Critical Success Factors Influencing Artificial Intelligence Adoption in the Food Supply Chains

Abstract

The adoption of Artificial Intelligence (AI) in food supply chain (FSC) can address unique challenges of food safety, quality and wastage by improving transparency and traceability. However, the technology adoption literature in FSC is still in infancy stage as a result of which little is known about the critical success factors that could impact the adoption of AI in FSC. Therefore, this study makes a pioneering attempt by examining the critical success factors (CSFs) influencing the adoption of Artificial Intelligence (AI) in the Food Supply Chain (FSC). A conceptual framework based on TOEH (Technology–Organisation–Environment–Human) theory is used to determine the CSFs influencing AI adoption in the context of Indian FSC. The rough-SWARA technique was used to rank and prioritise the CSFs for AI adoption using the relative importance weights. The results of the study indicate that technology readiness, security, privacy, customer satisfaction, perceived benefits, demand volatility, regulatory compliance, competitor pressure and information sharing among partners are the most significant CSFs for adopting AI in FSC. The findings of the study would be useful for AI technology providers, supply chain specialists, and government agencies in framing appropriate policies to foster the adoption of AI in FSC sector.

Keywords: Food Supply Chain; Critical Success Factors; Artificial Intelligence; Sustainability; TOEH (Technology–Organisation–Environment–Human); Rough Theory

1. Introduction

In the era of globalisation, fierce competition has forced firms to move towards a digital future, where Industry 4.0 enabled technologies have begun to play a crucial role (Rahman et al. 2020; Kumar, Ramachandran, and Kumar 2021; Raut et al. 2021). One of these technologies is Artificial Intelligence (AI) that encompasses programs, systems, algorithms and machines that signify intelligence (Huang and Rust 2018; Shankar 2018). Put succinctly, AI deals with understanding human intelligence and designing computer programs that can imitate human behaviour to create knowledge for problem solving (Min 2010; Aayog 2018). AI is crucial for a nation's economic growth and has the potential to contribute upto $15.7 trillion in the global economy by 2030 (PWC 2018). AI technologies have been applied extensively in the fields of engineering (Pham and Pham 1999), education (Chen, Chen, and Lin 2020), and business (Rauch-Hindin 1985). While AI has been in existence for decades, its applications in business research have received a glaring attention only in the recent past (Min, 2010). It is suggested that one of the avenues that are most likely to benefit from emerging AI technologies is supply chain management (Belhaldi et al. 2021). Despite the recent explosion of research on the subject, the potential of AI in supply chains remains not fully explored (Dubey et al. 2020). For instance, supply chain firms employ physical and digital networks and work with high volumes, thin margins, slender asset allocation and time bound deadlines, where AI technologies can help in optimisation and network coordination among channel partners in an effective way (Tourajipour et al. 2021). Given the complex and uncertain interactions encompassing supply chains (Chen et al. 2020), emerging technologies such as AI can be useful in developing synchronised supply chains that reap mutual gains by sharing information and resources in a cooperative way (Shore and Venkatachalam 2003).

While the above studies adequately discuss the importance of AI in supply chains, they fall behind in deriving context specific insights that managers can readily use while contemplating on the adoption of AI in their firms. Since industry characteristics play an important role in the adoption of new technologies, Tourajipour et al. (2021) urge researchers to study industry-specific applications of AI. Accordingly, the present paper aims to strengthen our understanding on this subject in the context of the food supply chain, which is in dire need of AI intervention due to unique challenges such as product perishability and wastage which can effectively address by appropriately harnessing AI technology in FSC. Precisely food supply chain refers to the varying system of organisation, people, activities, information and resources that are involved in the manufacturing, processing, distribution and disposal of the food for the movement of a good from farms to customers (Yu and Nagurney 2013; Dora et al. 2020). Unlike other supply chains, FSC involves continual changes in quality till the time consumers receive the product (Apaiah et al. 2005). Thus, maintaining food quality and safety along the FSC becomes an additional challenge (Aung and Chang 2014). It is argued that cutting edge technologies can drastically improve the visibility and traceability in FSC, thus addressing the quality and safety issues related with food and improving the supply chain's overall performance (Ben-Daya et al. 2020; Tsolakis et al. 2020). By enabling better integration of supply chain, AI can improve the efficiency of a food supply chain (Kittipanya-ngam and Tan 2020).

Taylor and Fearne (2006) have argued that developing a synchronised approach for demand and activity analysis in food supply chains would require the application of big data. AI intelligence is likely to be extremely advantageous in the use and exploitation of such big data for effective decision making in the food sector. Channel partners in supply chain may also benefit from better data management using AI (Ni, Xiao, and Lim 2019; Kayikci et al. 2020). Further, AI can be deployed to reduce costs, provide competitive advantage and enhance supply chain performance (Thow- Yick and Huu-Phuong 1990; Reyes, Visich, and Jaska 2020). While the existing literature provides an elaborate account of AI's impending benefits in supply chain management (Zhang et al. 2017; Tsang et al. 2018; Baryannis et al. 2019), the critical success factors influencing the adoption of AI are not that well explored, particularly in the FSC context.

So far, the existing literature on technology adoption has mostly focused at the firm level (Aboelmaged 2014; Yang et al. 2015; Calabrese et al. 2020). According to a report by Gartner (2017), almost 59 % of enterprises are in the process of obtaining information whether to adopt AI, and only 6% have installed AI. The report suggests that a large number of firms are yet unclear about the integration of AI adoption with their business strategy. Hence, the abysmal rate of AI adoption by firms is the primary motivation of this article. Another motivation of this research is derived from the Aayog (2018) on the national strategy of AI. The report highlights that the adoption of AI in India has remained limited with less than a quarter of firms using AI in their businesses for making business decisions. The extant literature highlights that most of the research on adoption of cutting-edge technologies such as AI is conducted for developed countries (Brock and Khan 2017), outside an Indian context (Yadegaridehkordi et al. 2018; Orji, Kusi-Sarpong, and Gupta 2020).

In this article, we focus on the FSC in India, in order to identify and evaluate CSFs for the adoption of AI in this sector. The existing literature recognizes that food supply chains present unique challenges such as product perishability, deterioration, food safety and wastage (Dora et al. 2020). These unique challenges in food supply chain highlights the necessity for adoption and implementation of AI in FSC (Ali et al. 2021). Traditional FSC, face challenges in terms of lack of transparency and traceability (Tayal et al. 2021). AI adoption will make the FSCs more transparent, traceable, efficient and will address challenges pertaining to food quality and safety (Saberi et al. 2019; Wong et al. 2020). However, given the heterogeneous nature of food supply chain, it is crucial to identify the CSFs that would help in easing out the complexities in AI adoption and will make the adoption process smooth and straightforward. The identification of these factors would help in developing better understanding of CSFs and will enable them to form appropriate strategies for implementation of AI in FSC. This paper develops a conceptual framework using various important dimensions identified from the 'technology-organisation-environment-human' theory to demonstrate the implementation of AI for FSC in an emerging market, India. The objectives of the study are hence formulated as follows:

RO1*- To develop a conceptual model using Technology–Organisation–Environment-Human based CSFs for successful adoption of AI in FSC.*

RO2*- To prioritise the CSFs that significantly impact AI adoption in food supply chain for Indian context.*

The paper attempts to make following contributions to the existing literature: First, it enriches the technology adoption literature in the food supply chain context by reviewing and ascertaining CSFs for adopting AI in the FSC. Next, an innovative conceptual model is formularised by using "Technology–Organisation–Environment–Human (TOEH)" framework to identify and classify vital factors that can significantly influence the adoption of AI in the FSC context. After this, Rough-SWARA is utilised to implement the proposed conceptual model based on managers' and experts' perspectives about the FSC. The extant literature identifies several studies on the use and application of Rough-SWARA in various areas such as supplier selection problem, logistics sector and textiles industry (Zavadskas et al. 2018; Vasiljević et al. 2018; Sremac et al. 2018; Ulutas 2020). The results of the study will assist policy makers, technology providers and supply chain specialists to focus on most significant factors that influence the adoption of AI in the food supply chain.

