Singh, RK, Modgil, S and Shore, A

Building artificial intelligence enabled resilient supply chain: a multi-method approach

Building Artificial Intelligence Enabled Resilient Supply Chain: A Multi-Method Approach

Journal:	*Journal of Enterprise Information Management*
Manuscript ID	JEIM-09-2022-0326.R3
Manuscript Type:	Research Article
Keywords:	Artificial intelligence, Transparency, Procurement Strategy, Personalized Solution, Last mile Delivery, supply chain resilience

Building Artificial Intelligence Enabled Resilient Supply Chain: A Multi-Method Approach

Abstract

Purpose: In the uncertain business environment, the supply chains are under pressure to balance routine operations and prepare for adverse events. Consequently, this research investigates how artificial intelligence is used to enable resilience among supply chains.

Research design: This study first analyzed the relationship among different characteristics of AI-enabled supply chain and how these elements take it towards resilience by collecting the responses from 27 supply chain professionals. Furthermore, to validate the results, an empirical analysis is conducted where the responses from 231 supply chain professionals are collected.

Findings: Findings indicate that the disruption impact of an event depends on the degree of transparency kept and provided to all supply chain partners. This is further validated through empirical study, where the impact of transparency facilitates the mass customization of the procurement strategy to last-mile delivery to reduce the impact of disruption. Hence, AI facilitates resilience in the supply chain.

Originality/value:

This study adds to the domain of supply chain and information systems management by identifying the driving and dependent elements that AI facilitates and further validating the findings and structure of the elements through empirical analysis. The research also provides meaningful implications for theory and practice.

Keywords: Artificial intelligence; Transparency; Procurement Strategy; Personalized Solution; Last mile Delivery; Reduced impact of disruption; supply chain resilience

1. Introduction

The recent pandemic has caused restrictions on the movement of vehicles and impacted the total effectiveness of the supply chain network. As a result, the concept of supply chain resilience is drawing the attention of researchers and practitioners. Organizations need to secure and strengthen their market position. This requires sincere efforts to bring resilience to the supply chain system to avoid any disruption in a situation like Covid-19 (Dubey et al. 2022; Gartner 2020). Apart from the pandemic, rapid globalization, and ever-changing customer needs, the entry of new entrants has increased the turbulence and volatility of the business environment. This increase in volatility has created more pressure on organizations to manage and efficiently control their supply chain.

The manufacturing sector is highly impacted due to disruption caused for a variety of reasons. According to a Fortune Magazine report published in early 2020, out of 1000 Fortune firms, 94 per cent of firms encountered disruptions in supply chains due to the pandemic. According to WHO reports, there were 1438 disclosed epidemics between 2011 and 2018 (Madhavi et al., 2021). End-to-end visibility is a challenge in international supply chains. For example, the auto industry is affected by a shortage of semiconductor chips, produced, in the main, by Taiwanese companies. Consequently, the car industry alone might face a revenue loss of $61 billion in 2021 (Forbes, 2021). Scholars and practitioners are growing more interested in the concept of resilience, particularly as it relates to the supply chain, as a result of the consequences of the previous pandemic on vehicle restrictions and the supply chain network's general performance. It is evident that supply chains become most vulnerable and most impacted during disruptions. There are many challenges organizations face while managing supply chains. Challenges include variability in demand, for example, retail supply chains have been disrupted uniquely, with high demand for necessities and low demand for luxury items, further challenging the operating margins and traditional retail supply chain models. Inventory variability (Kumar et al. 2020), optimisation of route problem (Suleman et al. 2019), and material availability are some of the challenges supply chain usually face. Outsourcing of material is impacted largely because of logistics restrictions and no cross-border trade during the pandemic; forecasting is inaccurate due to a change in demand pattern; unavailability of labour impacted the manufacturing industry at large (ILO, 2022). Other challenges faced by organizations during a pandemic include supply shortages, demand rise for certain products, demand and supply gaps, and reduction in productivity due to a variety of reasons (Modgil et al., 2021b).

During these difficult times, it is imperative for organizations to restore predictability and sense the demand pattern to reduce the disruption impact. According to the McKinsey report (2018), a long disruption in the supply chain can erase half of the earnings of an organization. The report suggested structural reforms in the supply chain to make it shock-free. According to the Gartner report (2020), resilient supply chains are more shock-free and it provides a six-point strategy to deal with any disruption risk, including inventory buffers, manufacturing diversification, multi-sourcing, near sourcing, plant harmonization, and ecosystem partnerships.

