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Adoption of Artificial Intelligence in Supply Chain Risk Management:
An Indian Perspective

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ABSTRACT

The study aims to examine factors that influence the adoption-diffusion process of artificial intelligence (AI) in supply chain risk management (SCRM) across manufacturing, wholesale trade, retail trade, and transportation industries in India. As part of this study, 11 constructs that influence the adoption-diffusion stages of AI in SCRM were identified and examined. A survey was conducted to collect data from supply chain executives, risk professionals, and AI consultants across the manufacturing, wholesale trade, retail trade, and transportation industries in India. Partial least squares structural equation modeling (PLS-SEM) was used to study the data. Results show that these factors have varying degrees of influence and direction on the three stages of adoption of AI in SCRM. The study will enable the leadership team in the organizations to build a roadmap for the adoption, implementation, and routinization of AI in SCRM.

KEYWORDS

ADANCO, Adoption, AI, Artificial Intelligence, PLS-SEM, SCRM, Supply Chain Risk Management, TOE Framework

1. INTRODUCTION

Numerous events including pandemics like COVID-19 and natural hazards, integration with global supply chain networks, the introduction of just-in-time processes, and others have resulted in exposing supply chains to added disruptions (Snyder et al., 2016). COVID-19 has pushed supply chain executives to prioritize actions that will help improve the resilience of their organizations to future shocks (Shih, 2020). While many of the disruptions have been caused by basic supply chain risks, there is also a growing concern about the complexity of global supply chains, rapid introductions of just-in-time processes, and other geopolitical events. Past research has shown that companies that have experienced supply chain disruptions have a high probability of suffering long-term financial impact (Kumar et al., 2018).

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Business leaders have been increasingly looking to explore Artificial Intelligence (AI) for specific use cases in Supply Chain Risk Management (SCRM) (Paul et al. 2020). However, past research on the adoption of AI in SCRM has been limited in the context of India. Furthermore, it is equally important to study the post-adoption stages of AI implementation and AI usage leading to routinization. Hence, this study aims to examine factors that influence the adoption-diffusion process of AI in SCRM at an organizational level across select industries in India. The industries considered include manufacturing, wholesale, retail, and transportation for this study. As part of this study, eleven factors that influence the adoption-diffusion stages of AI in SCRM, based on the technology–organization–environmental (TOE) framework, were identified. These independent factors are integrated data management, complexity, cost of ownership, and relative advantage as part of the technology context; talent, organizational agility, top management support, and enterprise risk management (ERM) alignment as part of the organizational context; and external pressure, disruption impact, and regulatory uncertainty as part of environmental context. The dependent factors considered are AI adoption in SCRM, AI implementation in SCRM, and AI routinization in SCRM. Data has been collected through a survey of supply chain executives, risk professionals, and AI consultants across the manufacturing, wholesale trade, retail trade and transportation industries in India. Partial least squares structural equation modeling (PLS-SEM) was used to study the data. Both the measurement and structural models were examined using ADANCO 2.3.1 software. The study attempts to enable supply chain executives, risk professionals and AI professionals to devise strategies for the adoption of AI in SCRM. The significant factors identified through this study and their predictive power will greatly benefit the business executives to evaluate, prototype, implement and start using AI for supply chain risk-related decision-making.

2. BACKGROUND

AI will change the decision-making process in an organization and how it interacts with other stakeholders and third parties (Haenlein & Kaplan 2019). It has also been argued that in organizations, thinking tasks will increasingly be taken over by AI systems (Huang et al., 2019) due to the promise of fast, accurate, repeatable, and human-like intelligence. AI is evolving, and accordingly, the scope, definition, applications, and usability of AI is under constant change. As per the Artificial Intelligence Index Report 2021, published by Stanford University, business establishments were most likely to identify AI techniques as those covering areas like deep learning, natural language processing, computer vision, and other machine learning techniques (Zhang et al., 2021).

With regards to SCRM, Gurtu and Johny (2021) have highlighted that the definition of SCRM is still evolving and there is no standard definition. Researchers have proposed multiple definitions over a period (Sudeep & Srikanta, 2014; Sodhi et al., 2012). Primarily, SCRM comprises four fundamental constructs, namely, (i) supply chain risk sources, (ii) risk consequences, (iii) risk drivers, and (iv) risk mitigation (Jüttner et al., 2010).

2.1 Application of AI in SCRM

Examples in the field of SCRM include an AI approach to curtailing the bullwhip effect inclusive of internal and external risks, as cited in a study by Aggarwal and Davè (2018). Other AI studies suggest it could model the likelihood of occurrence of risks (Ojha et al., 2018), diminish the risk in distribution management due to churn (Necula, 2017), predict and assess damage attributes in the field of logistics (Gürbüz et al., 2019), and forecast the level of integration in the supply chain to minimise risks (Muñoz et al., 2020). Advances in AI techniques and the massive growth in data generated along with the exponential rise in computing power have started benefiting the field of SCRM immensely. Hence, it has become important for organizations to explore AI adoption, implementation, and routinization to build a competitive advantage.

2.2 Technology Adoption Theories

Technology adoption has been studied in detail over the past few decades covering the adoption-diffusion stages. Adoption theories that apply at an organizational level include (i) the diffusion of innovation theory (DOI) (Rogers, 1995) and (ii) the technology–organization–environment (TOE) framework (Tornatzky & Fleischer, 1990). The DOI theory states that the adoption of innovation is influenced by perceived attributes of innovation, namely, relative advantage, compatibility, complexity, trialability, and observability (Rogers, 1995). Similarly, Tornatzky & Fleischer (1990) identifies three independent contexts, namely (i) technological context, (ii) organizational context, and (iii) environmental context. The TOE framework has been cited extensively concerning the adoption of various technological areas (Awa et al., 2017). At the same time past research has shown that the specific constructs as part of the three contexts are different across studies based on several criteria including the technology being studied, the industry or region being considered, and the stage of adoption (Chen *et al.*, 2021).

2.3 The TOE Framework

Tornatzky and Fleischer (1990) state that based on the perspective of the user, the decision and actions concerning the incorporation of a new tool, will be a variant on the following pattern: (a) awareness-problems, (b) matching-selection, (c) adoption-commitment, (d) implementation, and (e) routinization. While the adoption stage is important to study the initial acceptance of innovation, post-adoption stages are more important as they help with understanding the success of the innovation (Hossain *et al.*, 2014). Past applications of TOE include the adoption of technologies like big data analytics (Chen et al., 2019) and predictive analytics (Banerjee & Banerjee, 2017).

While there exists strong reasons to use TOE framework to technology adoption, not all factors or the underlying indicators cited as part of these theories can be used as-is to study AI adoption in SCRM. Hence the authors propose including factors that are added in the context of AI in SCRM.