The remainder of the paper is organised as follows: Section 2 reviews the existing literature and identifies the success factors which are vital for the AI adoption in the food supply chain. The methodology of the study is presented in section 3. Section 4 shows the application of a case study, Section 5 discusses the results and presents the sensitivity analysis, Section 6 highlights the contributions of the study and Section 7 contains the concluding remarks.

2. Literature review

2.1 AI in Food Supply Chain

Food security, safety and management is a major concern for nations worldwide (Mogale, Kumar, and Tiwari 2020; Tayal et al. 2021). The global food security is adversely affected due to large post-harvest losses (An and Ouyang 2016). According to statistical estimates the value of food losses and wastage for developed and developing nations is estimated to be around 680 and 310 billion dollars respectively (FAO 2011). Post-harvest losses contribute around 40 percent of food losses in developing markets such as India. Storage loss is one of the critical drivers of post-harvest losses of food grains (Sharon, Abirami, and Alagusundaram 2014). In India, around 12 to 16 million tonnes of food grains get wasted annually (Mogale, Kumar, and Tiwari, 2020). The primary reason for these losses is the ineffective food supply chain where issues like lack of storage facilities and improper coordination among supply chain channel partners are widespread (Maiyar and Thakkar 2017; Chauhan et al. 2020). At the same time various food scandals and cases across the world have highlighted the lack of transparency and traceability in food supply chain (Tayal et al. 2021). Most of the systems used in traditional food supply chains lacked transparency and traceability which adversely impacted the efficiency of the food supply chain and posed challenges in terms of food safety and quality. In an FSC, it is important for the user to track product reliability as the product demand is quite random and seasonal (Tayal et al., 2021). An FSC provides a very compelling context for research as food products have unique characteristics such as perishability, seasonality, and sensitivity to temperature (Fredriksson and Liljestrand 2015). Thus, FSC in addition to the other characteristics of a supply chain, face challenges in terms of product perishability and wastage (Gobel et al. 2015). Among other emerging technologies such as Blockchain, IOT etc., AI is well positioned and is more efficient in addressing these unique challenges of food supply chain. AI provides high end technology based solutions for food yield production and supply, thereby minimizing food wastage and ensuring food safety (Kollia, Stevenson, and Kollias, 2021). In food supply chain, data sharing can address challenges pertaining to food safety, quality, transparency and traceability (Durrant et al. 2021). Information or data sharing in food supply chain can also reduce waste and provide cost savings (Kaipia, Dukovska-Popovska, and Loikkanen 2013). The role of technologies becomes very prominent in data sharing, particularly in developing data sharing infrastructures (Durrant et al. 2021). The cutting edge technologies such as AI facilitates data sharing and information exchange and leads to better data management within supply chain (Ni, Xiao, and Lim 2019). Opara and Mazaud (2001) argue that investments in technology are critical for achieving traceability in supply chains. Traceability can also address safety and quality issues in food supply chains (Ben-Daya et al. 2020). By enabling better integration among channel partners, AI can improve the overall efficiency of a FSC (Kittipanya-ngam and Tan 2020). AI can aid in speeding up the complex processes involving a FSC, thus making it more reliable. In food supply chain, AI technologies can be harnessed to address critical issues pertaining to supply chain coordination, demand planning, information exchange and strategic alliances in supply chain (Min and Zhou 2002). Clearly, with the application of AI technologies, FSC will become more efficient (Koonce 2017).

The adoption of cutting edge technologies such as AI has huge prospects in the food sector, and therefore this study attempts to make sound theoretical and empirical contributions about AI adoption in the context of food supply chains. The existing literature has largely focussed on application and benefits of AI in food supply chain and has not appropriately explored the critical aspect of AI based facilitation of data sharing for improving the overall efficiency of food supply chain (Omid et al. 2013; Pang et al. 2015; Kumar et al. 2016; Chen et al. 2020; Misra et al. 2020). It can be seen from the literature of AI on food supply chain that vital success factors that could influence and determine AI adoption in FSC have not been methodically evaluated. Moreover, there is a dearth of literature focussing on the adoption and use of AI in supply chains in emerging markets such as India. An appropriate assessment of these vital factors for adoption of AI in FSC can be critical in leveraging this technology for enhancing a firms' image, efficiency and providing it with a competitive advantage (Thow-Yick and Huu-Phuong 1990). Thus, this present paper seeks to investigate the critical success factors influencing adoption of AI in FSC context in India. The importance of the topic on AI adoption in food supply chain and the scarcity of relevant academic research in this topic led us to examine the critical success factors for AI adoption in FSC.

2.2. *Conceptual model for the critical success factors for AI adoption in FSC*

Technology adoption and its use is the prime area of concern for researchers and practitioners worldwide (Dwivedi et al. 2019). The CSFs for the adoption and use of AI are studied through the lens of organisational, human, technological and environmental factors emanating from the TOE and HOT frameworks (Yang et al. 2013; Tashkandi and Al-Jabri 2015; Orji, Kusi-Sarpong, and Gupta 2020). Figure 1 below illustrates the proposed conceptual model for the present study. For each of these categories/dimensions, critical success factors for AI adoption in the FSC were identified using the existing literature and interviews of experts in FSC.

