Artificial intelligence adoption in supply chain risk management: Scale development and validation

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| **ARTICLE INFO** | **ABSTRACT** |
| **DOI:**10.46223/HCMCOUJS. econ.en.12.2.2142.2022Received: January 07th, 2022Revised: January 17th, 2022Accepted: February 25th, 2022*Keywords:* artificial intelligence; scale development; scale validation; SCRM; supply chain risk management  | Artificial Intelligence (AI) can play an important role in the post-Covid-19 world to proactively enable the identification, assessment, and mitigation of supply chain risks as well as provide managerial insights for responding to those risks. There has been a growing interest among supply chain executives to adopt AI for Supply Chain Risk Management (SCRM). The purpose of this paper is to develop an instrument to assess and measure the factors influencing the adoption of AI in SCRM. The development of the instrument has been done in stages covering factor identification, item generation, pre-testing, pilot testing, and scale validation. Data has been collected through a survey of supply chain executives, risk professionals, and AI consultants across manufacturing, wholesale trade, retail trade, and services industries in India. The questionnaire has been pre-tested based on interviews with nine industry experts and two academicians. The scale has been assessed for reliability and validity using Confirmatory Factor Analysis. The scale generated consists of eight factors that are modeled as latent variables covering a total of twenty-eight items. The systematic approach followed resulted in a scale fulfilling a need for the creation of an empirically validated instrument for AI adoption studies in the field of SCRM. This instrument can be used by supply chain executives and researchers to examine and measure factors that influence the adoption of AI in SCRM for the selected industries. |

# 1. Introduction

The Covid-19 pandemic has pushed supply chain executives to re-look at the resilience of their organizations and focus on supply chain risk management. Organizations have been affected severely because of Covid-19 exposing supply chain vulnerabilities and leading to performance bottlenecks and financial impact. 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).

Researchers have been increasingly studying the applications of Artificial Intelligence (AI) in Supply Chain Risk Management (SCRM). McKinsey and Company estimate that AI’s potential impact on supply chain management will be between 1.2 to 2.0 trillion USD, while the potential impact of AI in overall risk-related use cases will be 0.2 trillion USD globally (Chui et al., 2018). AI is a growing field and defining AI precisely is difficult because the definition tends to change based on the specific context of research or the specific application (Bughin, Seong, Manyika, Chui, & Joshi, 2018). The AI techniques that form the bulk of applications categorized as AI are those that involve artificial neural networks and deep learning (Haenlein & Kaplan, 2019). 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 computer vision, deep learning, natural language processing, and other machine learning techniques (Zhang et al., 2021). Likewise, for this paper, we consider the following focused set of AI techniques, namely (1) machine learning, (2) deep learning (using neural networks), (3) computer vision, and (4) natural language processing. Past research has also shown that managers can succeed in their organizations by incorporating more AI in the thinking tasks and gravitating employees toward tasks that require emotion, empathy, and personal relationship skills (Huang, Rust, & Maksimovic, 2019). Hence, it may be argued that supply chain executives and managers stand to benefit from the adoption of AI in the area of supply chain risk management.

Similarly, the field of SCRM has also been evolving. SCRM comprises four fundamental factors, namely, supply chain risk sources, risk consequences, risk drivers, and risk mitigation (Jüttner, Peck, & Christopher, 2003). Colicchia and Strozzi (2012) defined SCRM as managing supply chain risks through active collaboration between all supply chain partners to mitigate supply chain disruptions and lead to business continuity and profitability. The variables that influence supply chain risk include environmental variables, industry variables, organizational strategy variables, problem-specific variables, and decision-maker-related variables (Ritchie & Brindley, 2007). Recent research has shown that investments in the right set of technologies, and robust information sharing between supply chain partners ultimately lead to resilient supply chains that can withstand disruptive events (Katsaliaki, Galetsi, & Kumar, 2021).