3. RESEARCH MODEL AND HYPOTHESES

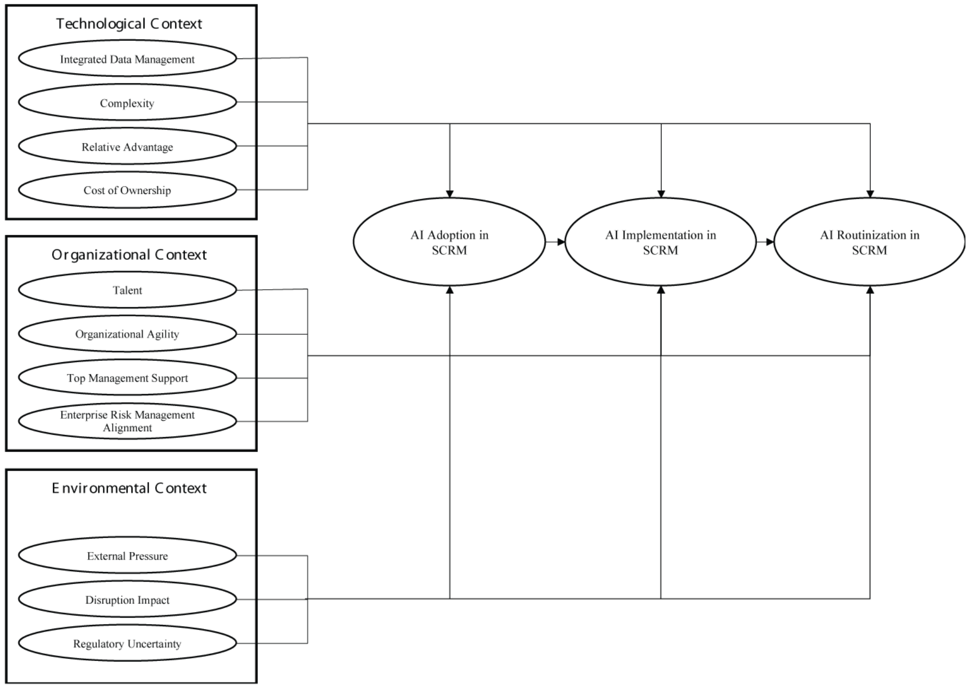
As per the TOE framework, the research model considers the technological, organizational, and environmental contexts. Paul et al. (2020) proposed a conceptual model for the adoption of AI in SCRM based on the TOE framework and introduced new factors based on a qualitative study in India. This study adopts and further builds on this conceptual model. Accordingly, eleven constructs were identified across the three contexts.

3.1 Technological Context

Four constructs have been identified based on past research for the technological context. *Integrated data management* has been cited in past research as critical infrastructure for digital transformation leaders (Brock and Wangenheim, 2019). Organizations that have IT teams and platforms to manage large and diverse datasets, structured and unstructured data, transactional data, and external data are better equipped to initiate AI projects. Perceived *complexity* has been defined in past literature as "the degree to which an innovation is perceived as relatively complex to understand, implement and use" (Rogers 2003). Also, the perceived *cost of ownership* is negatively related to technology adoption in past studies (Chan and Chong, 2013) and is an important factor to determine if top management would go ahead with the investments and commitment required to evaluate AI technologies. Moreover, *relative advantage* has been cited frequently in past technology adoption studies (Puklavec et al., 2018; Chandra and Kumar, 2018). These four technological factors are hypothesised to influence all the three stages of adoption-diffusion process.

Based on the above, the following hypotheses have been derived:

Figure 1. Research model



Hypothesis (H1): Integrated data management positively influences the adoption, implementation, and routinization of AI in SCRM.
Hypothesis (H2): Complexity negatively influences the adoption, implementation, and routinization of AI in SCRM.
Hypothesis (H3): Cost of ownership negatively influences the adoption, implementation, and routinization of AI in SCRM.
Hypothesis (H4): Relative advantage positively influences the adoption, implementation, and routinization of AI in SCRM.

3.2 Organizational Context

Four constructs have been proposed under the organizational context. *Talent* has been cited in past research as a critical factor for technology and innovation adoption (Queiroz & Telles, 2018). Based on a study to demystify AI in the context of digital transformations, Brock and Wangenheim (2019) cite *organizational agility* to be essential for AI success. Given that SCRM practices are under the wider Enterprise Risk Management (ERM) practice (Curkovic et al., 2013), any data and decision system must comply with the ERM policies and guidelines. The Committee of Sponsoring Organizations (COSO) of the Treadway Commission (COSO, 2004) provides a framework that enables organizations to integrate SCRM and ERM (Curkovic et al., 2013). *ERM alignment* is a critical factor from a business practise standpoint that was cited during the unstructured interviews conducted with industry Subject Matter Experts (SMEs) (Paul et al., 2020). Additionally, one of the top predictors in innovation adoption studies is *top management support* which has been cited often in past research (Banerjee & Banerjee, 2017; Lai et al., 2018). All the four organizational factors are hypothesised to influence all the three stages of adoption-diffusion process.

Based on the above, the following hypotheses have been derived:

Hypothesis (H5): Talent positively influences the adoption, implementation, and routinization of AI in SCRM.
Hypothesis (H6): Organizational agility positively influences the adoption, implementation, and routinization of AI in SCRM.
Hypothesis (H7): ERM alignment positively influences the adoption, implementation, and routinization of AI in SCRM.
Hypothesis (H8): Top management support positively influences the adoption, implementation, and routinization of AI in SCRM.

3.3 Environmental Context

Three constructs under the environmental context have been proposed. Two of these constructs, namely *disruption impact* and *regulatory uncertainty* have been newly created based on literature surveys and inputs from SMEs, while *external pressure* has been cited in past literature. *External pressure* has been cited as a significant factor in the adoption of research related to RFID technology (Hossain et al., 2016). Furthermore, the negative impact of disruptive events in the past influences AI adoption given the potential of AI to predict these events including their impact. Past research has cited that Bayesian network theory can be used to predict the likelihood of occurrence of risks (Ojha et al., 2018). Hence the factor *disruption impact* has been proposed. *Disruption impact* measures the extent to which past impact of disruptions propel an organization to adopt AI as part of its SCRM practices. In addition to these factors, past reports indicate that many government organizations are prioritising AI funding to support further research (Bughin et al., 2018). But on the other hand, government regulations on data privacy and data security could be limiting AI adoption. *Regulatory uncertainty* has been defined as the degree to which the regulatory environment in the country and beyond influences an organization to adopt AI in SCRM. All the three environmental factors are hypothesised to influence all the three dependent factors: *AI adoption, implementation,* and *routinization in SCRM*.

