence, it can be inferred that the data set is not associated with common method bias. The detailed results of paths, hypotheses, values with path coefficients, and remarks are shown in Table 7, along with a column "Remarks".

The path relations, p-values, R^2 values, and remarks are separately represented in another table shown in Appendix A3.

4.8. Mediation analysis

We verified the mediation effects in terms of procedures laid down by Preacher and Hayes (2004) and Hayes (2013) with the SPSS PROCESS macro (v.2.16). The macro was used particularly for multiple mediation analysis using bootstrapping process using 5000 resamples and assessing LLCI (Lower-Level Confidence Interval) and ULCI (Upper-Level Confidence Interval) (Zollo et al., 2019). In this way, we could estimate the effects of the independent variables on the goal. The detailed results are provided in Table 8.

4.9. Results

The results show that PEU and TR can explain PU to the extent of 46%, since the concerned value of $R^2 = 0.46$. It appears that PU, PEU, and TR can explain ATT to the tune of 57%, since the value of concerned R^2 is 0.57. PU and ATT can explain BI to the extent of 71% since the

Table 6
Structural equation modeling.

Fit index	Recommended value	Value in the model
Chi-square (χ2)/Degree of freedom (*df*)	$\leq$ 3.000 (Chin and Todd, 1995; Gefen, 2000)	2.002
Goodness of fit index (GFI)	$\geq$ 0.900 (Hoyle, 1995)	0.969
Adjusted goodness of fit index (AGFI)	$\geq$ 0.800 (Segars and Grover, 1993)	0.976
Comparative fit index (CFI)	$\geq$ 0.900 (Hoyle, 1995)	0.981
Tucker Lewis index (TLI)	$\geq$ 0.950 (Hu and Bentler, 1999)	0.957
Root mean square error (RMSE)	$\leq$ 0.080 (Hu and Bentler, 1999)	0.005

Table 7
Detailed results of Harman's single factor test for common method bias.

Path	Hypothesis	β-value	Significance Level	Remarks
PU→BI	H1a	0.81	$p < 0.01$ (**)	Supported
PU→ATT	H1b	0.012	$p > 0.05$ (ns)	Not Supported
PEU→ATT	H2a	0.83	$p < 0.01$ (**)	Supported
PEU→PU	H2b	0.80	$p < 0.01$ (**)	Supported
TR→ATT	H3a	0.68	$p < 0.05$ (*)	Supported
TR→AICS	H3b	0.016	$p > 0.05$ (ns)	Not Supported
TR→PU	H3c	0.021	$p > 0.05$ (ns)	Not Supported
ATT→BI	H4	0.69	$p < 0.01$ (**)	Supported
BI→AICS	H5	0.74	$p < 0.001$ (***)	Supported

Table 8
Mediation analysis.

Linkages	Hypotheses	Effects	IE	TE	LLCI	ULCI
PU → BI	H1a	0.81			0.79	0.83
BI → AICS	H5	0.74			0.71	0.77
PU → AICS			0.60	0.60		
PEU → ATT	H2a	0.83			0.76	0.90
ATT → BI	H4	0.69			0.55	0.83
BI → AICS	H5	0.74			0.71	0.77
PEU → AICS			0.43	0.43		
TR → ATT	H3a	0.68			0.61	0.75
ATT → BI	H4	0.69			0.64	0.74
BI → AICS	H5	0.74			0.71	0.77
TR → AICS	H3b	0.016			0.012	0.020
TR → AICS			0.24	0.25		

Note: IE → Indirect Effect; TE → Total effect.

value of the R^2 is 0.71. Besides, TR and BI can interpret the adoption of AICS in the Indian organization 76% of the time, since the concerned R^2 value is 0.76. The explanative power of the model is as high as 76%. The model is parsimonious and simple to handle. The results show that there are six constructs: PU, PEU, TR, ATT, BI, and AICS. There are nine hypotheses, out of which, three (H1b, H3b, and H3c) have not been supported, but the remaining six hypotheses have been supported, as is found from the validation test. TR was found not to have an adequate impact on AICS (H3b), the goal of this study. The value of the concerned path coefficient is considerably low (0.016). This result contradicts the results of another study (Chen et al., 2015), presumably because potential users have not acquired knowledge about the full outcomes of AICS in any of those organizations where they work. Mere optimism was not enough for the users to gain trust in this innovation. Therefore, the hypothesis H3b is not supported.