While applications of AI in SCRM have been studied in detail, there is a gap related to the study of factors that influence the adoption of AI in SCRM at an organizational level. Paul, Riaz, and Das (2020) have 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, the study does not provide a measurement instrument. Moreover, while past research has covered adoption studies on technologies like predictive analytics, big data analytics, and other similar technologies (Banerjee & Banerjee, 2017; Chen, Preston, & Swink, 2015; Malladi, 2013), that provide a measurement instrument, there is no relevant study on the adoption of AI in the context of SCRM that has provided an empirically tested measurement instrument. Hence, the objective of this study is to develop a measurement instrument and empirically test the scale for measuring factors that influence the adoption of AI in SCRM.

# 2. Theoretical basis

## 2.1. Scale development and validation

Scale development and validation processes have been defined in past research. Guidelines as provided by Churchill (1979) and Hensley (1999) for scale development and validation have been widely used in past research. Morgan, Robert, and Alexander (2018) used a three-stage process, with stage one covering item generation based on a literature survey and feedback by Subject Matter Experts (SMEs). Stage two covered conducting a survey of a sample of supply chain professionals with the data being divided into two halves, and the first half assessed using principal component analysis while the second half was used to reproduce the factor analysis process followed by a Confirmatory Factor Analysis (CFA) on the combined sample. Stage three involved conducting another survey using the scale to further assess reliability and validity. Furthermore, Punniyamoorthy, Thamaraiselvan, and Manikandan (2013) detailed a process for scale development and validation involving generating an initial list of items based on a literature survey, review by an expert group and updates, assessment of content validity, preparation of draft questionnaire and pilot study, data collection using survey, and assessment of reliability and validity of the instrument.

## 2.2. Technology adoption

There are several theories of the adoption of technology at an individual level, the ones that apply at an organizational level include the diffusion of innovation theory (DOI) (Rogers, 1995) and the Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990). The DOI theory at an organizational level argues that the adoption of innovation is influenced by perceived attributes of innovation, namely, relative advantage, compatibility, complexity, trialability, and observability (Rogers, 1995). Over the years, DOI has been applied to multiple technology adoption studies, including enterprise resource planning, e-business, websites, intranet, and various software applications (Molinillo & Japutra, 2017).

The TOE framework has three independent contexts or logical grouping of constructs that influence how an organization adopts new technologies, namely, technological, organizational, and environmental contexts. The TOE framework has been cited extensively with regard to the adoption of various technological areas: business intelligence, enterprise resource planning, electronic data exchange, websites, e-commerce, big data, e-business, knowledge management systems, service-oriented architecture, and other technological areas (Awa, Ojiabo, & Orokor, 2017). There have also been multiple research studies on the adoption of technologies that may be confused with AI or at times are part of AI, depending on the definitions of AI different researchers have used, like big data analytics (Chen et al., 2015) and predictive analytics (Banerjee & Banerjee, 2017). There is a need to review the literature for technology adoption theories and study their applicability for the adoption of AI techniques like deep learning in the context of SCRM. While there exists strong evidence of the applicability of both DOI and TOE frameworks to technology adoption, not all factors or the underlying indicators cited as part of these theories can be used in their current condition to study AI adoption in SCRM. AI adoption in SCRM is unique and requires consideration of new factors as part of the three contexts for the TOE framework: technological, organizational, and environmental contexts.

# 3. Research method

The objective of this study is to develop and test a measurement instrument to study the adoption of AI in SCRM. The development of the scale has been done in stages covering factor identification, item generation, pre-testing, pilot testing, and scale validation (Punniyamoorthy et al., 2013; Shahbaz, RM Rasi, & Ahmad, 2019) as shown in Figure 1.



**Figure 1.** Research method

## 3.1. Identification of constructs

Identification of the constructs or factors has been done based on a literature review. As discussed above, in the TOE framework three independent contexts have been considered. Given the uniqueness of AI adoption in SCRM, new factors have been proposed and a total of eight independent factors determined. While the contexts are based on the TOE framework, many of the factors are different when compared to past literature on technology adoption, and they are unique to the needs of AI adoption in SCRM for industries in India. Considering past research on AI adoption in SCRM (Paul et al., 2020) and taking into consideration feedback from SMEs, the following factors have been determined for each of the three contexts.