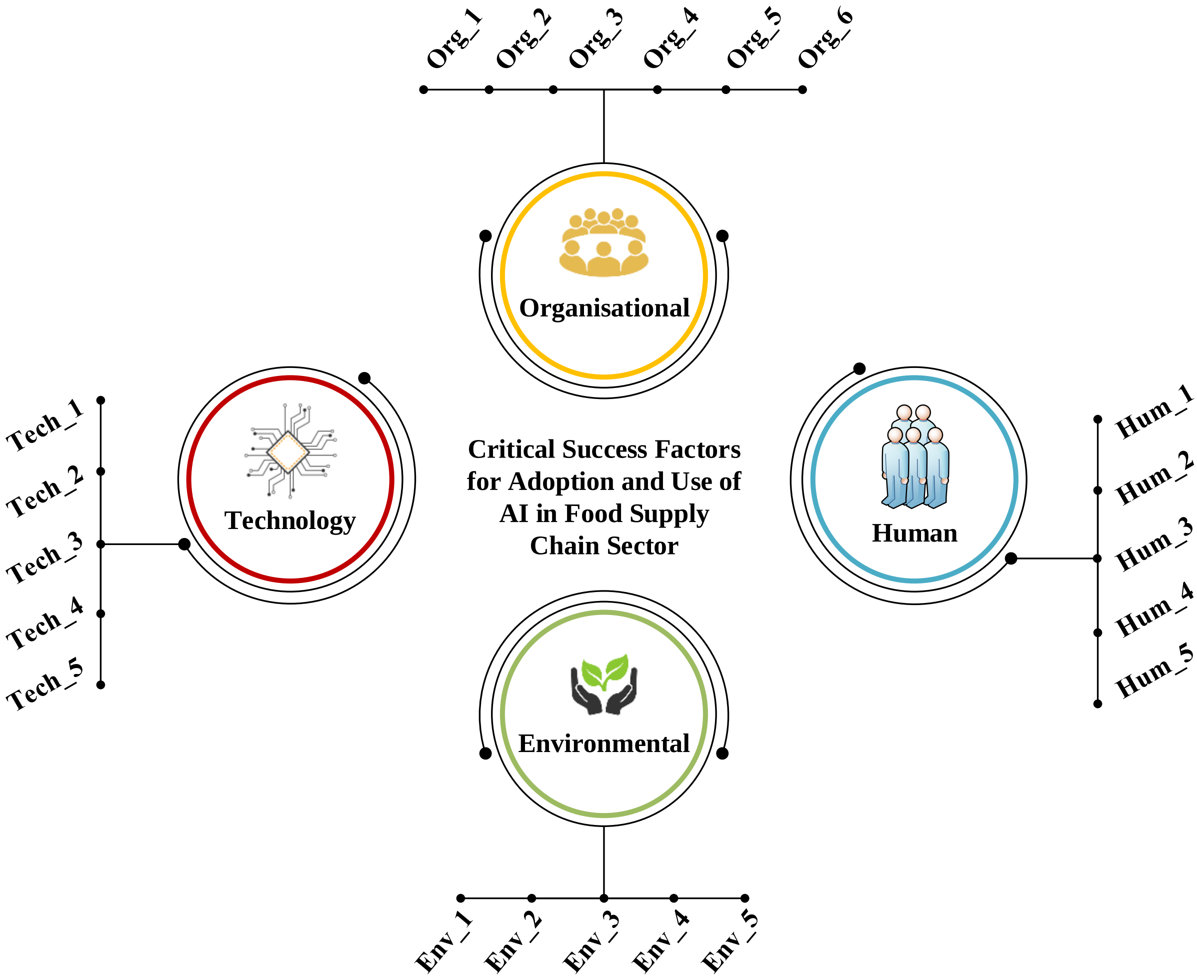

Figure 1: Proposed Conceptual Model

2.2.1 Technological Factors

These factors include an organisation's internal and external technologies, processes and equipment that highlight innovation traits or factors that were used in the technology adoption research (Nilashi et al. 2016). Technology readiness is identified as an important factor in this context, which refers to the ability of an enterprise to adopt new technologies (Janssen et al. 2020) such as artificial intelligence in FSC. Complexity is another critical factor that can influence the adoption of AI in FSC and is defined as the extent to which AI is in line with the existing values, past experiences and requirements of potential adopters of technology (Affia, Yani, and Aamer, 2019). AI technologies deal with a complex set of data that requires knowledgeable users and enabling conditions. Compatibility is another crucial factor identified in the technological context, which highlights how AI adoption suits the values, experience and needs of the adopter (Yadegaridehkordi et al. 2018). Another important factor in the technological dimension is the perceived benefit of AI as it considers the useful perception level of AI relative to other innovations (Verma and Bhattacharya 2017). Additionally, security and privacy issues could foster and promote the use of AI in FSC (Sun et al. 2018).

2.2.2 Organisational Factors

The AI adoption in FSC is influenced by several organisational factors such as dedicated resources, culture and other characteristics of the organisations (Elbaz and Haddoud 2017).

Organisational culture a vital organisational factor plays an important role in AI adoption in FSC (Hentschel, Leyh, and Baumhauer 2019) as it facilitates expressions and suggestions related to systems and procedures in the organisations. An important factor in the use of AI in FSC is strong management support as it ensures that firms can effectively handle the complexities related to cutting edge technologies and would improve their adoption rate (Ramamurthy, Sen, and Sinha 2008). Change management is another influential factor that highlights the requirement to formulate a change management program by the team implementing technology adoption and also considers the importance of implications for such projects (Nah and Delgado 2006). Change management initiatives can foster the use and adoption of AI in food supply chain. In order to foster effective AI adoption in FSC it is important to have a clear and strong linkage between vision and strategy (Duan et al. 2017). Establishing sufficient resources and competencies is a key factor as technological infrastructure, electronic databases, and sufficient human resources with adequate technology knowledge and business resources are critical for the successful adoption of AI in FSC (Alreemy et al. 2016). AI provider commitment and support is critical for the AI adoption and use in food supply chains (Dora, Kumar, and Gellynck 2016; Sun et al. 2018; Hentschel, Leyh, and Baumhauer 2019).

2.2.3 Environmental Factors

These factors are related to the environmental externalities of the organisation (Yadegaridehkordi et al. 2018). Institutional trust is a prominent factor that highlights the organisations beliefs about the safety concerned with the adoption of AI (Bahmanziari, Pearson, and Crosby 2003) in the FSC. Regulatory environment is another factor that highlights the important role of the government in food organisations for adopting technologies such as AI and blockchain (Hasibuan and Dantes 2012). Government support in terms of funding, equipment, tax concessions and technological support is a critical factor determining the adoption and use of traceability systems in food organisations (Duan et al. 2017). Demand volatility highlights the variance in the demand of FSC services and influences the adoption of AI in FSC (Nguyen 2013). Competitive pressure fosters AI adoption in FSC as greater amount of competition among organisations ensures greater technology adoption. Ethics in data collection highlights the privacy concerns associated with collecting user's private information (Sun et al. 2018) and may impact the adoption and use of technologies like AI (Sun et al. 2018; Affia, Yani, and Aamer 2019) in FSC.

2.2.4 Human Factors

Human factors are important for AI adoption in FSC. Employee competency and training is a critical factor that could foster the adoption of AI in FSC. Competent employees always seek innovative solutions for various business challenges and best utilise available opportunities through cutting edge technologies (Gangwar, Date, and Ramaswamy 2015; Nilashi et al. 2016). Therefore, it is important to educate employees and provide them with appropriate training so that they can obtain the necessary skills and possess the right attitude to contribute to the set standards as well as incessant improvements in an organisation (Yadegaridehkordi et al. 2018). Customer satisfaction is another prominent human factor that influences AI adoption in FSC. Orji, Kusi-Sarpong, and Gupta (2020) highlighted customer satisfaction as an important factor for the use of social media in the logistics industry. Establishing AI implementation team is very critical for the adoption and use of AI in FSC to ensure that benefits through AI are appropriately leveraged. Proper communication among supply chain channel partners is vital for the adoption of technologies such social media and AI in the supply chain and other sectors (Orji and Lui 2020; Orji, Kusi-Sarpong, and Gupta 2020).

Table 1. Summarising the Critical Success Factors for AI adoption in FSC

Main Dimension CSF	Sub-dimension CSF	References
Technology (TEC)	Technology readiness (TEC_1)	Brock and Khan (2017); Janssen et al. (2020)
	Relative advantage/Perceived benefit (TEC_2)	Verma and Bhattacharyya (2017)
	Data Complexity (TEC_3)	Affia, Yani, and Aamer (2019)
	Compatible facilities for testing and trial ability of AI technology (TEC_4)	Yadegaridehkordi et al. (2018)
	Sufficient privacy and security (TEC_5)	Sun et al. (2018); Spanaki et al. (2021)
Organisational (ORG)	Clear linkage between vision and strategy (ORG_1)	Alreemy et al. (2016); Duan et al. (2017); Sun et al. (2018)
	Adequate top management support and ownership (ORG_2)	Yang et al. (2015); Duan et al. (2017); Saberi et al. (2019)
	Behavioral change management initiatives for AI adoption (ORG_3)	Duan et al. (2017)
	Establish sufficient resources and competencies for AI adoption (ORG_4)	Alreemy et al. (2016)
	AI provider commitment and support (ORG_5)	Hentschel, Leyh, and Baumhauer 2019
	Organisation culture and environment (ORG_6)	Hentschel, Leyh, and Baumhauer 2019
Environment (ENV)	Demand volatility(ENV_1)	Gunasekaran et al. (2018); Sun et al. (2018)
	Regulatory and compliance requirements (ENV_2)	Hasibuan and Dantes (2012); Alreemy et al. (2016)
	Ethics in data collection (ENV_3)	Sun et al. (2018); Affia, Yani, and Aamer (2019)
	Peer/competitor Pressure (ENV_4)	Obal (2017); Tu (2018); Affia, Yani, and Aamer (2019)
	Institutional based trust (ENV_5)	Nguyen (2013); Purvis et al. (2016); Abolghasemi et al. (2020); Dubey et al. (2020); Janssen et al. (2020)
Human (HUM)	Proper training for staff and end-users (HUM_1)	Gangwar, Date, and Ramaswamy 2015; Duan et al. (2017)
	Establish AI implementation team (HUM_2)	Sun et al. (2018)
	Job security of employees post AI adoption (HUM_3)	Dora, Kumar, and Gellynck 2016
	Information sharing and communication among SC partners (HUM_4)	Orji and Lui (2020)

	Customer satisfaction (HUM_5)	Nguyen (2013); Kamble, Gunasekaran, and Arha (2019)