The same reason might apply for not supporting H3C. According to the results, out of PU, PEU, and TR, the construct PEU has the highest impact on ATT, since the concerned path coefficient (β-value) is 0.83. It has a significance level of $p < 0.01$. However, TR impacts ATT significantly, as the concerned path coefficient is 0.68 with a significance level of $p < 0.05$ (*), but PU impacts ATT insignificantly, as the concerned path coefficient is 0.012 with non-significance level of $p > 0.05$ (ns). Out of PEU and TR impacting on PU, the impact of PEU on PU is more compared to the effect of TR on PU, since the path coefficient (β-value) of PEU on PU is more (0.80) than that of TR on PU (0.021). The results also show that PU and ATT have an impact on BI. But, out of these two, the impact of PU on BI is much more (β-value = 0.81) compared to the impact of ATT on BI, which has a path coefficient of 0.69. The results indicate that TR and BI have an impact on AICS, which is the goal of this study. However, the effect of TR on AICS is insignificant, since the concerned path coefficient is a low 0.016, and the impact of BI on AICS is appreciable, as the concerned path coefficient is 0.74 with a significance level of $p < 0.001$. The impact of PU on ATT is significant in the present study, which was supported in other studies (Bashir and Madhavaiah, 2015; Zhang et al., 2012). The significant and strong impact of the mediating constructs ATT and BI on the goal implies that organizations' employees might intend to adopt AICS in their organizations depending on the strength of their attitudes. Several studies (Lu et al., 2010; Williams et al., 2015) have acknowledged this significant and meaningful relationship.

5. Findings and implications

5.1. The agility contextualization

As already highlighted, extracting the full potential of AICS in organizations is also linked to the organization's agile competencies. However, the true question arising from this is how should the organization be agile; in other words, what is the nature of this relationship and how can it be optimized? Agility, in this context, should not be considered a stand-alone capability but rather viewed as a collection of different specific competencies. These include adaptability, innovation, resilience, and sustainability (Holbeche, 2018). The study highlights that if the stakeholders of the organizations could understand the usefulness of AICS and feel that AICS is not that complex to use, they would be inclined to use it. For this to happen, the organization must be agile in extracting the potential of AICS by addressing the threats and challenges and by utilizing its capabilities in the best possible way (Overby, 2006). The organizations should be agile to structure their IT competencies to sense and respond to threats and uncertainty, which would develop stakeholders' trust. The validated results show that PU impacts BI (β = 0.81, $p < 0.01$), whereas PEU impacts PU (β = 0.80, $p < 0.01$), and earlier studies (Venkatesh and Davis, 2000) have also supported these linkages. Validation shows that trust impacts attitude, and intention impacts adoption, which earlier studies (DeConick, 2010) also supported. It appears that the impacts of PU on ATT and TR on AICS are insignificant, contradicting some earlier studies. The possible reasons for such deviation and contradiction have been explained earlier in detail. This study identified the antecedents that predict attitude, intention, and adoption after studying different models and by subsequently conducting statistical validation of the conceptual model. Fig. 3 helps us to provide the relevant regression equations, which are shown below.

$$PU = 0.80(PEU) + E \tag{i}$$

$$ATT = 0.83(PEU) + 0.68(TR) + E \tag{ii}$$

$$BI = 0.81(PU) + 0.69(ATT) + E \tag{iii}$$

$$AICS = 0.74(BI) + E \tag{iv}$$

It is noteworthy that, in these equations, the insignificant linkages have not been considered and "E" stands for relevant error factor.

5.2. Implications for theory

The study proposes a model and has tested it with standard statistical tools. While creating the model, two constructs of TAM2 (Venkatesh and Davis, 2000) were used. However, apart from considering PU and PEU, factors TR, ATT, and BI were added. The addition was made to explicitly consider individuals' characteristics, since prior research indicated that individuals' attitudes and intentions to use an innovation like AI-integrated CRM are important factors to assess (Alshare and Lane, 2011; Sumak et al., 2010). Thus, the proposed theoretical model is original and is not merely a modification of TAM2.