### 3.1.1. Technological context

For the technological context, the authors propose three factors as defined in Table 1. Organizations that manage large and diverse datasets, such as high-volume, high-velocity, and high-variety (Chen et al., 2015), or have undertaken digital transformation projects (Brock & Wangenheim, 2019) are in a better position to initiate AI projects as the availability of these diverse datasets is an essential ingredient for AI. Also, as pointed out by the industry SMEs, having data management capabilities is an essential starting point for any AI project. Hence, the factor of big data management has been added as a new factor. Relative advantage has been cited frequently in past technology adoption studies (Chandra & Kumar, 2018; Puklavec, Oliveira, & Popovič, 2018) across adoption studies. The perceived cost of ownership (Chan & Chong, 2013; Hossain, Quaddus, & Islam, 2016) has been shown in past research to be negatively related to technology adoption and hence considered for the study.

**Table 1**

Technological context factors

| **Factor** | **Description** |
| --- | --- |
| Big Data Management | The extent to which big data management systems for structured and unstructured data have been implemented |
| Relative Advantage | The degree to which AI in SCRM is perceived as being better than the current SCRM intelligence systems |
| Cost of Ownership | The degree to which AI in SCRM is perceived to be costly to adopt, implement and use |

Source: Author’s compilation

### 3.1.2. Organizational context

For the organizational context, the authors propose three factors, as defined in Table 2. Talent has been cited as a critical and significant factor in the adoption stages of innovation technologies (Jeble et al., 2018). Top management support has been cited as another significant factor influencing the organization’s decision to adopt innovative technologies (Chen et al., 2015; Lai, Huifen, & Jifan, 2018). A new factor that has been considered and is relevant in the field of SCRM is the integration with Enterprise Risk Management (ERM) policies and standards. SCRM is a part of ERM (Curkovic, Scannell, Wagner, & Vitek, 2013) and it was pointed out by the industry SMEs that alignment with ERM policies and standards is a critical requirement for any AI-based decision-making system to gain acceptance in the organization.

**Table 2**

Organizational context factors

| **Factor Name** | **Description** |
| --- | --- |
| Talent | Availability of knowledgeable and experienced employees who can lead and drive the adoption of AI in SCRM |
| Top Management Support | The extent to which the top management drives and supports AI adoption in SCRM |
| ERM Alignment | The extent to which SCRM processes are integrated and aligned with the Enterprise Risk Management strategy |

Source: Author’s compilation

### 3.1.3. Environmental context

For the environmental context, the authors propose two factors, as defined in Table 3. External pressure has been consistently cited under various terminologies and is a significant factor in adoption studies (Hossain et al., 2016). Also, a new factor has been introduced based on mentions in past literature and inputs collected from industry experts through unstructured interviews. Negative effects of disruptive events like man-made or natural disasters on the supply chain have fuelled interest in SCRM (Sodhi, Son, & Tang, 2012). Past research provides evidence of predicting the likelihood of occurrence of risks (Ojha, Ghadge, Tiwari, & Bititci, 2018). Given that AI can help not just in risk identification but also in areas of risk response (Baryannis, Validi, Dani, & Antoniou, 2019), businesses that have experienced a negative impact from past disruptive events and looking at a proactive mitigation strategy are likely to adopt AI as part of their disruption response processes.