Given below are the hypotheses based on the above discussions:

Hypothesis (H9): External pressure positively influences the adoption, implementation, and routinization of AI in SCRM.
Hypothesis (H10): Disruption impact positively influences the adoption, implementation, and routinization of AI in SCRM.
Hypothesis (H11): Regulatory uncertainty negatively influences the adoption, implementation, and routinization of AI in SCRM.

3.4 Dependent Constructs

Most of the past literature covers only the adoption stage. A past study cites that managers, across businesses globally, have limited knowledge on how to implement AI in their companies' operations (Brock & Wangenheim, 2019). The authors argue that the mixed evidence of AI implementation and the limited empirical insight into its implementation necessitates further research on the current state of AI in business, which would explore key factors influencing AI implementation. Hence, it is important to further study aspects of AI implementation, and not just the intention to adopt AI. Furthermore, prior research suggests that while the adoption stage is important to study the initial acceptance of innovation, post-adoption stages are more important as they help with understanding the success of the innovation (Hossain et al., 2016). Therefore, in addition to AI adoption and implementation intentions, it is important to also study the routinization of AI in SCRM. This study covers the diffusion process in terms of the following three stages: (i) *AI adoption in SCRM*, (ii) *AI implementation in SCRM*, and (iii) *AI routinization in SCRM*. Accordingly, provided below are the hypotheses based on the above discussions:

Hypothesis (H12): Adoption of AI in SCRM positively influences the implementation of AI in SCRM.
Hypothesis (H13): Implementation of AI in SCRM positively influences the routinization of AI in SCRM.

4. RESEARCH METHODOLOGY

Content validation of the research model was conducted with nine industry subject matter experts (SMEs) from India, based on unstructured interviews. The industry panel comprised of delegates from manufacturing (4), retail (2), wholesale (1), AI consulting (1), and risk consulting (1). All SMEs are decision-makers and hold positions in senior management, e.g., chief executive officers, directors, and business heads. To test the hypotheses, primary research was conducted in India, covering organizations across four industries namely, manufacturing, wholesale trade, retail trade, and transportation. The measurement instrument covered a total of 61 questions to capture the demographics related to the respondents along with the level of agreement to the questions on the independent and dependent items of the constructs. Table 5 provides the item descriptions. These items have been adopted as well as suitably adapted from past studies on information systems' adoption. Responses to the questions were made on a 5-point Likert scale with 1 indicating 'strongly disagree' while 5 indicating 'strongly agree'. Google forms were used to create and administer the online questionnaire.

A randomly selected list of 450-plus organizations in India was identified, targeting senior leadership and mid-level leadership respondents after carefully validating their profiles on the professional networking site LinkedIn. A total of 1600-plus respondents were surveyed. After repeated follow-ups, reminders and answering every query about the survey, 282 completed responses were obtained. Out of these responses, 4 responses were found to be incomplete and hence a final list of 278 responses was considered for analysis.

Past research has considered the minimum size of the sample to be (i) ten times greater than the indicators on the most complex formative construct or (ii) the largest number of antecedent constructs leading to an endogenous construct, whichever is greater (Barclay et al., 1995; Hossain et al., 2016). Given that the research model has reflective constructs, and the maximum number of antecedent constructs leading to an endogenous construct is twelve, the required minimum sample size is 120. Therefore, the sample size of 278 for the analysis was considered sufficient (Hossain et al., 2016).

Table 1 provides the respondent profiles, with 62% from manufacturing and 21% from IT and consulting services who provide AI consulting and implementation support to their clients in manufacturing, retail trade, wholesale trade and transportation industries. Among the respondents, 6% are from top management, 16% represent the senior management while 59% represent the middle management.

5. DATA ANALYSIS AND RESULTS

Variance-based or composite-based SEM using partial least squares (PLS) was adopted for this study. PLS has been widely cited in past research, covering information systems, strategic management, marketing, and other areas (Henseler et al., 2016). PLS-SEM formulates linear combinations of indicators and subsequently uses the ordinary least squares method to estimate model parameters. It makes no distributional assumptions; thus, it is non-parametric. PLS-SEM applies in cases where theory is not well developed and is more exploratory (Ravand, 2016). Both the measurement and structural models were examined. ADANCO 2.3.1 software was used for the study.

5.1 Measurement Model

All constructs are reflective, and this reflective measurement model was assessed for both reliability and validity (Hair et al., 2014). Table 5 provides the loadings for all the items along with the composite

Table 1. Respondent demographics

Demographic Categories	No. of Respondents	% of Respondents
Years of Experience		
0 – 5 years	45	16%
5 – 10 years	49	18%
10 – 15 years	73	26%
15 – 20 years	64	23%
20 + years	47	17%
Grand Total	278	100%
Major Industry		
Manufacturing	178	62%
Transportation	33	12%
Wholesale Trade	7	3%
Retail Trade	2	3%
IT & Consulting Services	58	21%
Grand Total	278	100%
Sales Turnover		
Micro (INR 0 - 5 Crore)	11	4%
Small (INR 5 - 50 Crore)	35	13%
Medium (INR 50 - 250 Crore)	68	24%
Large (INR 250 - 1000 Crore)	78	28%
Very Large (INR 1000+ Crore)	86	31%
Grand Total	278	100%
Current Position		
Top Management	17	6%
Senior Management	44	16%
Middle Management	165	59%
Others	52	19%
Grand Total	278	100%

reliability (CR), average variance extracted (AVE) and Cronbach's alpha (Cronbach, 1951) for the constructs. First, all constructs had CR values greater than 0.7 (Hair et al., 2014). The CR is an estimate of the reliability of sum scores of a reflective measurement model and is also referred to as factor reliability, Dillon-Goldstein's rho, or Joreskog's rho (Henseler et al., 2016). Additionally, all factors had Cronbach's alpha value greater than the suggested minimum value of 0.5 (Koh et al., 2007). Second, for validity, each construct was tested for convergent validity and discriminant validity. For convergent validity, item reliability and internal consistency were examined. This study considered the minimum cut-off level of 0.6 for item loading (Ursachi et al., 2015). All item loadings were greater than the minimum cut-off as mentioned in Table 5. Also, AVE values were checked to assess the internal consistency of the research model. All constructs met the acceptable criterion for AVE (0.5 or more) (Ursachi et al., 2015).

For discriminant validity, two methods were used, namely the Fornell and Larcker (1981) criterion and cross-loadings (Hair et al., 2014). As provided in Table 6, the AVE of each construct is higher than the highest squared correlation with any other construct, thereby confirming discriminant validity at the construct level. The second discriminant validity criterion requires that the loadings of each indicator on its construct are higher than the cross-loadings on other constructs (Hair et al., 2014). As can be seen in Table 7, all items are loaded higher on the construct being measured than on the other constructs.

