Organizational Adoption of Artificial Intelligence in Supply Chain Risk Management

Souma Kanti Paul[1](✉), Sadia Riaz[2], and Suchismita Das[1]

[1] S P Jain School of Global Management, Mumbai, India
souma.dj19dba001@spjain.org
[2] S P Jain School of Global Management, Dubai, UAE

Abstract. With the growing complexity of global supply chains, geopolitical events, pandemics, and just-in-time processes, organizations can benefit immensely in managing supply chain risks by adopting artificial intelligence (AI). Building upon past research in technology adoption, we study factors influencing the adoption intention of AI in SCRM across organizations in India. Based on a qualitative study, we discuss the applications and uniqueness of AI adoption in the field of supply chain risk management (SCRM) and propose a research model on the adoption, implementation, and routinization intention of AI in SCRM at an organizational level. Secondly, we discuss the implications of the study and the benefits to decision-makers and supply chain planners in devising effective strategies when adopting AI in SCRM.

Keywords: Adoption · Artificial intelligence · Supply Chain Risk Management

1 Introduction

Growing incidences of events like natural disasters, pandemics, just-in-time processes, and global supply chain networks have resulted in increased vulnerability of supply chains to disruptions [1]. A report [2] on the impact of Covid-19 on global Gross Domestic Product (GDP) cites that more than five million companies, including greater than 90% Fortune 1000 companies, had one or multiple tier-2 suppliers in the impacted region in China during the initial months of the pandemic. There has been a growing interest in the application of Artificial Intelligence (AI) in Supply Chain Risk Management (SCRM). However, there has been limited research on the adoption of AI in SCRM at an organizational level across industry verticals in India. The objective of this research is to identify factors that influence the adoption intention, implementation intention, and routinization intention of AI in SCRM at an organizational level in India. The industries considered for this study cover consumer-packaged-goods (CPG), consumer durables, wholesale, logistics, and retail.

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2 Literature Review

2.1 Definition of AI

The field of AI has evolved over the past few decades and accordingly, the definition and scope of AI have been continually evolving. Today, Artificial Neural Networks (ANN) and Deep Learning (DL), form the core of applications classified under AI [3]. Accordingly, for this study we consider deep learning techniques that use artificial neural networks as the definition of AI.

2.2 Definition of SCRM

Based on past research, SCRM is defined as the management of supply chain risks through active coordination between all supply chain partners to identify, assess, and respond to risks ensuring disruptions are mitigated leading to business continuity and profitability [4]. It should also be noted that SCRM is a part of Enterprise Risk Management (ERM) [5].

2.3 Application of AI in SCRM

Recent studies have argued that AI will fundamentally change the way organizations make decisions and interact with their external stakeholders [6]. Due to the rise of big data and advances in computing, it is today possible to analyze billions of real-time transactions, process a wide range of unstructured data like pictures, videos, and natural language, and generate predictive and prescriptive insights for decision making. These advances in the field of AI stand to benefit SCRM immensely and hence the growing interest in the application of AI in SCRM. Recent studies cite the use of AI to predict the probability of occurrence of risks and costs of risks [7], reduce risk of churn in distribution management [8], predict damage parameters in logistics [9], and forecasting the level of integration of supply chain to minimize risks [10].

2.4 The Uniqueness of AI Adoption

Organizational agility, in terms of rapidly responding to external shocks like pandemics or geopolitical situations, adapting to market changes, or responding to customer demands plays a critical role in AI adoption. It is also important to note that the implementation of AI solutions, often in conjunction with other advanced digital technologies [11], involves an entire ecosystem of technologies right from high-end computing hardware, big data platforms, data processing tools, analytical tools, and open source technologies. Moreover, AI adoption, implementation, and routinization intentions in SCRM greatly depend on the integration and compliance of AI solutions to ERM policies and processes.

2.5 Applicability of Technology Adoption Theories to AI Adoption in SCRM

The Technology-Organisation-Environment (TOE) framework [12] identifies three independent contexts that influence the adoption, implementation, and routinization intention of technologies at an organizational level. Based on the TOE framework, past researchers have studied the adoption intention of technologies like Big Data Analytics [13] and Predictive Analytics [14]. But there is clearly a need to study the applicability of the TOE framework for AI adoption in the field of SCRM. A recent study cites that managers of global organizations have limited empirical advice on how to implement AI in the companies' operations [11]. It also calls for a study on the current prevalence of AI in business and the exploration of key dimensions of AI implementations. Hence, it is important to study the implementation intention and routinization intention of AI and not just the intent to adopt AI. Given the earlier cited uniqueness of AI adoption in SCRM, the authors suggest using the three contexts of the TOE framework, namely technological context, organizational context, and environmental context but include factors that are newly added and defined by the authors in the context of AI.

3 Research Model and Hypothesis

The authors have used keyword-based search of past technology adoption studies indexed in ProQuest, EBSCO, and Google Scholar, coupled with interviews of nine industry subject matter experts (SMEs) in India to identify and validate independent factors as part of the technological, organizational, and environmental contexts of TOE framework. The adoption intention, implementation intention, and routinization intention of AI in SCRM have been identified as dependent variables (Fig. 1).