The analysis highlights that the proposed theoretical model effectively explains the meaningful mechanisms for ensuring organizations' adoption of AICS. This has been possible because we included some better-suited measures in the present context and did not blindly follow one standard adoption model. Our theoretical model can contribute theoretical knowledge on how organizations can adopt AICS for improved customer-centric operations. However, organizations need to

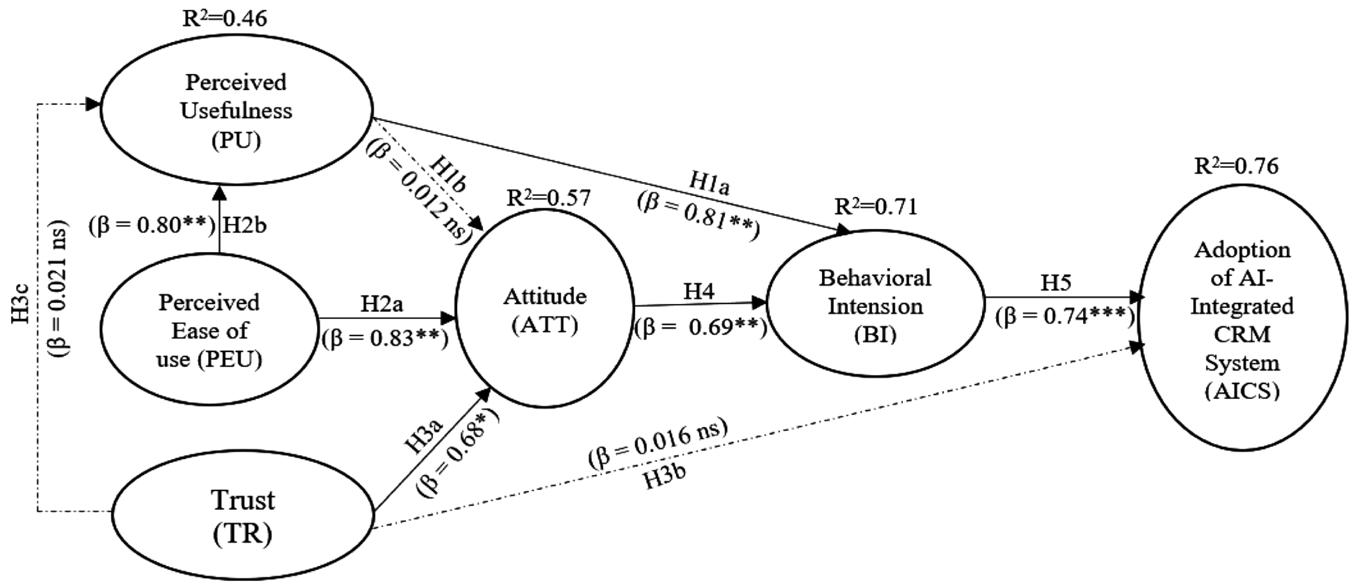

Fig. 3. Structural equation modeling with path weights and significance level.

translate the model's theoretical knowledge into effective action. To do this, they must possess adaptability and resilience, which are the vital competencies of an agile organization (Holdeche, 2018).

Our model should generally be associated with guiding employees' behavior, which is associated with employee culture. Where the employees believe in traditional foresight and existing scenario planning, it will be necessary for the organization to be agile to upgrade to AICS technology by motivating the employees accordingly (Fourné et al., 2014; Vecchiato, 2015). To adopt a system, social involvement is also essential. One may raise a point that these factors have not been considered in the present model, and therefore it is, in that sense, lagging. But the model has been simplified by only considering the mediating factor BI. It includes behavioural control (Armitage and Conner, 2001), which includes complexity (Godin and Kok, 1996), which in turn includes social involvement (Gibbons et al., 2004). Since behavioural control includes a sense of complexity, at the outset the employees might be uncertain about using the organization's new AICS, which they also find threatening. But in this context, the organization must be agile to quickly respond to employees' negative feelings (R. Shams et al., 2020). That would help to earn their trust, thus impacting their intention to adopt AICS.