5.2 Structural Model

To examine the structural model, path coefficient, t-statistics, and p-values were checked. To generalise from a sample to a population, the path coefficients were evaluated for significance (Henseler et al., 2016). The results detailing the path coefficients, t-statistics, and p-values are summarised in Table 8. Further analysis and discussion on Table 8 are provided in the discussion section. Table 2 provides the coefficient of determination (R^2) of the endogenous constructs, indicating that the model explained 57.83% of the variance in AI adoption in SCRM, 56.67% of the variance in AI implementation in SCRM, and 62.13% of the variance in AI routinization in SCRM.

5.3 Assessing Goodness-of-Fit

The overall goodness-of-fit is the starting point of model assessment (Henseler et al., 2016). To test the global-fit measure for PLS path modelling, ADANCO 2.3.1 provides the following measures (i) standardized root mean squared residual (SRMR), (ii) unweighted least squares discrepancy (d_{ULS}), and (iii) geodesic discrepancy (d_G). ADANCO 2.3.1 uses bootstrapping to provide the 95%-percentile ("HI95") and the 99%-percentile ("HI99") for the measures if the theoretical model was true (Henseler, 2017). If the measures exceed these values, it is unlikely that the model is true. Table 3 and Table 4 provide these measures for the saturated model and the estimated model.

The lower the value for d_{ULS}, d_G, and SRMR, the better is the theoretical model's fit. SRMR provides the approximate model fit criteria (Henseler et al., 2016). A value of 0 for the SRMR would indicate a perfect fit and, generally, an SRMR value less than 0.05 indicates an acceptable fit (Byrne, 2013). From the above tables it can be concluded that, since the SRMR values for the saturated and estimated model are 0.0383 and 0.0388 respectively, the model has an acceptable fit.

Table 2. Coefficient of determination

Construct	Coefficient of determination (R^2)	Adjusted R^2
AI Adoption in SCRM	0.5783	0.5608
AI Implementation in SCRM	0.5667	0.5471
AI Routinization in SCRM	0.6213	0.6042

Table 3. Goodness of model fit (saturated model)

Goodness-of-fit measures	Value	HI95	HI99
SRMR	0.0383	0.0282	0.0303
d_{ULS}	2.2544	1.2251	1.4148
d_G	1.9637	1.7834	1.9115

Table 4. Goodness of model fit (estimated model)

Goodness-of-fit measures	Value	HI95	HI99
SRMR	0.0388	0.0283	0.0304
d_{ULS}	2.3141	1.2301	1.4253
d_G	1.9854	1.7861	1.9117

6. DISCUSSION

6.1 Overall Findings

This study explores and assesses eleven independent factors and three dependent factors. Overall, *AI adoption in SCRM* is dependent on *integrated data management, complexity, disruption impact* and *regulatory uncertainty*. Similarly, *AI implementation in SCRM* is dependent on *integrated data management, complexity, regulatory uncertainty, and AI adoption in SCRM*. Finally, *AI routinization in SCRM* is dependent on *integrated data management, complexity, ERM alignment, external pressure, disruption impact*, *regulatory uncertainty, AI adoption in SCRM* and *AI implementation in SCRM*. These significant relationships are based on the t-statistics and p-values summarized in Table 8.

6.1.1. Technological Context

First, *integrated data management* has a positive and significant relationship with all the three dependent factors: *adoption, implementation, and routinization of AI in SCRM* (H1) as can be seen in Table 8. This finding supports the very premise that AI use-cases are data guzzlers, and organizations are most likely to adopt AI only if they have sufficient data and data management capabilities, to begin with. Brock and Wangenheim (2019) identified that *integrated data management* was the number one organizational characteristic that differentiated the leaders from laggards in the context of implementing 'realistic artificial intelligence'. The authors further stated that managing internal and external data at an enterprise scale in a holistic and integrated fashion allowed for maximum value capture and knowledge generation. Furthermore, Chen et al. (2020) while studying the factors that impact the adoption of AI in the telecom sector in China, highlighted that "the support of big data has constantly driven the development of AI". Organizations in India planning to explore AI are well advised to first have a blueprint to set up the data management platforms that integrate data across the enterprise applications. Having a strong data ecosystem is a prerequisite and a strong predictor of not just adoption but implementation and routinizations as well.

Second, *complexity* has a negative and significant relationship with all the three dependent factors: *adoption, implementation, and routinization of AI in SCRM* (H2). This is supported in the literature. Chen et al. (2020) reported that *complexity* has a negative and significant relationship with AI adoption in the telecom sector in China. The complexity of AI solutions stems from the fact that it involves a plethora of tools and technologies for implementation, need for both structured and unstructured data, along with enablers like cloud. Add to this the algorithmic and mathematical know-how along with the nuances of the business use case. While there have been few successful AI implementations, there is also a growing gap between AI ambition and execution (Reeves et al., 2017). Furthermore, the routinization of AI in SCRM requires integration with existing systems and the ability to integrate the results from the AI systems into the company's decision-making process. Hence it may be concluded that organizations in India need to deep-dive into the complexities of AI development and usage and accordingly detail the roadmap and project plans.

It is seen that the other factors namely, *cost of ownership (H3),* and *relative advantage* (H4) have a positive but insignificant relationship with the *adoption, implementation, and routinization of AI in SCRM* and hence these relationships cannot be generalized to the population.

Table 5. Item wise loadings, composite reliability, AVE, and Cronbach's alpha(α)

#	Construct	Item Code	Item Description	Loadings	CR	AVE	Cronbach's alpha(α)
1	Integrated Data Management	BDM1	The company has an Information Technology (IT) team responsible for data management, data quality and data integration	0.9253	0.9647	0.8455	0.9543
2		BDM2	The company has implemented data management projects	0.9267			
3		BDM3	The company stores various types of data including structured and unstructured data, internal and external data related to supply chain	0.9312			
4		BDM4	The company has set up data quality systems and processes to cleanse and curate the data	0.9099			
5		BDM5	The company has partnerships to procure data from supply chain partners and 3rd part data providers	0.9042			
6	Complexity	CPX1	The company believes AI system development for SCRM is a complicated process	0.8663	0.9394	0.7561	0.9203
7		CPX2	Deployment of AI systems in the production environment is complex	0.8613			
8		CPX3	Interactions with AI systems can be difficult for employees of the company	0.8661			
9		CPX4	The skills needed to use AI in supply chain risk management are too complex for the company	0.8675			
10		CPX5	The outputs of AI system lack clarity and is difficult to explain	0.8863			
11	Cost of Ownership	COO1	AI implementation cost is high for the company	0.8885	0.9510	0.7951	0.9357
12		COO2	AI integration cost is high for the company	0.8873			
13		COO3	AI maintenance cost is high for the company	0.9004			
14		COO4	AI usage cost is high for the company	0.8941			
15		COO5	The cost of ownership of AI systems is higher compared to my current decision support systems	0.8881			
16	Relative Advantage	RAD1	AI can provide better supply chain risk insights for the company than existing systems	0.9325	0.9694	0.8877	0.9578
17		RAD2	AI can provide faster responses to the company than existing systems	0.9493			
18		RAD3	AI can provide a high return on investment to the company	0.9346			
19		RAD4	AI can provide highly accurate predictive and actionable insights for the company	0.9523			
20	Talent	TAL1	The company has associates with requisite AI skills	0.9098	0.9466	0.8554	0.9155
21		TAL2	The company knows whom to partner with to implement AI solutions	0.9300			
22		TAL3	The company has the budget to hire AI professionals	0.9346			
23	Organizational Agility	AGL1	The company regularly assesses the ability to rapidly and flexibly respond to customers' needs	0.9178	0.9401	0.8395	0.9046
24		AGL2	The company regularly assesses how quickly and frequently it can adapt its processes and offerings compared to its competitors	0.9130			
25		AGL3	The company regularly assesses how rapidly it can adopt technological innovations	0.9180			
26	Top Management Support	TMT1	The leadership team promotes AI as a strategic priority	0.9356	0.9726	0.8765	0.9648
27		TMT2	The leadership team proactively invests in AI solutions	0.9377			
28		TMT3	The leadership team is aware of the potential of AI in supply chain risk management	0.9293			
29		TMT4	The leadership team supports the training and development of AI	0.9474			
30		TMT5	The leadership team promotes policies and procedures to encourage innovation	0.9311			