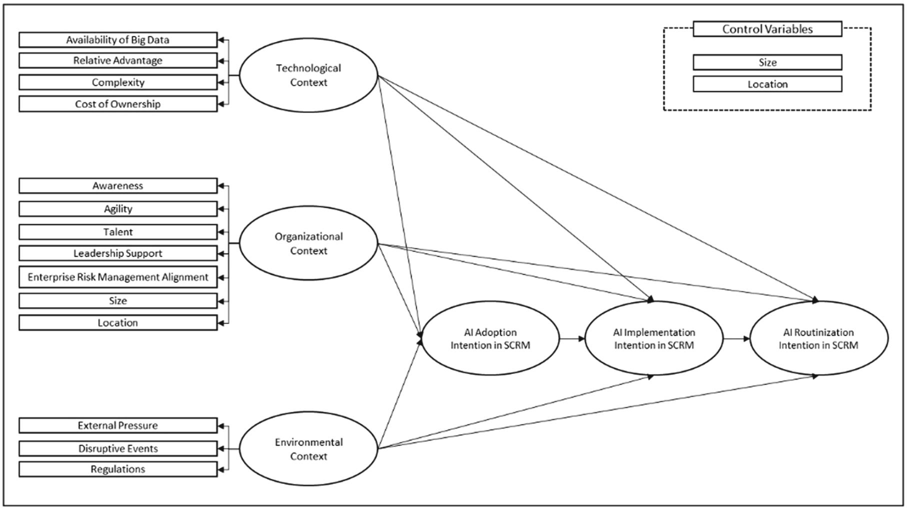

Fig. 1. Research model

3.1 Technological Context

The authors argue that organizations that have large and diverse datasets available across supply chain systems [13] like transactional data, pictures, videos, texts, and real-time data are in a better position to initiate AI projects. Past studies have shown relative advantage and complexity as oft used factors to study technology adoption [15] and is applicable to AI as well. Also, the cost of ownership is a critical determinant [13] of AI adoption in a market like India. Taking these factors into consideration, the following hypotheses have been proposed: (H1) Availability of big data is positively related to AI adoption intention, AI implementation intention, and AI routinization intention in SCRM, (H2) Relative advantage is positively related to AI adoption intention, AI implementation intention, and AI routinization intention in SCRM, (H3) Complexity is negatively related to AI adoption intention, AI implementation intention, and AI routinization intention in SCRM, and (H4) Cost of ownership is negatively related to AI adoption intention, AI implementation intention, and AI routinization intention in SCRM

3.2 Organizational Context

Apart from organizational characteristics like location and size, organizational awareness of AI's possibilities and understanding of how to best utilize the capabilities of AI in SCRM is an important determinant [11]. Organizational agility has been cited as a key determinant of AI success [11]. The availability of talent has been cited as an important indicator of the adoption of innovation [16]. As cited by past research, one of the best predictors is leadership support by influencing the organization's intention to adopt innovative technologies [14]. Given that SCRM is a part of ERM, it is essential that any AI-based decision making complies to ERM policies and is integrated into ERM systems and processes. Based on the above factors, following hypotheses have been proposed: (H5) Awareness of AI is positively related to AI adoption intention, AI implementation intention, and AI routinization intention in SCRM, (H6) Organizational agility is positively related to AI adoption intention, AI implementation intention, and AI routinization intention in SCRM, (H7) Talent is positively related to AI adoption intention, AI implementation intention, and AI routinization intention in SCRM, (H8) Leadership support for AI is positively related to AI adoption intention, AI implementation intention, and AI routinization intention in SCRM, (H9) ERM alignment is positively related to AI adoption intention, AI implementation intention, and AI routinization intention in SCRM, (H10) Organizational size is positively related to AI adoption intention, AI implementation intention, and AI routinization intention in SCRM, and (H11) Organizational location is positively related to AI adoption intention, AI implementation intention, and AI routinization intention in SCRM.

3.3 Environmental Context

External pressure has been cited to be a significant factor in adoption research [17] for innovative technologies. Also, past negative effects of disruptive events on the supply chain are a strong predictor of AI adoption given its potential to predict such events and its impact. Recent reports indicate a growing involvement of governments in prioritizing AI and taking proactive steps to fund AI research [18]. On the other hand, government regulations on data privacy and data security could be limiting AI adoption. The following hypotheses have been proposed: (H12) External pressure is positively related to AI adoption intention, AI implementation intention, and AI routinization intention in SCRM, (H13) Disruptive event is positively related to AI adoption intention, AI implementation intention, and AI routinization intention in SCRM, and (H14) Regulation is negatively related to AI adoption intention, AI implementation intention, and AI routinization intention in SCRM.

3.4 Dependent Variables

The authors propose the following hypothesis based on the adoption stages for the dependent variables namely, the AI adoption intention, AI implementation intention, and AI routinization intention in SCRM: (H14) AI adoption intention is positively related to AI implementation intention in SCRM, and (H15) AI implementation intention is positively related to AI routinization intention in SCRM.

4 Implications

From a short to mid-term perspective, as businesses in India gradually emerge from a global pandemic that has devasted operations and supply chains globally, the need to adopt, implement and routinize AI in the field of SCRM is rapidly becoming a business priority. Also, the value of AI as applied to the larger supply chain risk domain will attract a lot of attention and research in the coming years. To do so, it is imperative to first understand the factors influencing the adoption, implementation, and routinization intention. The authors argue that the proposed research model based on the TOE framework with newly added factors will enable further studies and empirical research. Furthermore, this study will greatly benefit business leaders, supply chain planners, and risk professionals to devise strategies in their respective organizations to adopt, implement, and routinize AI in the field of SCRM.

5 Conclusion

This study provides an in-depth analysis of factors influencing AI adoption, implementation, and routinization intention. It proposes a research model that can be used for further empirical research across industries in India.

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