The proposed model is simple and frugal, as it has made a trade-off between its complexity and explanative power. The complexity has been considerably reduced by not including many constructs from different adoption theories. Its explanative power is as high as 76%, since the organization is perceived to have used an agile approach so it could simultaneously and optimally balance exploration and exploitation to strategize its process of synchronizing incremental innovation using AICS (Raisch and Birkinshaw, 2008). The introduction of TR, ATT, and BI has proved the theoretical model to be strong, since these factors play a vital mediating role. Again, since the adoption of AICS in organizations is a new and special concept, the model considers these idiosyncratic characteristics, thus achieving success.

An organization can achieve success by adopting AICS if it can exhibit agility by appropriately conceptualizing and reacting to the available opportunities with speed and resilience, by reconfiguring the resources, and by reducing the risk of being stuck in rigid traps, which often result in business failure (Doz, 2020; R. Shams et al., 2020).

5.3. Implications for practice

This research indicates that ATT and BI play a vital role in adopting and using AICS in organizations. Specifically, we observed that ATT acted as a strong determinant of BI (H4). This indicates that the concerned organizations attempting to adopt AICS to improve business should make a holistic and agile effort to shape the ATT of employees to reorient their intention to adopt this new system. Therefore, top executives of the organization should implement appropriate policy for providing training programs or help desks to the employees to correctly use the new system. To execute this policy, the organizations must be agile with the innovative idea by adjusting multichannel management, keeping in mind that agility is construed as a cause, and innovation as its effect (R. Shams et al., 2020).

It is seen that PEU and TR are the antecedents of ATT (H2a, H3a). The employees expect that using the system should be less complex and it should be trustworthy, therefore designers, developers, and system analysts should focus more attention on minimizing its complexity. Also, the system design cannot have the slightest security or privacy vulnerabilities. The top executives or policymakers of the concerned organizations should be involved in sincerely communicating the system's capabilities to their employees with live demonstrations, product brochures, and published success stories (Koh et al., 2010; San Martín and Herrero, 2012). This would enhance employees' sense of trust in using the organizations' AICS. The leadership of the organization needs to react immediately when employees become uncertain about technological or managerial issues in using AICS. For this, the organization must be proactive and agile to help employees trust the system.

The results show that PU has an insignificant impact on ATT (H1b), and therefore H1b is not supported. This is presumably because the organizations we surveyed had not yet fully adopted an AI-integrated CRM system, so the users had not seen its benefits. Therefore, PU was found not to influence the ATT. In this study, social influence was not considered. Usually, adopting a new system is associated with social influence, and it is always suggested that, to achieve the best results, this human-centric issue is important. The organizations' management, including top executives, should proactively manage social influence of their employees, so the employees are not influenced by any negative feedback concerning the use of this new system. To achieve this, the organizational process approach must be agile.

It is noted that, for organizations to adopt AICS, the leadership needs to focus on some salient points. The leadership should emphasize that its goal is to achieve strategic and operational agility in adopting AICS. It also should embrace an atmosphere of change and dynamism, so employees do not cling to existing practices. Attention is to be given to developing the employees' capabilities (Smith and Tushman, 2005). The leadership should also exhibit their agility by promptly responding to any threat or uncertainty perceived by the employees when adopting AICS.

6. Concluding remarks, limitations, and future research avenues

The research highlights that organizational agility facilitates the development of exploitative and explorative competences and strengthens existing capabilities for the rise and successful adoption of AICS in organizations for competitiveness. More specifically, in the proposed model, attitude and behavioral intention act as effective mediators mostly on exogenous constructs in the adoption of AICS in organizations. The model effectively explains the variance in organizations' adoption of AICS, and it appears to have outperformed the alternative allied models.