**Table 3**

Environmental context factors

| **Factor Name** | **Description** |
| --- | --- |
| External Pressure | The extent of influence from the external environment that drives the organization to adopt AI in SCRM |
| Disruption Response | The degree to which AI can support mitigation and response to disruptive events in the supply chain |

Source: Author’s compilation

## 3.2. Generation of items

To ensure content validity, items for each of the factors were selected and suitably adapted from past literature containing validated instruments (Priyadarshinee, Raut, Jha, & Kamble, 2017). The items have been adopted as well as suitably adapted from past studies with validated instruments. These items have been described in Table 4. While studies on the adoption of AI in SCRM are limited, items have been adopted from the sources mentioned in the table below or suitably adapted and contextualized for AI in SCRM from validated instruments across areas including big data analytics, predictive analytics, cloud computing, business intelligence, and business analytics. Inputs from the nine industry SMEs and two academicians were considered for the three new factors, namely, big data management, ERM alignment, and disruption response, and further supported by a literature review.

The factors as part of the technological context, namely, relative advantage, and cost of ownership are well-developed factors for technology adoption studies and primarily have been measured as reflective factors in past studies. The new factor under technological context: big data management has been modeled with reflective items. Similarly, the factors as part of the organizational context, namely, talent, and top management support have been cited in past literature to be measured as reflective factors, while the new factor of ERM alignment has been developed as a reflective factor. Moreover, the factor of external pressure as part of the environmental context has been cited in past literature to be reflectively measured while the new factor of disruption response has been developed as a reflective factor.

**Table 4**

Items and Sources

| **Factor Name** | **Items** | **Sources** |
| --- | --- | --- |
| **Technological Context:** |
| Big Data Management | My company has an Information Technology (IT) team responsible for data management | Jeble et al. (2018)Brock and Wangenheim (2019)Chen et al. (2015) |
| My company has access to all supply chain transactional data |
| My company stores various types of data including structured and unstructured data, internal and external data related to supply chain |
| My company has implemented data management and data quality systems |
| Relative Advantage | AI can provide better risk insights for my company than existing systems | Puklavec et al. (2018)Chandra and Kumar (2018) |
| AI can provide faster results to my company |
| AI can provide a higher ROI to my company |
| AI can provide highly accurate predictive and actionable insights |
| Cost of Ownership | AI technology cost is high for my company | Chan and Chong (2013)Hossain et al. (2016) |
| AI integration cost is high for my company |
| AI talent cost is high for my company |
| **Organizational Context:** |
| Talent | My company has AI skills | Jeble et al. (2018)Brock and Wangenheim (2019) |
| My company knows whom to partner with to implement AI solutions |
| My company has budgets to hire AI professionals |
| Top Management Support | The top management promotes AI as a strategic priority in my company | Jeble et al. (2018)Lai et al. (2018)Chen et al. (2015) |
| The top management invests in AI solutions |
| The top management is keen to experiment with new AI techniques |
| ERM Alignment | The use of AI in SCRM complies with my company’s enterprise risk management policies and procedures | Curkovic et al*.* (2013)Inputs from Industry SMEs |
| AI systems in SCRM are integrated with enterprise risk management systems in my company |
| AI-based decisions are reviewed by enterprise risk professionals in my company |
| Risk management professionals use the insights from AI systems for decision making in my company |
| **Environmental Context:** |
| External Pressure | Our competitors have already adopted AI | Chen et al. (2015)Lai et al. (2018) |
| Our partners have already adopted AI |
| Market trends point to higher adoption of AI |
| Disruption Response | My company has experienced negative effects from past events like natural disasters, geopolitical events, etc.  | Singh et al. (2019)Baryannis et al*.* (2019)Katsaliaki et al. (2021)Inputs from Industry SMEs |
| Early warning signals can enable my company to respond proactively to supply chain disruptions |
| AI can provide insights to respond effectively to supply chain disruptions in my company |
| AI can help mitigate the impact of disruption to the supply chain in my company |