2.3 Research Gaps and highlights

Various studies have been conducted to investigate the practical adoption of disruptive technologies models in various industries (Orji, Kusi-Sarpong, and Gupta 2020). Despite the increased number of studies in the field of disruptive technologies like Block chain technology (BT), Cloud computing (CC), Internet of things (IoT), Big data analytics (BDA), Drones, etc., research on the role of CSFs in the AI adoption process in food supply chain is very limited (Queiroz and Wamba 2019; Pillai and Sivathanu 2020; Tsolakis et al. 2020). According to the literature, AI has a lot of promise for bringing about reformation in FSC. On the other hand, because Indian FSCs are very complicated, unorganised, semi-integrated, and involve various intermediaries (Viswanadham and Kameshwaran 2013), It requires an appropriate integration platform, where technologies such as AI could play a crucial role. Furthermore, as public awareness grows, consumers are more concerned about food safety and demand sustainable compliance. AI adoption in FSC is now required to ensure such actions in real-world setting (Zhao et al. 2020). As a result, this is the first study of its kind to use extended TOEH frameworks to identify CSFs and analyse them using novel rough-SWARA. It is remarkable for providing practitioners and academicians with insights on how to improve organisational supply chain performance through successful adoption of AI technology. The list of twenty-one CSFs under technological, organisational, environmental and human considerations are broad enough to encompass the context of CSFs that influence the process of AI adoption in the food supply chain in emerging economies context. As a result, the goal of this study is to look into how CSFs affect the adoption of AI. The existence of this gap has prompted researchers to do research in this field, with a focus on FSC. It gives professionals and managers in the field of SC advice on how to effectively adopt AI by delivering insights. It also assists managers and experts in identifying areas where intervention is required and resources must be allocated in order for AI to be effectively implemented.

3. Research Methodology

The proposed research is carried out into two phases: In the first phase, identification of CSFs was done through exhaustive literature review and they were finalised after various deliberations with domain experts. In the second phase Rough SWARA (R-SWARA) was utilised to determine the relative importance weight of CSFs for AI adoption in FSC in an Indian context. The flow of research is highlighted in Figure 2 below.

As examined in previous literature, the adoption of AI and its applicability would altogether contribute to a resilient FSC. In the first phase of the study, a list of twenty-one CSFs relevant to the adoption of AI in FSC (see Table 1) were identified from the literature and finalised after various deliberations with domain experts. The CSFs of AI adoption in FSC have been extracted through an exhaustive literature review by searching the various catchphrases such as artificial intelligence + food industry; digital + supply chain, AI + food supply chain; critical factors + AI adoption; food + supply chain; technology adoption + agro supply chain; critical success factors (CSFs)/criteria/enablers/drivers etc. The catchphrases were chosen dependent on key research themes in existing literature and scholarly reviews concentrated on a fundamental premise. In this investigation, an exhaustive technological and theoretical know-how of the adoption factors will facilitate experts to make decision by deciding the overall significance of recognised CSFs of AI adoption in the FSC utilising R-SWARA. This investigation is the primary endeavor to recognise the CSFs of AI selection and afterward categorised them based on Technology-Organisation-Environment (TOE) and Human-Organisation-Technology (HOT) frameworks.

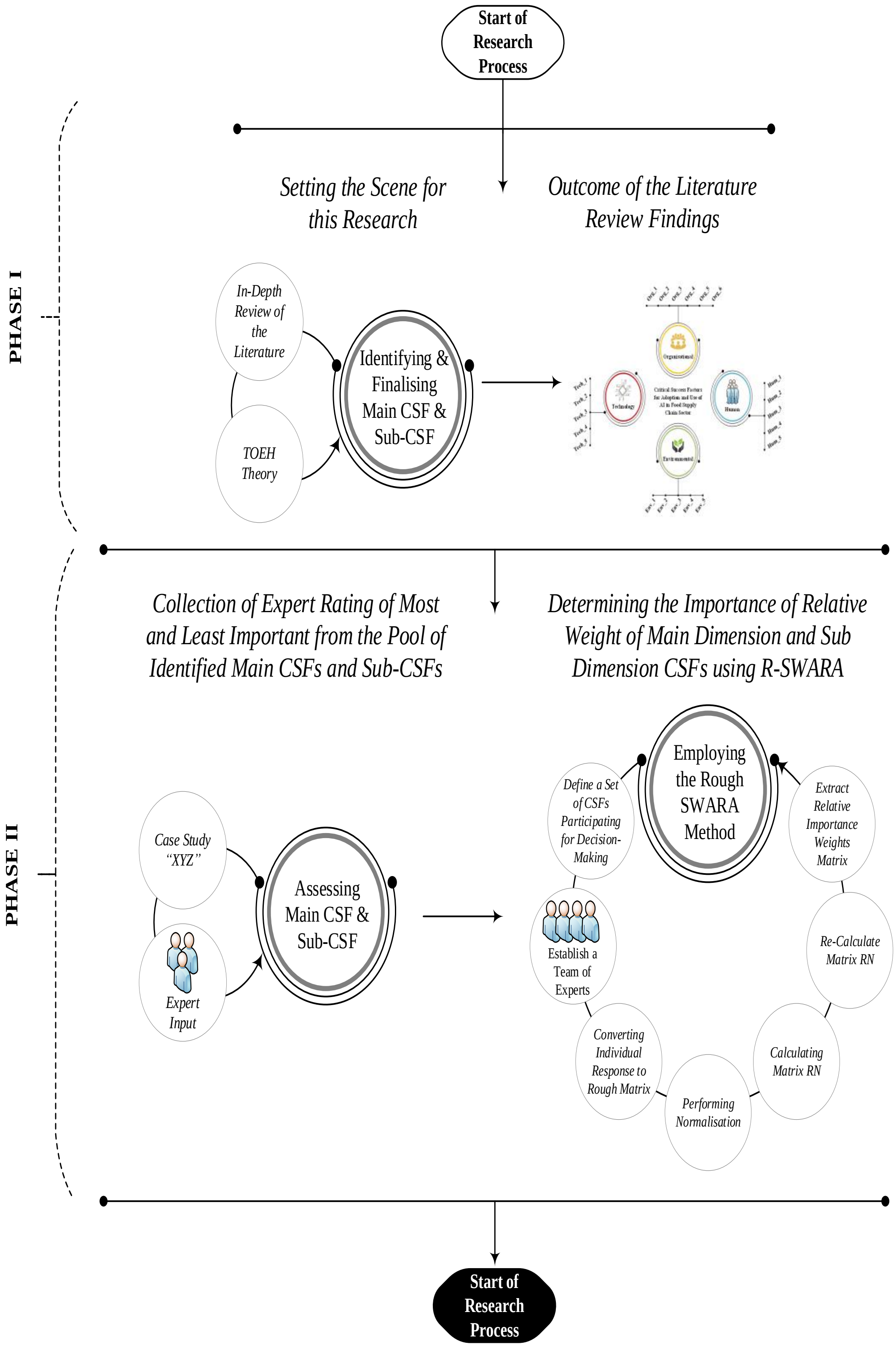

Figure 2. Research Design

3.1 Rough-SWARA Method

"R-SWARA technique was developed by Zavadskas et al. (2018), and is widely used for determining the relative importance weights of the factors/criteria by utilizing rough numbers that decreases the subjectivity and vulnerability in complex dynamic problems. Recently it has been observed that a considerable number of studies in the existing literature on Multi-Criteria Decision Making (MCDM) techniques and rough set numbers have employed R-SWARA for analysis (Vasiljević et al. 2018; Sremac et al. 2018; Stefanović et al. 2019; Ulutas 2020). As compared to other popular MCDM techniques such as Analytic Hierarchy Process, Analytic Network Process, Best Worst Method etc, R-SWARA is a simple and less tedious method employed for capturing domain experts' information and judgment rating for determining the relative importance weights of the CSFs (Zolfani, Yazdani, and Zavadskas 2018). R-SWARA method offers following advantages: Firstly, it requires less numbers of pair-wise comparisons among factors when contrasted with other MCDM methods. Secondly, SWARA method is the likelihood to estimate experts or vested group opinion on importance ratio of the criteria's in the process of weight assessment (Karabasevic et al. 2016). Furthermore, this method has turned out to be a user-friendly procedure for evaluating the priority weights of criteria's finalised for making decision (Zolfani, Yazdani, and Zavadskas 2018)."