continued on following page

Table 5. Continued

#	Construct	Item Code	Item Description	Loadings	CR	AVE	Cronbach's alpha(α)
31	Enterprise Risk Management Alignment	ERM1	The use of AI in supply chain risk management complies with the company's enterprise risk management policies and procedures	0.8998	0.9578	0.8503	0.9415
32		ERM2	AI systems in supply chain risk management are integrated with enterprise risk management systems in the company	0.9360			
33		ERM3	AI-based decisions are reviewed by enterprise risk professionals in the company	0.9300			
34		ERM4	Risk management professionals use the insights from AI systems for decision making in the company	0.9223			
35	External Pressure	EXP1	Competitors have already adopted AI	0.9017	0.9416	0.8012	0.9174
36		EXP2	The partners have already adopted AI	0.8884			
37		EXP3	Market trends point to higher adoption and usage of AI	0.9023			
38		EXP4	Without AI the company may lose customers to our competitors	0.8877			
39	Disruption Impact	DEI1	Business impact from past events like natural disasters, geopolitical events, etc. lead to higher adoption of AI	0.8430	0.9479	0.7846	0.9312
40		DEI2	The company has been impacted by recent disruptive events like pandemics and geopolitical events	0.8699			
41		DEI3	AI can help identify and estimate the impact of disruptive events in my supply chain network	0.8944			
42		DEI4	AI can provide insights to reduce the impact of disruptive events on the company	0.9115			
43		DEI5	AI can provide early warning signals to respond proactively to supply chain disruptions	0.9083			
44	Regulatory Uncertainty	REG1	Data privacy and data security regulations may stifle AI adoption in the company	0.9208	0.9467	0.8554	0.9156
45		REG2	New regulations may inhibit AI implementation	0.9312			
46		REG3	Regulations requiring explaining AI results may be difficult for employees of the company	0.9227			
47	AI Adoption in SCRM	ADO1	The company intends to adopt AI technologies	0.9039	0.9373	0.8330	0.8997
48		ADO2	The company has evaluated AI tools and technologies	0.9289			
49		ADO3	The company has undertaken or completed proof of concepts on AI technologies	0.9050			
51	AI Implementation in SCRM	IMP1	The company has committed budgets to implement AI solutions	0.9046	0.9333	0.8236	0.8929
52		IMP2	The company has hired and trained resources to implement AI systems	0.9182			
53		IMP3	The company has approved project plans to implement AI systems	0.8996			
56	AI Routinization in SCRM	ROU1	Supply chain managers and risk professionals in the company use AI as part of their daily work	0.8961	0.9322	0.8210	0.8913
58		ROU2	The company has embedded AI in all supply chain risk management tasks	0.9190			
59		ROU3	The use of AI systems for supply chain risk management is commonplace in the company	0.9030			

6.1.2. Organizational Context

As can be seen from Table 8, *ERM alignment* has a positive and significant relationship with the *routinization of AI in SCRM (H7)*. But this does not hold true for the *adoption* and *implementation of AI in SCRM*. It is to be noted that as part of the content validation of the research model, *ERM alignment* was pointed out by the industry SMEs to be a critical factor. The alignment of the SCRM decision making process with the ERM policies and standards is a critical requirement for any AI-based decision-making system to gain acceptance in the company. And this continual usage of AI

Table 6. Correlation of latent variables and the square root of AVE

Construct	BDM	CPX	COO	RAD	TAL	AGL	TMT	ERM	EXP	DEI	REG	ADO	IMP	ROU
BDM	**0.8455**													
CPX	0.3900	**0.7561**												
COO	0.4126	0.6276	**0.7951**											
RAD	0.7040	0.3503	0.4274	**0.8877**										
TAL	0.6624	0.2963	0.3982	0.6693	**0.8554**									
AGL	0.6608	0.3238	0.4395	0.6673	0.7004	**0.8395**								
TMT	0.7053	0.3599	0.3964	0.7634	0.6704	0.6938	**0.8765**							
ERM	0.6266	0.3863	0.4805	0.6292	0.6211	0.6203	0.7027	**0.8503**						
EXP	0.6096	0.3384	0.4440	0.6077	0.6790	0.6674	0.6290	0.6789	**0.8012**					
DEI	0.5485	0.3813	0.4926	0.5935	0.5856	0.6383	0.5627	0.5185	0.6455	**0.7846**				
REG	0.4672	0.4048	0.4984	0.4914	0.4763	0.4468	0.4836	0.5907	0.5476	0.5043	**0.8554**			
ADO	0.4704	0.1208	0.2156	0.4102	0.3909	0.4356	0.3834	0.3951	0.4273	0.4106	0.3656	**0.8330**		
IMP	0.3772	0.0977	0.1705	0.3141	0.3249	0.3258	0.3313	0.3193	0.3079	0.2527	0.2768	0.5237	**0.8236**	
ROU	0.2755	0.0373	0.0932	0.2374	0.2546	0.2465	0.2801	0.3421	0.3057	0.1500	0.2969	0.4636	0.4813	**0.8210**

systems in the decision-making process only happens in the routinization phase. This could possibly explain why *ERM alignment* has a positive and significant relationship only with the *routinization of AI in SCRM* when users of the AI-based systems use the insights to support decisions, which in turn must be integrated with the enterprise-wide decision-making processes and systems under ERM.