In terms of limitations and future research directions, it cannot be construed that this research study is generalizable. The sample size and focus, albeit statistically able to provide valid and reliable results, cannot be generalized, nor necessarily applied in a non-Indian context. Particularly, as the successful adoption of AICS has been shown to relate to key micro-foundational elements, including 'soft' ones, such as behavior and attitude, it is logical to extrapolate that contextual differences would alter contextual findings. Ergo, the research needs to be repeated in other contexts and cross-compared with other studies for more generalizable findings that might also identify some universal, influential factors. Moreover, the model demands further and differing methodological approaches (e.g., longitudinal ones) towards greater refinement, elaboration, and extension/contextualization. This could be achieved by including additional factors that the present sample could not include, such as actual usage; the factor of image, from IDT (Rogers, 1995); or determinants of adopting AICS in organizations, such as performance and effort expectancy, which the adoption model of UTAUT did not take into account (Venkatesh et al., 2003).

Our research does not claim to be absolute, definitive, or complete. Scientific research, by nature, never is. We have, nonetheless, provided for the first time a tested model on the successful adoption and application of artificial intelligence-integrated customer relationship management systems, as well as the functional link with and contextual role of organizational agility in the process. The boundaries between technology and business have never been less distinct, knowledge about customers has never been more valuable, and swift adaptation to environmental changes has never been more critical as a business success factor. Consequently, the link between AI/digitalization, CRM, and agility has de facto, unequivocally, and irrevocably arisen as one of the most important organizational relationships both notionally, as a concept, and functionally, as a process. Our research has set the foundation for better understanding of this triangular interaction, and we hope and trust that future research shall find it valuable in its own furthering of our knowledge on the subject.

Appendix

Table A1. Summary of questionnaire

Items	Statements	Response[SD][D][N][A][SA]
PU1	I hope that AI-CRM system will benefit the organizations	[1][2][3][4][5]
PU2	CRM is useful and if AI is embedded to it, organization would flourish much more	[1][2][3][4][5]
PU3	AI-CRM System is deemed to be useful in any business organization	[1][2][3][4][5]
PU4	Employee would feel comfortable using new AI-integrated CRM system	[1][2][3][4][5]
PU5	In developed countries AI-CRM has brought in grand success	[1][2][3][4][5]
PU6	AI-CRM system will be acceptable if its benefits are perceived	[1][2][3][4][5]
PEU1	Everyone would like to use AI-CRM system if it is felt compatible	[1][2][3][4][5]
PEU2	Users will use the AI-CRM system if it is simple to use	[1][2][3][4][5]
PEU3	AI-CRM system can address all our organizational needs	[1][2][3][4][5]
PEU4	Operating AI-integrated CRM system is easy	[1][2][3][4][5]
PEU5	Training will help to use the AI-integrated CRM system easily	[1][2][3][4][5]
PEU6	Transition from legacy CRM system to AI-CRM system will be easy	[1][2][3][4][5]
TR1	The AI-CRM system is reliable	[1][2][3][4][5]
TR2	The new AI-integrated CRM system would provide greater certainty	[1][2][3][4][5]
TR3	Employee will trust the new AI-CRM system in the organization	[1][2][3][4][5]
TR4	The new AI-CRM system is more trustworthy than the legacy CRM system	[1][2][3][4][5]
TR5	As the AI-CRM system matures in the organization, trust will grow	[1][2][3][4][5]
ATT1	I am comfortable using the new AI-CRM system	[1][2][3][4][5]
ATT2	I know that the new AI-CRM system will help me in my work	[1][2][3][4][5]
ATT3	Use of AI-integrated CRM system would make me more efficient	[1][2][3][4][5]
ATT4	I am adequately trained to use new AI-CRM system	[1][2][3][4][5]
ATT5	The new AI-CRM system provides more insights than legacy CRM system	[1][2][3][4][5]
ATT6	The AI-integrated CRM system would help me in quick decision making	[1][2][3][4][5]
BI1	Use of AI-CRM system will provide better understanding of my business	[1][2][3][4][5]
BI2	The new AI-CRM system will help to achieve business goal effectively	[1][2][3][4][5]
BI3	I will get more accurate information if I use the new AI-CRM system	[1][2][3][4][5]
BI4	I will get the necessary information in a timely manner using the AI-CRM system	[1][2][3][4][5]
BI5	Switching from traditional CRM to AI-CRM would enhance my capability	[1][2][3][4][5]
AICS1	The new AICS system is cost effective	[1][2][3][4][5]
AICS2	AICS would bring more efficiency in the organization	[1][2][3][4][5]
AICS3	The new AICS will help increasing employees' satisfaction level	[1][2][3][4][5]
AICS4	AICS will address the security and privacy vulnerabilities or the organization	[1][2][3][4][5]
AICS5	The new AICS will enhance the employee-productivity of the organization	[1][2][3][4][5]