The R-SWARA comprises of various steps as referenced by Zavadskas et al. (2018).

- *Step 1:* Define a set of CSFs that participate or strive for the decision-making process.
- *Step 2:* Establish a team of "k" experts who will rate the attribute as indicated by their relative significance, from the highly significant to the least considerable CSFs. Subsequently, "Sj" is determined in such a way, beginning with the second criterion, that we can pick how imperative criterion C1 is contrasted with basis C1-n.
- *Step 3:* In this progression, every individual response of each expert (K1, K2 ……. Kn) is converted into the rough matrix (Cj) using equations (1) – (6) mentioned by Zavadskas et al., (2018).

$$RN\left(C_j\right) = \left[C_{j,}^{L}\ C_j^U\right]_{1x\,m} \tag{7}$$

- *Step 4:* In this step, normalisation can be done of matrix $RN\left(C_j\right)$ in order to determine the matrix $RN\left(S_j\right)$ by using equation (8).

$$RN\left(S_j\right) = \left[S_j^L, S_j^U\right]_{1xm} \tag{8}$$

By using equation (9), we can determine the elements of matrix $RN\left(S_j\right)$.

$$RN\left(S_j\right) = \frac{\left[C_{j,}^{L}\ C_j^U\right]}{\max_r\left[C_{r,}^{L}\ C_r^U\right]} \tag{9}$$

The first element of matrix $RN\left(S_j\right)$, i.e., $\left[S_j^L, S_j^U\right]$ =[1.00, 1.00], because $j = 1$. For other elements $j > 1$, the equation (9) can be calculated using equation (10):

$$RN\left(S_j\right) = \left[\frac{C_j^L}{\max C_r^L}; \frac{C_j^U}{\max C_r^U}\right]_{1xm} \quad j = 2,3,\ldots,m \tag{10}$$

- *Step 5:* In this step, calculate the matrix $RN\left(K_j\right)$ by using equation (11)- (12).

$$RN\left(K_j\right) = \left[K_j^L, K_j^U\right]_{1xm} \tag{11}$$
$$RN\left(K_j\right) = \left[S_j^L+1, S_j^U + 1\right]_{1xm} \qquad j = 2,3, \ldots, m \tag{12}$$

- *Step 6:* In this step, re-calculated matric $RN\left(Q_j\right)$ can be obtained by using equation (13) – (14).

$$RN\left(Q_j\right) = \left[q_j^L, q_j^U\right]_{1xm} \tag{13}$$
$$RN\left(Q_j\right)\left[q_j^L = \begin{cases} 1.00\, j = 1 \\ \dfrac{q_{j-1}^L}{K_J^L} \quad j > 1 \end{cases}; q_j^U = \begin{matrix} 1.00\, j = 1 \\ \dfrac{q_{j-1}^U}{K_J^U} \quad j > 1 \end{matrix}\right] \tag{14}$$

- *Step 7:* Finally, relative importance weights matrix $RN\left(W_j\right)$ are calculated by using equation (15).

$$RN\left(W_j\right) = \left[w_j^L, w_j^U\right] = \left[\frac{\left[q_j^L, q_j^U\right]}{\sum_{j=1}^{m}\left[q_j^L, q_j^U\right]}\right] \tag{15}$$

4. Application of Case study

This study used a case study methodology to obtain an in-depth knowledge of artificial adoption critical success factors in the Indian food supply chain. A company “XYZ” is considered a case company that is further used for the study as recognised as one of the largest public food supply and distribution businesses. The case company was first established in 1986 and now has a distribution in neighbouring countries like Nepal, Bhutan, Sri Lanka, and so on. A recent report by Niti Aayog (2018) on national strategy for AI highlighted that among the various recommendations towards the implementation of AI in the Indian supply chain, the major ones include forming of large foundational annotated data set to democratise data across the value chain. One of the essential parts of our aspiration of AI for all incorporates responsible AI: ensuring satisfactory protection, security, and IP based concerns and offsetting moral contemplations with the requirement for technological innovation.

In view of the above national strategy for AI adoption and digital India initiatives by GOI (Government of India), Case company “XYZ” wishes to serve as a serious cutting-edge technology platform and is ready to switch from offline processing to AI-based operational processing of data as they are forwarding to increase their business flexibility and cut the high cost involved in the hardware system. The company “XYZ” has a certain understanding of the advantages of the AI adoption that helps to upgrade the technological competitive focal point; however, it is still looking for a systemic way to evaluate the potential benefits and risks. Due to the scarcity of the information to conduct research on AI adoption, the case company “XYZ” has sought some researchers to develop a proposed solution framework to utilise for the adoption. The researchers exhibit how the case company effectively utilised the proposed framework to investigate the defined CSFs influencing its intention to adopt AI in FSC businesses.

In order to collect data, a team of fifteen key domain experts was constructed for decision making panel includes four senior general managers, four supply chain managers, three logistics managers, three information and technology officers, and one company financial officer having more than 10 years of domain expertise. Table 2 below presents the profile of the experts. After various rounds of deliberation with experts, the finalised list of 21 CSFs of AI adoption in FSC has been arranged into four significant primary measurements based on the TOEH framework. These are, to be specific: Technological, Organisational, Environmental, and Human measurement. At last, the major dimension CSFs and sub-CSFs are arranged with an exact depiction and introduced in Table 1.

Table 2. Experts/Respondent Profile Information

Expert	Job Profile	Domain Experience (in years)
Expert 1	Senior Level Supply Chain Manager	14
Expert 2	Senior Technology Support Manager	13
Expert 3	Senior Level Supply Chain Manager	15
Expert 4	Logistics Manager	15
Expert 5	Senior Level Supply Chain Manager	13
Expert 6	Deputy Manager IT	12
Expert 7	Senior Logistics Manager	12
Expert 8	General Manager Strategy	13
Expert 9	General Manager Strategy	15
Expert 10	Deputy Manager IT	10
Expert 11	Middle Level Logistics Manager	11
Expert 12	Senior Financial Manager	13
Expert 13	General Manager Strategy	15
Expert 14	Senior Level Supply Chain Manager	12
Expert 15	General Manager Strategy	15

4.1 Computational Analysis of CSFs of AI Adoption and Use in FSC

In this phase of the study, the novel Rough-SWARA strategy was utilised to examine the experts' ratings to decide the relative weight and positioning of primary measurement CSFs and sub-measurement CSFs of AI adoption in FSC. The experts' judgment rating was gathered by methods for poll overview and administrated with the assistance of the recommended lattice given by Yazdani, Gonzalez, and Chatterjee (2019). In this examination, each experts were asked to figure out the most significant and least significant CSFs for the main category and the sub-dimension category. The preference rating of experts is presented in Table 3 below.

Table 3. Experts' Rating for Main Dimension CSFs of AI Adoption and Use in FSC

Main CSFs	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13	E14	E15
TEC	1	1	2	1	1	2	1	2	1	1	2	1	1	2	1
ORG	4	3	4	2	4	4	4	4	3	4	4	3	4	4	3
INT	2	2	1	3	2	1	2	1	2	3	1	2	2	1	2
HUM	3	4	3	4	3	3	3	3	4	2	3	4	3	3	4

Based on experts' assessment, ten out of fifteen experts recognised that the technological (TEC) factors stand the most significant CSF among other primary measurement CSFs of AI adoption in FSC. The external environmental or institutional factors were perceived as the most significant CSF by five experts. The organisational factors (ORG) were perceived as least significant by ten experts, while the human factor (HUM) checked five times as the least significant CSF in the fundamental measurement class. In the subsequent stage, all the individual responses were converted into rough matrix RN (Cj) based on the above rating by utilising condition (7) and introduced in Table 4.