With regards to the other factors of *talent, organizational agility,* and *top management support,* they have been found to have insignificant relationships with the dependent factors and hence the hypotheses H5, H6, and H8 are not supported. Although past research has pointed to the fact that *top management support* is a key driver for the adoption of technological innovations, it is inconclusive in the case of Indian businesses in the current context, perhaps due to either the respondents not seeing enough awareness and/ or push from the top management when it comes to investing in the evaluation of AI technologies or committing to a roadmap to implement AI across SCRM processes. Similarly, while *talent* has been cited as a key factor in past research, it may be worthwhile to mention that India is one of the leading providers of IT and professional services support to global organizations and the respondent of the survey may have noted the wide availability of the talent pool in India. As cited by Brock and Wangenheim (2019), *agility* is a key driver for AI implementation in an organization based on survey data collected globally that did not include India. *Organizational agility* also did not show any significant relationship with the dependent factors. All these three factors would need to be further investigated in subsequent studies by either increasing the sample size, expanding on the profile of the respondents, or covering additional industries.

6.1.3. Environmental Context

First, as can be seen from Table 8, *external pressure* has a positive and significant relationship only with the *routinization of AI in SCRM* but does not have a significant relationship with *the adoption* and *implementation of AI in SCRM* (H9). *External pressure* was found to be significant in past studies related to RFID adoption in Australia when it comes to the stages of initiation, adoption, and extension but not for routinization (Hossain *et al.*, 2016). At the same time, Chen et al. (2020) reported that factors like market uncertainty and competitive pressure do not play a role in the process of AI adoption in the telecom sector in China. However, in the context of this study, *external pressure* influences Indian businesses to drive the usage and routinization of AI-based insights to remain competitive, and benefit from increased collaboration with partners.

Table 7. Cross loadings

Indicator	BDM	CPX	COO	RAD	TAL	AGL	TMT	ERM	EXP	DEI	REG	ADO	IMP	ROU
BDM1	**0.9253**	0.5051	0.5471	0.7851	0.7654	0.7643	0.7660	0.6973	0.7149	0.6811	0.6159	0.6774	0.6106	0.5031
BDM2	**0.9267**	0.5537	0.6026	0.7962	0.7795	0.7941	0.7967	0.7377	0.7262	0.7115	0.6252	0.6710	0.5505	0.4677
BDM3	**0.9312**	0.5949	0.5892	0.7813	0.7189	0.7346	0.7899	0.7497	0.7178	0.6791	0.6523	0.6419	0.5621	0.4884
BDM4	**0.9099**	0.6369	0.6239	0.7426	0.7256	0.7137	0.7607	0.7419	0.6947	0.6554	0.6247	0.5788	0.5321	0.4753
BDM5	**0.9042**	0.5903	0.5961	0.7496	0.7510	0.7273	0.7473	0.7158	0.7366	0.6769	0.6257	0.5761	0.5643	0.4776
CPX1	0.5981	**0.8663**	0.7170	0.5568	0.5262	0.5502	0.5751	0.5860	0.5430	0.5675	0.6122	0.3900	0.3583	0.2250
CPX2	0.5048	**0.8613**	0.6622	0.4887	0.4470	0.4720	0.5295	0.5314	0.5086	0.5297	0.5324	0.2806	0.2244	0.1422
CPX3	0.5097	**0.8661**	0.6787	0.5102	0.4622	0.4727	0.4837	0.4886	0.4731	0.5341	0.5330	0.2683	0.2333	0.1423
CPX4	0.5149	**0.8675**	0.6737	0.4763	0.4442	0.4547	0.4630	0.5153	0.4784	0.5128	0.5113	0.2633	0.2443	0.1410
CPX5	0.5589	**0.8863**	0.6977	0.5198	0.4610	0.4965	0.5293	0.5566	0.5071	0.5254	0.5476	0.2671	0.2561	0.1613
COO1	0.5646	0.7122	**0.8885**	0.5839	0.5544	0.5859	0.5433	0.6184	0.6003	0.6448	0.6184	0.4554	0.3829	0.2919
COO2	0.5509	0.7273	**0.8873**	0.5494	0.5272	0.5284	0.5482	0.5816	0.5569	0.6308	0.6401	0.3773	0.3323	0.2201
COO3	0.5880	0.7401	**0.9004**	0.5937	0.5527	0.5870	0.5709	0.6394	0.5877	0.5969	0.6466	0.3810	0.3697	0.2849
COO4	0.5613	0.6786	**0.8941**	0.5768	0.5502	0.5775	0.5793	0.6168	0.5869	0.5722	0.6159	0.3617	0.3602	0.3045
COO5	0.5949	0.6774	**0.8881**	0.6051	0.6202	0.6637	0.5657	0.6295	0.6307	0.6763	0.6283	0.4795	0.3886	0.2553
RAD1	0.7812	0.5053	0.5345	**0.9325**	0.7465	0.7579	0.8175	0.7485	0.7055	0.6748	0.6280	0.6177	0.5307	0.4693
RAD2	0.8017	0.5829	0.6347	**0.9493**	0.7875	0.7713	0.8206	0.7426	0.7463	0.7498	0.6559	0.6309	0.5281	0.4258
RAD3	0.7780	0.5771	0.6442	**0.9346**	0.7413	0.7470	0.8244	0.7449	0.7162	0.7072	0.6701	0.5364	0.4853	0.4710
RAD4	0.8007	0.5675	0.6525	**0.9523**	0.8053	0.8003	0.8309	0.7536	0.7682	0.7700	0.6882	0.6235	0.5640	0.4705
TAL1	0.7439	0.4480	0.5391	0.7490	**0.9098**	0.7733	0.7254	0.7223	0.7328	0.6809	0.6278	0.6258	0.5417	0.4821
TAL2	0.7654	0.5573	0.6362	0.7644	**0.9300**	0.7610	0.7773	0.7397	0.7778	0.7169	0.6429	0.5463	0.5094	0.4556
TAL3	0.7486	0.5093	0.5791	0.7561	**0.9346**	0.7865	0.7707	0.7243	0.7770	0.7265	0.6439	0.5577	0.5283	0.4603
AGL1	0.7614	0.5085	0.6186	0.7651	0.7631	**0.9178**	0.7569	0.7410	0.7560	0.7243	0.6257	0.6353	0.5484	0.5081
AGL2	0.7311	0.5436	0.6175	0.7433	0.7567	**0.9130**	0.7784	0.7213	0.7377	0.7275	0.5874	0.5650	0.4968	0.4170
AGL3	0.7401	0.5145	0.5861	0.7357	0.7806	**0.9180**	0.7557	0.7014	0.7510	0.7448	0.6219	0.6095	0.5203	0.4335
TMT1	0.7926	0.5135	0.5486	0.8365	0.7884	0.7724	**0.9356**	0.7661	0.7379	0.7143	0.6184	0.5929	0.5693	0.4987
TMT2	0.7856	0.5640	0.6008	0.8154	0.7666	0.7820	**0.9377**	0.7755	0.7311	0.6984	0.6197	0.5428	0.5349	0.4713
TMT3	0.7883	0.5690	0.5873	0.8189	0.7879	0.7637	**0.9293**	0.7876	0.7522	0.7043	0.6578	0.5885	0.5288	0.5031
TMT4	0.7832	0.5732	0.6033	0.8067	0.7546	0.8039	**0.9474**	0.7924	0.7466	0.6956	0.6673	0.5875	0.5243	0.4982
TMT5	0.7812	0.5896	0.6087	0.8119	0.7347	0.7774	**0.9311**	0.8023	0.7443	0.6982	0.6913	0.5848	0.5359	0.5051
ERM1	0.7708	0.5373	0.6268	0.7556	0.7682	0.7549	0.7660	**0.8998**	0.7774	0.6787	0.7130	0.6766	0.6166	0.5854
ERM2	0.7282	0.5998	0.6541	0.7388	0.7369	0.7332	0.7919	**0.9360**	0.7766	0.6620	0.7219	0.5474	0.5013	0.5369
ERM3	0.6837	0.5632	0.6334	0.6837	0.6693	0.6779	0.7444	**0.9300**	0.7117	0.6319	0.6948	0.5261	0.4631	0.5103
ERM4	0.7226	0.5958	0.6409	0.7368	0.7175	0.7273	0.7856	**0.9223**	0.7636	0.6756	0.6995	0.5433	0.4781	0.5110
EXP1	0.7031	0.4854	0.5881	0.7089	0.7497	0.7474	0.6985	0.7182	**0.9017**	0.7067	0.6568	0.6165	0.5625	0.5453
EXP2	0.6807	0.5115	0.5773	0.6708	0.7401	0.7226	0.7029	0.7436	**0.8884**	0.6712	0.6611	0.5064	0.4546	0.4817
EXP3	0.7099	0.5203	0.5958	0.7193	0.7660	0.7505	0.7129	0.7194	**0.9023**	0.7828	0.6458	0.6382	0.5009	0.4553
EXP4	0.7007	0.5707	0.6255	0.6892	0.6927	0.7021	0.7275	0.7739	**0.8877**	0.7126	0.6884	0.5691	0.4583	0.4929
DEI1	0.6252	0.6062	0.6658	0.6366	0.6719	0.6660	0.6441	0.6309	0.7068	**0.8430**	0.6488	0.5114	0.4361	0.3307
DEI2	0.6679	0.5841	0.6306	0.6880	0.6902	0.7084	0.6532	0.6509	0.7278	**0.8699**	0.6546	0.5632	0.4517	0.3034
DEI3	0.6351	0.5081	0.5782	0.6855	0.6294	0.7080	0.6498	0.6056	0.6685	**0.8944**	0.5698	0.5371	0.4219	0.3073