Source: Author’s compilation

## 3.3. Pre-testing

The pre-testing covered areas including the items, sentence construction, question quality, and identifying biases and errors (Shahbaz et al., 2019). This activity has been done along with nine industry Subject Matter Experts (SMEs) from India, based on unstructured interviews. The industry experts consisted of four SMEs from the manufacturing industry, two SMEs from the retail industry, one SME from the wholesale industry, one SME from AI consulting, and one SME from risk consulting. All SMEs held positions in senior management, e.g., directors, and business heads, and are all decision-makers in their respective organizations. Additionally, the items have been discussed and validated with two professors from academia. The suggestions and comments from both the industry SMEs and experts from academia have been carefully studied and incorporated. While comments related to language and clarity were promptly incorporated, an additional construct was added to the instrument on ERM alignment based on detailed inputs received from one of the SMEs with expertise in risk consulting. The further literature review was done on the integration of SCRM and ERM in practice and items identified and re-validated with the risk consulting SME.

## 3.4. Final questionnaire development and pilot testing

A five-point Likert scale was used for each item asking respondents to grade each item in the range of 1 (strongly disagree) to 5 (strongly agree). Google forms were used to create and distribute the online questionnaire. The survey instrument was designed to ensure face validity and improve readability for the respondents. It was initially pilot tested by exploratory study with a limited set of 15 respondents randomly chosen from the list of planned respondents. No issues were observed in terms of responses captured or any other issues.

## 3.5. Questionnaire distribution and data collection

For data collection, a survey was conducted in India covering organizations across manufacturing, wholesale trade, and retail trade industries in India. An online survey covering a randomly selected set of 300 leading organizations was conducted covering the target industries. Senior and mid-level leadership in the supply chain, operations, and production were targeted after carefully validating their profiles on the professional networking site LinkedIn. In addition, AI consultants from leading services firms like Information Technology, and data and analytics firms supporting the target industries were covered as part of the survey. After repeated follow-ups and reminders, 123 completed responses were received.

## 3.6. Data screening and data analysis

All the 123 responses were complete with no missing values as the questions were set as mandatory in the online portal. The distribution of the data as mentioned in Tables 5, 6, and 7 show that majority of the respondents (56%) are from middle management, manufacturing industry coverage was the maximum (37%) and a majority of the respondents were in the experience bracket of 11 years to 20 years (54.5%).

**Table 5**

Distribution of respondents by job role

|  |  |  |
| --- | --- | --- |
| **Role** | **# Of Respondents** | **% Of Respondents** |
| Lower Management | 28 | 22.8% |
| Mid Management | 69 | 56.1% |
| Top Management | 26 | 21.1% |
| **Grand Total** | **123** | **100.0%** |

Source: Survey results of 123 respondents in India (2021)

**Table 6**

Distribution of respondents by industry

| **Industry** | **# Of Respondents** | **% Of Respondents** |
| --- | --- | --- |
| Manufacturing | 46 | 37.4% |
| Retail Trade | 21 | 17.1% |
| Wholesale Trade | 12 | 9.8% |
| Services | 44 | 35.8% |
| **Grand Total** | **123** | **100%** |

Source: Survey results of 123 respondents in India (2021)

**Table 7**

Distribution of respondents by years of experience

| **Experience Range (years)** | **# Of Respondents** | **% Of Respondents** |
| --- | --- | --- |
| 0 - 10 | 52 | 42.3% |
| 11 - 20 | 67 | 54.5% |
| 21+ | 4 | 3.3% |
| **Grand Total** | **123** | **100.0%** |

Source: Survey results of 123 respondents in India (2021)

## 3.7. Assessing reliability and validity

The scale has been assessed for reliability and validity using the licensed version of ADANCO 2.2.1 software. Since the measurement model is reflective, consistent PLS (Dijkstra & Henseler, 2015) has been used to obtain consistent loadings. It is to be noted that if “Mode A consistent” is used as the weighting scheme for all the constructs, ADANCO performs a Confirmatory Factor Analysis (Henseler, 2017). The results are discussed in the section below.