$\widetilde{\mathrm{TEC}} = \{1,1,2,1,1,2,1,2,11,2,11,2,1\}$
$\underline{Lim}\ (1) = 1$
$\overline{Lim}\ (1) = 1.333$
$\underline{Lim}\ (2) = 1.333$
$\overline{Lim}\ (2) = 2$
$TEC^L = 1.110$
$TEC^U = 1.555$
$\widetilde{\mathrm{ORG}} = \{4,3,4,2,4,4,4,4,3,4,4,3,4,4,3\}$
$\underline{Lim}\ (2) = 2$
$\overline{Lim}\ (2) = 3.600$
$\underline{Lim}\ (3) = 2.800$
$\overline{Lim}\ (3) = 3.714$
$\underline{Lim}\ (4) = 3.600$
$\overline{Lim}\ (4) = 4$
$ORG^L = 3.280$
$ORG^L = 3.897$
$\widetilde{\mathrm{ENV}} = \{2,2,1,3,2,1,2,1,2,3,1,2,2,1,2\}$
$\underline{Lim}\ (1) = 1$
$\overline{Lim}\ (1) = 1.800$
$\underline{Lim}\ (2) = 1.615$
$\overline{Lim}\ (2) = 2.200$
$\underline{Lim}\ (3) = 1.800$
$\overline{Lim}\ (3) = 3$
$ENV^L = 1.435$
$ENV^U = 2.173$
$\widetilde{\mathrm{HUM}} = \{3,4,3,4,3,3,3,3,4,2,3,4,3,3,4\}$
$\underline{Lim}\ (2) = 2$
$\overline{Lim}\ (2) = 3.267$
$\underline{Lim}\ (3) = 2.900$
$\overline{Lim}\ (3) = 3.357$
$\underline{Lim}\ (4) = 3.267$

$\overline{Lim}\ (4) = 4$
$HUM^L = 2.962$
$HUM^U = 3.565$

Table 4. Rough Group Matrix $RN\ (C_j)$ of Major Dimension CSFs

$RN\ (C_{TEC})$	[1.110, 1.555]
$RN\ (C_{ENV})$	[1.435, 2.173]
$RN\ (C_{HUM})$	[2.962, 3.565]
$RN\ (C_{ORG})$	[3.280, 3.897]

Afterwards, the value of normalised rough group matrix $RN\ (S_j)$ was obtained by employing equations (8) and (9). Further, least significant CSF namely organisational (ORG) has the maximum value as per the value derived from the rough group matrix, whereas most technological CSFs (TEC) were denoted by one, while other CSFs of the $RN\ (C_j)$ matrix divided them by the maximum value i.e. $RN\ (C_{ORG})$ = [3.280, 3.897] (see Table 5).

Table 5. Rough Matrix $RN\ (S_j)$ of Major Dimension CSFs

$RN\ (S_{TEC})$	[1.000, 1.000]
$RN\ (S_{ENV})$	[0.368, 0.663]
$RN\ (S_{HUM})$	[0.760, 1.087]
$RN\ (S_{ORG})$	[0.842, 1.188]

Afterwards, the normalised rough group matrix $RN\ (S_j)$ should be added by one except the value of (S_{TEC}) by using equation (12). The obtained matrix $RN\ (K_j)$ is presented in Table 6.

Table 6. Rough Matrix $RN\ (K_j)$ of Major Dimensions CSFs

$RN\ (K_{TEC})$	[1.000, 1.000]
$RN\ (K_{ENV})$	[1.368, 1.663]
$RN\ (K_{HUM})$	[1.760, 2.087]
$RN\ (K_{ORG})$	[1.842, 2.188]

In this step, the values of matrix $RN\ (K_j)$ are re-evaluated by applying equation (14) that define "j – 1" represents the previous attribute in relation to j in order to obtain the value of matrix $RN\ (Q_j)$ as depicted in Table 7.

Table 7. Rough Matrix $RN\ (Q_j)$ of Major Dimensions CSFs

$RN\ (Q_{TEC})$	[1.000, 1.000]
$RN\ (Q_{ENV})$	[0.601, 0.731]
$RN\ (Q_{HUM})$	[0.288, 0.415]
$RN\ (Q_{ORG})$	[0.132, 0.225]

Lastly, the relative weights and final ranking of main dimension CSFs of AI adoption in FSC were determined by employing equation (15) as shown in Table 8. The calculation of matrix $RN\ (W_j)$ is presented below.

Table 8. Weights and Ranking of Main Dimension CSFs of AI Adoption in FSC

Main CSF	Weights		Crisp	Rank
	Min	*Max*		
TEC	0.422	0.495	0.458	1
ORG	0.056	0.112	0.084	4
ENV	0.254	0.362	0.308	2
HUM	0.122	0.205	0.163	3

Similarly, the same procedure was followed for the sub-dimension CSFs category and experts were requested to rate the most significant and least significant sub-dimension CSFs among them. Finally, the global weight or global ranking of all the main dimensions and sub-dimension CSFs of AI adoption in FSC was calculated by using the rating of all the experts with the application of above calculations (presented in Table 9).

Table 9. Global Weights and Rankings of CSFs of AI Adoption and Use in FSC

Main CSF	Weights	Sub-CSF	Weights	Global Weights	Global Ranking
Technological (TEC)	0.458	TEC_1	0.405	0.186	1
		TEC_2	0.169	0.077	5
		TEC_3	0.051	0.023	14
		TEC_4	0.102	0.047	8
		TEC_5	0.277	0.127	2
Organisational (ORG)	0.084	ORG_1	0.387	0.032	10
		ORG_2	0.290	0.024	13
		ORG_3	0.029	0.002	21
		ORG_4	0.169	0.014	17
		ORG_5	0.099	0.008	18
		ORG_6	0.055	0.005	20
Environmental (ENV)	0.308	ENV_1	0.189	0.058	7
		ENV_2	0.279	0.086	4
		ENV_3	0.051	0.016	16
		ENV_4	0.389	0.120	3
		ENV_5	0.100	0.031	11
Human (HUM)	0.163	HUM_1	0.185	0.030	12
		HUM_2	0.098	0.016	15
		HUM_3	0.050	0.008	19
		HUM_4	0.278	0.045	9
		HUM_5	0.400	0.065	6

5. Discussions

This study employed a TOEH framework to evaluate the critical success factors that contribute to the successful adoption of artificial intelligence in the FSC in the context of emerging economies. Initially, the finalised CSFs of AI adoption were categorised into four major dimensions: technological, organisational, environmental and human factors. In this section, the findings of the present study were clubbed using these major dimensions of AI adoption in FSC.

Technological (TEC) critical success factors ranked top among the other major dimension CSFs of AI adoption in FSC as presented in Table 8. Within the technological CSFs category, sub-dimensions CSFs are ranked in an order as follows: technology readiness (TEC1) > sufficient privacy and security (TEC5) > relative advantage/perceived benefit (TEC2) > compatible facilities for testing and transability of AI technology (TEC4) > data complexity (TEC3). According to the analysis, technology readiness (TEC1) holds the top position among other technological CSFs. Gangwar, Date, and Ramaswamy (2015) suggested that technological readiness such as the availability of skilled human resource and a well-established infrastructure are key for the successful integration of an AI adoption. Sufficient privacy and security (TEC5) hold the second position among the technological sub-dimension CSFs. For the successful adoption of AI technology in FSC, the service providers need to ensure the adequate security and confidentiality for data protection and data access, so that the information and data cannot be used for unauthorised purposes by service providers (Gangwar, Date, and Ramaswamy 2015; Sun et al. 2018;). The third important sub-dimension CSF is perceived benefit (TEC2) which plays a vital role for AI adoption. Yadegaridehkordi et al. (2018) supported the fact that raising cognizance on the benefits and advantages of big data and AI technologies will help to build a sustainable environment of usefulness among the supply chain firms which will lead to a high rate of AI adoption. Transability and testing (TEC4) of AI technologies enable decision makers to consider and explore the latest technological innovations while carrying out the AI adoption decision process (Verma and Bhattacharyya 2017).