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Table 7. Continued

Indicator	BDM	CPX	COO	RAD	TAL	AGL	TMT	ERM	EXP	DEI	REG	ADO	IMP	ROU
DEI4	0.6572	0.5194	0.6198	0.6930	0.6918	0.7233	0.6849	0.6556	0.7271	**0.9115**	0.6385	0.5826	0.4609	0.4028
DEI5	0.6916	0.5247	0.6174	0.7069	0.7031	0.7305	0.6878	0.6451	0.7266	**0.9083**	0.6334	0.6345	0.4542	0.3635
REG1	0.6435	0.5853	0.6573	0.6526	0.6422	0.6394	0.6375	0.7191	0.6802	0.6426	**0.9208**	0.6016	0.5039	0.5499
REG2	0.6118	0.5618	0.6302	0.6395	0.6433	0.6116	0.6341	0.7055	0.6952	0.6632	**0.9312**	0.5257	0.4634	0.4707
REG3	0.6389	0.6171	0.6697	0.6517	0.6287	0.6010	0.6575	0.7065	0.6782	0.6657	**0.9227**	0.5449	0.4896	0.4854
ADO1	0.6303	0.3559	0.4516	0.5912	0.5845	0.6062	0.5814	0.6087	0.6149	0.5658	0.5664	**0.9039**	0.6482	0.6415
ADO2	0.6343	0.2951	0.4079	0.5960	0.5803	0.6162	0.5835	0.5735	0.5998	0.6227	0.5697	**0.9289**	0.6611	0.6240
ADO3	0.6127	0.2998	0.4113	0.5655	0.5459	0.5839	0.5288	0.5371	0.5741	0.5651	0.5178	**0.9050**	0.6730	0.5977
IMP1	0.5633	0.2914	0.3578	0.5155	0.5268	0.5151	0.5550	0.5074	0.5044	0.4500	0.4548	0.5865	**0.9046**	0.5900
IMP2	0.5505	0.2737	0.3653	0.5090	0.5275	0.5195	0.5146	0.5055	0.4926	0.4632	0.5043	0.6619	**0.9182**	0.6193
IMP3	0.5583	0.2858	0.4001	0.5015	0.4980	0.5191	0.4983	0.5250	0.5133	0.4552	0.4728	0.7192	**0.8996**	0.6777
ROU1	0.5058	0.1617	0.2736	0.4959	0.5193	0.5145	0.5156	0.5454	0.5668	0.4136	0.5314	0.6801	0.6710	**0.8961**
ROU2	0.4619	0.1758	0.2752	0.4184	0.4202	0.4263	0.4678	0.5203	0.4509	0.3114	0.4853	0.5881	0.6056	**0.9190**
ROU3	0.4538	0.1894	0.2810	0.4011	0.4222	0.3982	0.4490	0.5210	0.4748	0.3178	0.4578	0.5722	0.6019	**0.9030**

Second, *disruption impact* positively influences the *adoption of AI,* negatively influences the *routinization of AI* and does not have a significant relationship with the *implementation of AI in SCRM* (H10). This is an interesting finding and may be explained basis the fact that in the current times, COVID-19 has pushed businesses to prioritize actions that will help improve the resilience of their organizations to future shocks (Shih, 2020). So based on learnings from past experiences, executives would prefer to explore the adoption of technologies like cloud, AI and blockchain to build resilient supply chains. However, this may not lead to pushing the usage of the AI-based insights for day-to-day decision making and hence this could explain the negative relationship with *routinization of AI in SCRM*.

Finally, *regulatory uncertainty* has been found to have a positive and significant relationship with the *adoption, implementation, and routinization of AI in SCRM* (H11). This outcome is rather surprising in an area where there are multiple forces at play. It may be argued that the lack of regulations specific to AI may enable businesses to push forward their AI implementation roadmap without any compliance-related costs and hurdles. While uncertainty around new regulations may not be in favour of businesses, till such time there are no new regulations introduced, the effects of an uncertain environment may not be detrimental to businesses in the near term.