# 4. Research results

First, for testing the reliability of the scale, the construct’s internal consistency reliability was measured. Cronbach’s α-value and Composite Reliability (CR) were used to check the reliability. As mentioned in Table 8, all factors have Cronbach’s α-value greater than 0.7 and CR values greater than 0.7 (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014). Second, for validity, each factor was tested for convergent validity and discriminant validity. This study considered the minimum cut-off level of 0.6 for item loading (Ursachi, Horodnic, & Zait, 2015). The scale had all items exceeding the 0.6 criteria for item loading as shown in Table 8. Also, the Average Variance Extracted (AVE) was checked to assess the internal consistency and all factors 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 mentioned in Table 9, the AVE of each factor is higher than the highest squared correlation with any other factor, thereby confirming discriminant validity at the factor level. The second discriminant validity criterion requires that the loadings of each indicator on its factor are higher than the cross-loadings on other factors (Hair et al*.*, 2014). As mentioned in Table 10, all items loaded higher on the factor being measured than on the other factors.

In addition to assessing reliability and validity, the scale has been studied to evaluate the effects of Common Method Variance (CMV) as it has been established to be a leading contributor to systematic error within survey research (Craighead, Ketchen, Dunn, & Hult, 2011). Based on the following reasons it has been concluded that CMV is unlikely to be a source of bias. First, given that the study covers a very niche interdisciplinary field, the utmost care has been taken to identify respondents who are SMEs in the field and have demonstrated extensive experience in AI as applicable to the field of SCRM. Hence the potential of CMV has been minimized (Chenet al., 2015). Second, as per Harman’s single-factor test conducted, the first factor did not account for most of the variance (Harman, 1967) leading to the conclusion that CMV may not be a problem. Third, qualitative validation (Craighead et al., 2011) by complementing the survey results with qualitative information captured through unstructured interviews of industry SMEs with expertise in risk management and AI consulting respectively has been done and found acceptable.

**Table 8**

Item wise loadings, composite reliability, and AVE

| Construct | Item Code | Item Description | Loadings | Cronbach’s alpha(α) | CR | AVE |
| --- | --- | --- | --- | --- | --- | --- |
| Big Data Management | BDM1 | My company has an Information Technology (IT) team responsible for data management | 0.829 | 0.879 | 0.884 | 0.650 |
| BDM2 | My company has access to all supply chain transactional data | 0.870 |
| BDM3 | My company stores various types of data including structured and unstructured data, internal and external data related to supply chain | 0.742 |
| BDM4 | My company has implemented data management and data quality systems | 0.778 |
| Relative Advantage | RAD1 | AI can provide better risk insights for my company than existing systems | 0.809 | 0.872 | 0.872 | 0.630 |
| RAD2 | AI can provide faster results to my company | 0.773 |
| RAD3 | AI can provide a higher ROI to my company | 0.780 |
| RAD4 | AI can provide highly accurate predictive and actionable insights | 0.812 |
| Cost of Ownership | COO1 | AI technology cost is high for my company | 0.867 | 0.893 | 0.895 | 0.738 |
| COO2 | AI integration cost is high for my company | 0.891 |
| COO3 | AI talent cost is high for my company | 0.818 |
| Talent | TAL1 | My company has AI skills | 0.771 | 0.780 | 0.786 | 0.547 |
| TAL2 | My company knows whom to partner with to implement AI solutions | 0.763 |
| TAL3 | My company has budgets to hire AI professionals | 0.682 |
| Top Management Support | TMT1 | The top management promotes AI as a strategic priority | 0.867 | 0.864 | 0.867 | 0.683 |
| TMT2 | The top management invests in AI solutions | 0.795 |
| TNT3 | The top management is keen to experiment with new AI techniques | 0.815 |
| ERM Alignment | ERM1 | The use of AI in SCRM complies with my company’s enterprise risk management policies and procedures | 0.810 | 0.906 | 0.908 | 0.709 |
| ERM2 | AI systems in SCRM are integrated with enterprise risk management systems in my company | 0.861 |
| ERM3 | AI-based decisions are reviewed by enterprise risk professionals in my company | 0.877 |
| ERM4 | Risk management professionals use the insights from AI systems for decision making in my company | 0.817 |
| External Pressure | EXP1 | Our competitors have already adopted AI | 0.809 | 0.829 | 0.830 | 0.619 |
| EXP2 | Our partners have already adopted AI | 0.766 |
| EXP3 | Market trends point to higher use of AI | 0.785 |
| Disruption Response | DIS1 | My company has experienced negative effects from past events like natural disasters, geopolitical events, etc.  | 0.686 | 0.855 | 0.864 | 0.605 |
| DIS2 | Early warning signals can enable my company to respond proactively to supply chain disruptions | 0.858 |
| DIS3 | AI can provide insights to respond effectively to supply chain disruptions in my company | 0.780 |
| DIS4 | AI can help mitigate the impact of disruption to the supply chain in my company | 0.776 |