Environmental or Institutional (ENV) factors stand second in the major dimension CSFs of AI adoption in FSC. Within the environmental or institutional CSFs category, sub-dimensions CSFs are ranked in an order as follows: peer/competitive pressure (ENV4) > regulatory and compliance requirement (ENV2) > demand volatility of food supply chain services (ENV1) > institutional based trust (ENV5) > ethics in data collection (ENV3). According to the global ranking in Table 9, peer and competitive pressure obtained the highest rank in this study. Peer and competitive pressure (ENV4) are highly important for the Indian FSC industry as this can promote the use of cutting-edge technologies such as internet of things (IoTs), AI, machine learning (ML), and block-chain technology (BT) to achieve the objective of an agile and resilient FSC channel (Affia, Yani, and Aamer 2019). Due to this peer and competitive pressure, supply chain industries may always mimic the tactics of other firms in order to prove to their rivals their ability (Verma and Bhattacharyya 2017).

This in line with the popular institutional theory that an organisation, in its operational decisions, would mimic other similar firms' operations (Nilashi et al. 2016). Regulatory and compliance required (ENV2) ranked second among the environmental or institutional sub-dimension priority list. Generally, FSC companies have limited access and control over the regulatory compliance framework issued by federal agencies. Henceforth, the existence of well-suited regulations and sufficient monetary funding can endorse the use of AI technologies in the supply chain (Hasibuan and Dantes 2012; Alreemy et al. 2016). This is due to the fact that government regulators can foist pressure on firms to adopt new technologies in their supply chain operation. Afterwards, demand volatility of supply chain (ENV1) was recognised as one of the key CSFs in the environmental or institutional sub-dimension category. To avoid the uncertainty and volatility of the market demand of the food supply, firms must adopt innovative technologies to demonstrate the high level of agility as a result of unpredictable fluctuations in demand (Purvis et al. 2016; Abolghasemi et al. 2020).

Human (HUM) factors hold the third position among the major dimension for vital success factors of AI adoption in the FSC. Within the human success factor category, customer satisfaction (HUM5) achieved the highest rank in the human factors sub-dimension list. A study by Nguyen (2013) suggested that organisations need to pay more attention towards customer satisfaction. Customer satisfaction can be achieved by reaping the benefits of an AI technologies integration in the supply chain i.e. error reduction, better traceability, better demand forecast, delivery cycle improvement, etc., (Kamble, Gunasekaran, and Arha 2019). Secondly, information sharing and communication among the FSC partners (HUM4) is complicated due to the involvement of multi-actors in the entire supply chain. Therefore, it needs a proper information sharing between the FSC partners providing comprehended information to fulfil customers' demand (Govindan 2018). Next, as AI technology is a complex knowledge-based system, an organisation should provide proper training to their employees and end-users (HUM1) prior to the implementation of the AI system in their operation and supply chain activities (Duan et al. 2017). Consequently, AI adoption helps to reduce the anxiety of the stakeholders and offers a clear understanding and motivation of the benefits and threats (Gangwar, Date, and Ramaswamy 2015). Finally, post implementation job security of employees (HUM3) ranked last in the AI adoption process in the food supply chain.

Organisational (ORG) success factors received the least priority among the major dimension CSFs of AI adoption in the FSC. The key critical success factor within an organisational dimension is the clear linkage between vision and strategy (ORG1). Saberi et al. (2019) suggested that if supply chain firms wish for a resilient and efficient supply chain, they need to integrate AI and information technologies across the supply chain network, so as to maintain the leverage between vision and mission of the organisation. Top management support and commitment (ORG2) ranked second among another human factor category. A study by Yang et al. (2015) acknowledged that top management support has strong relationship with technology adoption and commitment is highly required for developing strategies and steering the latest emerging technologies. Managers must have evaluated the infrastructure and support environment necessary for AI adoption in supply chain activities (Yang et al. 2015; Duan et al. 2017; Saberi et al. 2019). Next, sufficient resources and IT competencies (ORG4) are positively related to AI adoption in FSC (Alreemy et al. 2016). AI provider commitment and support (ORG5) proved as a key success factor for the adoption of AI technologies in the food supply chain. AI technologies providers offer their customers functions that range from the installation of services to maintenance. Supply chain firms using AI technologies services therefore do not need multiple experts to maintain and update the infrastructure. If any supply chain firm encounter problems, they can contact the AI provider's company and ask them to fix the issue (Sun et al. 2018; Hentschel, Leyh, and Baumhauer 2019).

5.1 Sensitivity Analysis

In this study, utilising rough-SWARA, technological factor (TEC) is positioned as the most significant amongst all the main dimension CSFs category. In this manner, the relative importance weight of technological CSFs is altered with the incremental addition of 0.1 from run 1 to 9 (Kumar and Dixit 2019). Accordingly, the changes have to be made for other main dimensions CSFs simultaneously. The relative importance weights of all other main dimension CSFs using sensitivity investigation are presented in Table 10. Due to the incremental addition in relative weights of main dimensions CSFs, the relative importance weight and rankings of sub-dimension CSFs, are likewise changed. At the point when the technological factor (TEC) is assigned the change in weight from run 4 to run 9, (TEC1) shows dominance in the sensitivity analysis. Similarly, when the weight is altered from run 6 to run 9, (TEC5) has the subsequent position, followed by (TEC2) holds the third position. During the variety of the weight changes from run 1 to run 9, (ORG3) contains the last place, and presented in figure 2. Thus, it tends to be presumed that technological CSFs should be at prime focus in stakeholders' decision-making process while designing the short-run strategies for adopting AI technologies in the FSC. Thus, the study outcomes are robust to expert assessment and can be used for decision-making.

Table 10. Sensitivity Analysis of Main Dimension CSFs of AI Adoption and Use

Main CSF	Normalised value	Run 1 0.1	Run 2 0.2	Run 3 0.3	Run 4 0.4	Run 5 0.5	Run 6 0.6	Run 7 0.7	Run 8 0.8	Run 9 0.9
TEC	0.458	0.100	0.200	0.300	0.400	0.500	0.600	0.700	0.800	0.900
ORG	0.084	0.137	0.122	0.107	0.092	0.077	0.062	0.047	0.032	0.017
ENV	0.308	0.506	0.451	0.395	0.340	0.284	0.229	0.173	0.118	0.063
HUM	0.163	0.269	0.240	0.210	0.181	0.151	0.122	0.092	0.063	0.033
Total	1	1	1	1	1	1	1	1	1	1

Finally, Table 11 depicted the rankings of sub-dimension CSFs utilising sensitivity analysis in the study.

Table 11. Represent the Changes in Ranking Using Sensitivity Analysis

Sub-CSFs	Run 1 0.1	Run 2 0.2	Run 3 0.3	Run 4 0.4	Normalised Value (0.458)	Run 5 0.5	Run 6 0.6	Run 7 0.7	Run 8 0.8	Run 9 0.9
TEC1	9	5	2	1	1	1	1	1	1	1
TEC2	15	12	8	6	5	4	3	3	3	3
TEC3	20	19	17	14	14	13	10	8	6	5
TEC4	18	16	13	9	8	8	6	4	4	4
TEC5	11	7	5	3	2	2	2	2	2	2
ORG1	6	8	9	10	10	10	11	11	11	11
ORG2	10	11	12	13	13	14	14	14	14	14
ORG3	21	21	21	21	21	21	21	21	21	21
ORG4	14	15	16	17	17	17	17	17	17	17
ORG5	16	17	18	18	18	18	18	18	18	18
ORG6	19	20	20	20	20	20	20	20	20	20
ENV1	4	4	6	7	7	7	8	9	9	9
ENV2	2	2	3	4	4	5	5	6	7	7
ENV3	13	14	15	16	16	16	16	16	16	16
ENV4	1	1	1	2	3	3	4	5	5	6
ENV5	7	9	10	11	11	11	12	12	12	12
HUM1	8	10	11	12	12	12	13	13	13	13
HUM2	12	13	14	15	15	15	15	15	15	15
HUM3	17	18	19	19	19	19	19	19	19	19
HUM4	5	6	7	8	9	9	9	10	10	10
HUM5	3	3	4	5	6	6	7	7	8	8