6.1.4. Dependent Constructs

As can be seen from Table 8, *implementation of AI in SCRM* has a positive and significant relationship with the *adoption of AI in SCRM* (H12) while *routinization of AI in SCRM* has a positive and significant relationship with the *implementation of AI in SCRM* (H13). Additionally, there is an indirect effect of *adoption* on the *routinization of AI in SCRM*. These are highly influencing factors driving implementation and routinization of AI technologies as part of a sequential process post an adoption intention. As studied in past research, results show that as part of the diffusion process, companies are more likely to move sequentially from one stage of diffusion to the next (Chan and Chong, 2012).

6.2 Implications

As organizations emerge from the effects of COVID-19 that have devasted business operations and supply chains globally, business leaders and supply chain executives have more than eager to explore and invest in innovative solutions like AI, cloud, blockchain and other technologies to reduce

Table 8. Evaluation of the structural model

Effect	Original coefficient	Standard bootstrap results				
		Mean value	Standard error	t-value	p-value (2-sided)	p-value (1-sided)
BDM -> ADO	0.4319	0.4353	0.1071	4.0316	0.0001	0.0000
BDM -> IMP	0.3948	0.4024	0.1057	3.7339	0.0002	0.0001
BDM -> ROU	0.2472	0.2621	0.1124	2.1984	0.0281	0.0141
CPX -> ADO	-0.2855	-0.2835	0.0727	-3.9276	0.0001	0.0000
CPX -> IMP	-0.2470	-0.2436	0.0857	-2.8833	0.0040	0.0020
CPX -> ROU	-0.3552	-0.3606	0.0841	-4.2212	0.0000	0.0000
COO -> ADO	-0.0191	-0.0269	0.0844	-0.2265	0.8208	0.4104
COO -> IMP	0.0493	0.0310	0.0960	0.5132	0.6079	0.3039
COO -> ROU	-0.0696	-0.0742	0.0888	-0.7839	0.4333	0.2167
RAD -> ADO	0.0534	0.0471	0.0928	0.5755	0.5651	0.2825
RAD -> IMP	-0.0304	-0.0201	0.1117	-0.2722	0.7856	0.3928
RAD -> ROU	-0.0739	-0.0704	0.0977	-0.7563	0.4496	0.2248
TAL -> ADO	-0.1019	-0.1070	0.1019	-1.0000	0.3175	0.1588
TAL -> IMP	0.0393	0.0257	0.1234	0.3186	0.7501	0.3750
TAL -> ROU	-0.0564	-0.0564	0.1102	-0.5119	0.6088	0.3044
AGL -> ADO	0.1638	0.1647	0.1059	1.5465	0.1223	0.0612
AGL -> IMP	0.1007	0.1065	0.1297	0.7765	0.4376	0.2188
AGL -> ROU	0.0674	0.0751	0.1088	0.6197	0.5356	0.2678
TMT -> ADO	-0.1193	-0.1073	0.1095	-1.0890	0.2764	0.1382
TMT -> IMP	0.0787	0.0753	0.1060	0.7424	0.4580	0.2290
TMT -> ROU	0.1037	0.0958	0.1113	0.9315	0.3518	0.1759
ERM -> ADO	0.0834	0.0771	0.0909	0.9171	0.3593	0.1797
ERM -> IMP	0.0642	0.0646	0.1348	0.4761	0.6341	0.3170
ERM -> ROU	0.2989	0.2885	0.1100	2.7181	0.0067	0.0033
EXP -> ADO	0.0908	0.0931	0.1011	0.8975	0.3697	0.1848
EXP -> IMP	0.0208	0.0252	0.1218	0.1705	0.8646	0.4323
EXP -> ROU	0.2426	0.2411	0.1202	2.0192	0.0437	0.0219
DEI -> ADO	0.2087	0.1959	0.0914	2.2837	0.0226	0.0113
DEI -> IMP	-0.0261	-0.0320	0.1013	-0.2575	0.7969	0.3984
DEI -> ROU	-0.2466	-0.2579	0.1056	-2.3344	0.0198	0.0099
REG -> ADO	0.2314	0.2500	0.0753	3.0719	0.0022	0.0011
REG -> IMP	0.2046	0.2142	0.1023	2.0000	0.0458	0.0229
REG -> ROU	0.3904	0.4063	0.0933	4.1848	0.0000	0.0000
ADO -> IMP	0.5565	0.5653	0.0708	7.8548	0.0000	0.0000
ADO -> ROU	0.2686	0.2757	0.0501	5.3638	0.0000	0.0000
IMP -> ROU	0.4826	0.4863	0.0517	9.3349	0.0000	0.0000

disruptions. Through this study, it has been established that while the TOE framework is applicable, new factors need to be devised. Given the uniqueness of AI, new constructs created through this study extend past research related to the adoption of technological innovations, especially in the field of AI. These new include constructs include *ERM alignment* as part of the organizational context, and *disruption impact* and *regulatory uncertainty* as part of the environmental context. However, these new factors need to be tested further across different industries and geographies to ascertain their applicability and predictive power.

Moreover, this study has cited significant factors that are critical from an organization's technology footprint and business process point of view, such as the *integrated data management* and *ERM alignment*. Knowing the predictive power of these factors will greatly benefit an organization's leadership teams to create a detailed blueprint to introduce AI in SCRM. Having a strong data management ecosystem is an essential prerequisite; deep-diving into the implementation complexities and usage challenges need careful planning and project management; integrations with the enterprise-wide decision-making processes and systems under ERM will lead to greater continual usage; being aware of external pressures and adapting accordingly, learning from past impacts of disruption, and finally benefitting from regulations are key findings.

7. CONCLUSION

This study applied the TOE framework with new constructs and items to analyze and investigate the *adoption*, *implementation*, and *routinization* of AI in SCRM across organizations in select industries in India. This study fills a void as there has been limited study conducted on the adoption-diffusion process on AI across industries in India. The results show that the factors have a varying degree of influence and direction on the dependent factors. Finally, the implications of the study are important and business leaders would be recommended to study the key findings.

This study has certain limitations that should be addressed in future research. First, the respondents of this research are limited to a few industries in India. To generalise the research model, further studies are required covering other industries and geographies.

Second, the research model needs to be tested across a wide base of Indian industries, especially the micro, small, and medium enterprises that form most of the Indian business ecosystem. Third, the influence of *regulatory uncertainty* needs a thorough examination as there are new regulations and guidelines related to data privacy, AI ethics, and AI explainability that are expected in the coming months and years in India. Finally, this study is limited to cross-sectional survey data taken at a single time. Additional studies using longitudinal data would enable further examination of the constructs influencing the three adoption-diffusion stages of AI in SCRM.

CONFLICT OF INTEREST

The authors of this publication declare there is no conflict of interest.

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