 Source: Author’s ADANCO output

**Table 9**

Correlation of latent variables and the square root of AVE

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Construct | Big Data Management | Relative Advantage | Cost of Ownership | Talent | Top Management Support | ERM Alignment | External Pressure | Disruption Response |
| Big Data Management | **0.650** |  |  |  |  |  |  |  |
| Relative Advantage | 0.153 | **0.630** |  |  |  |  |  |  |
| Cost of Ownership | 0.127 | 0.233 | **0.738** |  |  |  |  |  |
| Talent | 0.281 | 0.163 | 0.040 | **0.547** |  |  |  |  |
| Top Management Support | 0.312 | 0.347 | 0.139 | 0.472 | **0.683** |  |  |  |
| ERM Alignment | 0.152 | 0.106 | 0.001 | 0.245 | 0.383 | **0.709** |  |  |
| External Pressure | 0.269 | 0.212 | 0.085 | 0.430 | 0.525 | 0.484 | **0.619** |  |
| Disruption Response | 0.294 | 0.141 | 0.087 | 0.184 | 0.223 | 0.137 | 0.336 | **0.605** |

Source: Author’s ADANCO output

**Table 10**

Cross loadings

| Item | Big Data Management | Relative Advantage | Cost of Ownership | Talent | Top Management Support | ERM Alignment | External Pressure | Disruption Response |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| BDM1 | **0.829** | 0.328 | 0.319 | 0.534 | 0.521 | 0.405 | 0.533 | 0.558 |
| BDM2 | **0.870** | 0.273 | 0.257 | 0.471 | 0.457 | 0.335 | 0.433 | 0.425 |
| BDM3 | **0.742** | 0.318 | 0.276 | 0.352 | 0.389 | 0.196 | 0.277 | 0.346 |
| BDM4 | **0.778** | 0.350 | 0.301 | 0.340 | 0.429 | 0.309 | 0.418 | 0.411 |
| RAD1 | 0.414 | **0.809** | 0.435 | 0.362 | 0.428 | 0.174 | 0.410 | 0.293 |
| RAD2 | 0.305 | **0.773** | 0.420 | 0.344 | 0.530 | 0.367 | 0.447 | 0.399 |
| RAD3 | 0.329 | **0.780** | 0.349 | 0.376 | 0.538 | 0.296 | 0.385 | 0.298 |
| RAD4 | 0.195 | **0.812** | 0.331 | 0.204 | 0.379 | 0.205 | 0.227 | 0.208 |
| COO1 | 0.320 | 0.453 | **0.867** | 0.299 | 0.360 | 0.103 | 0.372 | 0.388 |
| COO2 | 0.330 | 0.477 | **0.891** | 0.125 | 0.328 | 0.082 | 0.258 | 0.213 |
| COO3 | 0.266 | 0.308 | **0.818** | 0.087 | 0.270 | -0.113 | 0.116 | 0.157 |
| TAL1 | 0.385 | 0.245 | 0.071 | **0.771** | 0.463 | 0.354 | 0.480 | 0.223 |
| TAL2 | 0.337 | 0.306 | 0.228 | **0.763** | 0.411 | 0.387 | 0.408 | 0.369 |
| TAL3 | 0.462 | 0.353 | 0.145 | **0.682** | 0.671 | 0.358 | 0.578 | 0.368 |
| TMT1 | 0.463 | 0.506 | 0.362 | 0.557 | **0.867** | 0.450 | 0.549 | 0.394 |
| TMT2 | 0.507 | 0.418 | 0.250 | 0.666 | **0.795** | 0.581 | 0.679 | 0.424 |
| TMT3 | 0.416 | 0.534 | 0.308 | 0.485 | **0.815** | 0.509 | 0.573 | 0.355 |
| ERM1 | 0.383 | 0.419 | 0.107 | 0.370 | 0.686 | **0.810** | 0.632 | 0.278 |
| ERM2 | 0.392 | 0.330 | 0.010 | 0.479 | 0.532 | **0.861** | 0.683 | 0.373 |
| ERM3 | 0.281 | 0.221 | -0.007 | 0.482 | 0.490 | **0.877** | 0.558 | 0.324 |
| ERM4 | 0.258 | 0.131 | 0.000 | 0.328 | 0.379 | **0.817** | 0.467 | 0.266 |
| EXP1 | 0.534 | 0.361 | 0.260 | 0.582 | 0.666 | 0.518 | **0.809** | 0.523 |
| EXP2 | 0.278 | 0.280 | 0.147 | 0.500 | 0.543 | 0.571 | **0.766** | 0.309 |