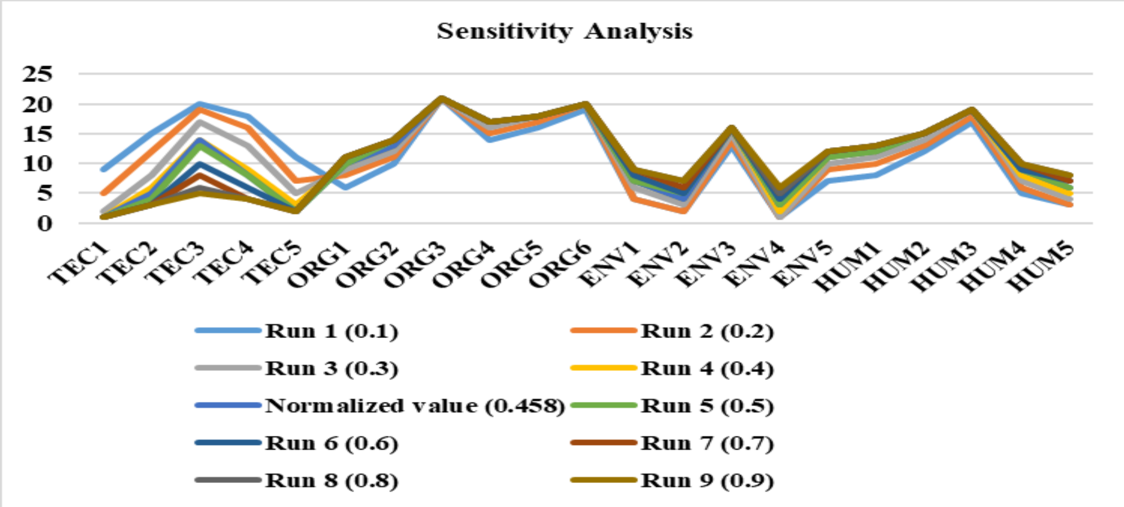

Figure 3. Represents the Overall Variation in the Sensitivity Analysis

6. Study Contributions

The present study provides novel contributions in terms of theoretical and practical implications which are discussed in subsequent subsections.

6.1 Theoretical Implications

In the previous literature, various authors highlighted the motivators/drivers/CSFs/enablers that influence the technology adoption in service industries such as AI technologies, machine learning, block chain technology, cloud computing adoption (Queiroz and Wamba 2019; Pillai and Sivathanu 2020) but very few authors reported the same in the context of the FSC. This study offers several theoretical implications to bridge the existing gaps in the literature, for instance:

- This research is an early attempt to contribute to the CSF theory by divulging that an organisational integration of AI technologies is determined by success factors, which help organisations in achieving sustainable FSC, which can lead to firm competitive advantages.
- This study proposes a conceptual framework by integrating the TOE and HOT theoretical viewpoints to validate the CSFs of AI adoption in FSC. The adoption of AI technologies for an efficient FSC is affected by the TOEH perspective (Technology, Organisation, Environment, and Human). Due to this competitive environment and intense rivalry among supply chain firms because of client satisfaction and government supportable prerequisites, there is a need to incorporate the TOEH framework to investigate their relative significance of CSFs of AI adoption in the FSC. At last, a theoretical lens on the TOEH framework and the result outcomes of the study in an emerging economies context is expected to contribute to and enrich the ever-growing literature on AI-SCM by knowing the contextual diversity of technology adoption models.
- Our research compliments the literature Yadav et al. (2020) that adoption of disruptive technologies like AI, blockchain and machine learning can contribute to achieve resilience and agility to Indian agro-food supply chain industries.
- However, it is essential to call attention to that while a few success factors, (for example, technical readiness, sufficient security and privacy, competitive pressure, regulatory and compliance requirement and perceived benefit) we recognised are conventional and noticeable from other technological development receptions, most of

the elements got from our studies are exceptional to AI adoption. Thusly, the present study serves as a foundation for future exploration to additionally approve or potentially grow the variables we have identified in other operation and supply chain settings.
- Finally, as a methodological application, this study is an initial effort to use novel Rough-SWARA method to analyse the CSFs to facilitate the AI adoption in the Indian FSC context.

6.2. Managerial Implications

The study highlights various implications for practitioners and supply chain managers that are directly involved in the technology deployment in FSC. They are discussed as follows:

- Since disruptive technologies like AI, Block-chain technology, machine learning are a relatively new concept for supply chain companies, the finding of the present study provide initial guidance regarding the critical success factors to be kept in mind while incorporating AI technologies into the FSC.
- The present study provides fruitful insights for managers of food supply chain companies in emerging economies like India, Bangladesh, and Sri Lanka. Practitioners and managers can use a comprehensive framework, which includes an exhaustive list of CSFs related to the AI adoption in the FSC.
- This research assists organisational managers, decision-makers, and policymakers in developing successful strategies and policies for the deployment of AI technology. The time-frame required, the infrastructure needed, and the need for knowledge and training services for effective adoption may also be examined. Based on the findings of the present work, it is suggested that technical readiness, sufficient security and privacy, competitive pressure, regulatory and compliance requirement and perceived benefit can foster the adoption of AI in Indian FSC industries. The research findings in line with Gangwar, Date, and Ramaswamy (2015) regarded that technological readiness such as the availability of skilled human resource and a well-established infrastructure are key to adoption of artificial intelligence technologies. In addition, Yadegaridehkordi et al. (2018) also supports the important role that 'sufficient security and privacy' plays in facilitating the actualisation of AI technologies in FSC.
- The FSC firms can utilise AI technologies to improve the operational efficiencies by providing real-time tracking information to minimise various challenges during shipments.
- Finally, the finding of the study enables the role of the AI technology service providers to ensure the food supply chain firms that their business data is safe, secure and is accessible at any point of time. They must establish dependability, confidence, faith, and trust in their services to FSCs. FSC may be given the opportunity or a trial period to try out AI technologies before they are fully implemented.

7. Conclusion

This work is an underlying endeavor to investigate the AI adoption and use for business organisations in the FSC. The study tries to identify the CSFs of AI adoption and use with the help of a literature review. We finalised twenty-one CSFs after various deliberations with domain experts. This study employed a TOEH framework for technological innovation diffusion that is pertinent to the setting of the Indian FSC industry to successfully integrate the AI technologies in their operation and supply activities. Besides, the finding of this investigation demonstrates that the reconciliation of AI technologies in the Indian FSC context is still in the nascent phase, which signifies the slow rate of integrating AI technologies in supply chain activities. Furthermore, a novel Rough-SWARA technique was employed to determine the relative importance weight and priority ranking of the CSFs for AI adoption in the FSC. The findings of the study indicate that technology readiness, sufficient privacy and security, customer satisfaction, perceived benefits, demand volatility, regulatory compliance, competitor pressure and information sharing among partners are assessed to be profoundly influential success factors in AI adoption particularly in the FSC context. The findings of this research will guide policy makers, strategy managers and professionals in obtaining deeper insights into the integration of AI technologies for effective and resilient FSC operations.

7.1 Research Limitations and Recommendations

Like any other study, this study also has its limitations.

- First, it considers inputs from a small group of industry experts, thereby challenging the generalisation of the results.
- Second, as AI still is in the nascent stage and is presently undergoing rapid transformation, this study may not have utilised the full advantage of the emerging technology.
- Third, this study employed an extended TOEH framework that added the human factors dimension to examine the AI adoption in the FSC; there are certain critical success factors that might have been omitted.

Future studies could analyse other technology innovations such as machine learning adoption, cloud computing adoption, and block chain technology adoption in different industry sectors by employing various quantitative and qualitative approaches. Further studies may consider cross- country or among emerging economies that are more technically advance. Since the study is done in an Indian context it may not be able to adequately capture the challenges facing other developing economies as these nations may differ in terms of factors such as culture, support from the government etc.

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