Table A2: Computation of loading and cross loading factors

	PU	PEU	TR	ATT	BI	AICS
PU1	**0.946**	0.480	0.391	0.411	0.512	0.456
PU2	**0.892**	0.492	0.393	0.417	0.517	0.431
PU3	**0.877**	0.551	0.396	0.419	0.574	0.409
PU4	**0.899**	0.407	0.407	0.421	0.511	0.317
PU5	**0.901**	0.502	0.411	0.431	0.496	0.391
PU6	**0.926**	0.308	0.488	0.444	0.498	0.438
PEU1	0.409	**0.944**	0.451	0.417	0.499	0.490
PEU2	0.407	**0.926**	0.433	0.480	0.411	0.491
PEU3	0.411	**0.971**	0.503	0.483	0.501	0.438
PEU4	0.476	**0.979**	0.591	0.488	0.490	0.417
PEU5	0.561	**0.892**	0.509	0.503	0.461	0.411
PEU6	0.492	**0.867**	0.561	0.506	0.456	0.462
TR1	0.473	0.491	**0.888**	0.417	0.477	0.431
TR2	0.481	0.488	**0.896**	0.490	0.471	0.426
TR3	0.480	0.487	**0.892**	0.461	0.488	0.405
TR4	0.499	0.490	**0.895**	0.411	0.431	0.417
TR5	0.506	0.502	**0.899**	0.417	0.411	0.409
ATT1	0.562	0.506	0.406	**0.896**	0.311	0.309
ATT2	0.411	0.409	0.407	**0.991**	0.390	0.332
ATT3	0.406	0.453	0.411	**0.902**	0.356	0.322
ATT4	0.400	0.431	0.491	**0.943**	0.331	0.312
ATT5	0.417	0.488	0.498	**0.847**	0.409	0.417
ATT6	0.488	0.470	0.496	**0.892**	0.405	0.420
BI1	0.419	0.417	0.417	0.431	**0.809**	0.392
BI2	0.416	0.426	0.478	0.456	**0.922**	0.462
BI3	0.417	0.444	0.301	0.444	**0.910**	0.451
BI4	0.431	0.404	0.356	0.472	**0.965**	0.438
BI5	0.532	0.504	0.371	0.490	**0.947**	0.417
AICS1	0.492	0.451	0.376	0.411	0.411	**0.888**
AICS2	0.390	0.592	0.420	0.517	0.417	**0.896**
AICS3	0.407	0.460	0.431	0.566	0.486	**0.892**
AICS4	0.500	0.571	0.481	0.561	0.481	**0.921**
AICS5	0.508	0.576	0.504	0.511	0.490	**0.906**

Note: The bold values show loading factors, whereas values in regular font show the cross-loading factors.

Table A3. Analysis of the theoretical model

Measure	Hypothesis	β-value	*p*-value	Remarks
Effect on PU	$R^2 = 0.46$			
By PEU	H2b	0.80	< 0.01 (**)	Supported
By TR	H3c	0.021	> 0.05 (ns)	Not Supported
Effect on ATT	$R^2 = 0.57$			
By PU	H1a	0.012	> 0.05 (ns)	Not Supported
By PEU	H2a	0.83	< 0.01 (**)	Supported
By TR	H3a	0.68	< 0.05 (*)	Supported
Effect on BI	$R^2 = 0.71$			
By PU	H1a	0.81	< 0.01 (**)	Supported
By ATT	H4	0.69	< 0.01 (**)	Supported
Effect on AICS	$R^2 = 0.76$			
By TR	H3a	0.016	> 0.05 (ns)	Not Supported
By BI	H5	0.74	< 0.001 (***)	Supported

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