| EXP3 | 0.406 | 0.446 | 0.279 | 0.463 | 0.497 | 0.555 | **0.785** | 0.531 |
| DIS1 | 0.472 | 0.220 | 0.263 | 0.447 | 0.371 | 0.347 | 0.465 | **0.686** |
| DIS2 | 0.431 | 0.345 | 0.251 | 0.305 | 0.420 | 0.285 | 0.444 | **0.858** |
| DIS3 | 0.461 | 0.332 | 0.219 | 0.361 | 0.416 | 0.355 | 0.530 | **0.780** |
| DIS4 | 0.331 | 0.261 | 0.192 | 0.243 | 0.262 | 0.173 | 0.371 | **0.776** |

Source: Author’s ADANCO output

# 5. Conclusions

In this study, the measurement instrument has been created based on a multi-stage process covering factor identification, item generation, pre-testing, pilot testing, and scale validation. Data has been collected from 123 professionals across the roles of supply chain executives, risk professionals, and AI consultants representing manufacturing, wholesale trade, and retail trade industries in India. The questionnaire has been pre-tested based on interviews with nine industry experts and two academicians. The scale has been assessed for reliability and validity using Confirmatory Factor Analysis (CFA). The scale generated consists of eight factors that are modeled as latent variables covering a total of twenty-eight items. The results show that the instrument is valid and reliable and can be used as a tool to further study the factors influencing the three stages of adoption of AI in SCRM. This measurement scale can be used by supply chain executives and researchers to examine and study factors that influence the adoption of AI in SCRM for the selected industries.

As companies emerge from the pandemic that has resulted in disruptions of both local as well as global operations and supply chains, the need for such an instrument has become a business necessity. The results of the study have important implications for supply chain executives and risk professionals to study and measure the factors influencing AI adoption in SCRM. In addition to the measurement instrument, this study has contributed to the identification of new factors influencing the adoption of AI in SCRM. These new factors, namely, big data management as part of the technological context, ERM alignment as part of the organizational context, and disruption response as part of the environmental context would enable researchers to use them in the context of studying the adoption of AI in SCRM.

This study has certain limitations that should be addressed in future research. First, the respondents of this research are limited to a few industries, and further studies are required to cover other industries. Second, the measurement scale has been developed and tested in the context of Indian businesses. Finally, this study is limited to cross-sectional survey data taken at a single point in time. Additional studies using longitudinal data would enable an in-depth examination of the measurement scale.

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