Redesign and reshaping of supply chains are essential and characterized by both resilience and responsibility. Businesses can better handle unpredictability and interruptions when their supply chains are resilient (Ambulkar et al., 2015). It permits firms to make structural changes by amending the supply chain strategies, technology used, or products to deal with the unanticipated changes in demand and supply without having much impact on cost and quality (Hussain et al., 2022; de Lima, 2018.)

Firms need to have a holistic approach and must build flexible and resilient capabilities to manage their supply chains. The capabilities can be built by leveraging available digital technologies (Li et al., 2022; Annarelli et al. 2021, Cetindamar and Abedin, 2021; Ivanov et al. 2021; Matrani et al., 2013) like machine learning or artificial intelligence (AI) (Mikalef & Gupta 2021; Queiroz, and Fosso Wamba, 2021). Resilient capabilities in the supply chain systems can be instilled and further strengthened using AI (Bawack et al., 2021; Dwivedi et al., 2019). AI is useful in bringing in end-to-end visibility and predicting the right forecast (Modgil et al., 2021a). AI can identify the problems associated with the supply chain and its vulnerable linkages, and provide the right solution (Wambe and Akter, 2019).

To make their supply chain networks more agile, supply chain managers must use scenario planning to adjust an ideal base plan for inescapable variables. Advance planning is essential for scenarios of unexpected occurrences such as a labour strike, increased fuel prices, or the temporary closure of a shipping port. This kind of responsive supply chain can be created by an intelligent AI-driven system that can analytically determine the corresponding causes and consequences of a particular occurrence along with its influence and suggest corrective methods to counter it. AI can identify the problems associated with the supply chain, and its vulnerable linkages and provide the right solution (Wamba and Akter, 2019). Studies have discussed how transparency helps in developing a sustainable commodity of supply chains (Gardner et al., 2019; Islam et al., 2020). Another study by Astill et al., (2019) reviewed the enabling technologies' role in transparency. However, most of the studies are silent on exploring how a resilient supply chain can be developed and how different aspects of a resilient and AI-driven supply chain are related. Hence, this study proposes the research question: *How are the key characteristics of an AI-enabled resilient supply chain related to each other?* To answer this research question, this study adopted a multi-method approach. First, a TISM approach is incorporated to identify the relationship between different aspects of a resilient supply chain. Second, the study adopted an empirical approach to further test and verify the relationship that emerged from the TISM. This study contributes to unveiling the relationship structure among the factors that contribute to minimum disruption and that lead to AI-enabled intelligent and resilient supply chains.

The supply chain resilience that AI can enable is evident from the above. To answer the question posed, the study seeks to provide a comprehensive framework to strengthen supply chains' resilience by identifying the various aspects of AI-enabled supply chain resilience and empirically testing the framework. The remaining portions of the paper are organized as follows: section 2 discusses the underpinning elements, whereas section 3 discusses factors. Section 4 indicate the research design. Section 5 provides the detailed analysis. Section 6 present findings and discussion. The final section concludes the study along with future scope.

2. Underpinning elements

2.1 Artificial Intelligence

AI is an emerging technology and a branch of computer science (Gupta et al. 2021) that is designed to think and act like humans (Kazancoglu et al. 2022). Machines that can mimic human behaviour and demonstrate human cognitive abilities are referred to as having "artificial intelligence”. AI was developed by computer scientists John McCarthy along with Alan Turin (McCarthy et al., 2006). The gaining importance of AI is due to the capacity to manage and process plenty of data with decreased data management time and expense (Modgil et al. 2023; Dubey et al. 2022; Wamba, 2022; Dubey et al. 2019a, 2019b). AI is predicted to generate $3.9 trillion in revenue by 2022, up from $1.2 trillion in 2018, a 70 per cent increase from 2017 (Dhamija and Bag 2020; Richards et al., 2019). The complexity of processing the large volume of data and the usage of data for analytics and business understanding purposes has increased the attention for building and installing AI capabilities in firms (Modgil et al. 2020, Scholten et al., 2014).

Managing the supply network is a complex task that involves procurement of material, inventory management, manufacturing, warehousing, delivery, and distribution of goods (Kumar et al. 2021, Singh et al. 2020a, 2020b). There are numerous supply chain partners involved, complexity further increases with the increasing scale of production and adding more supply chain partners (Kumar et al. 2020). Supply chain managers face various challenges while managing supply chains, including accurate forecasting, the timely arrival of materials, hassle-free inventory management, ensuring complete visibility throughout the supply chain from beginning to end, and maintaining a delivery schedule (Modgil et al., 2021a; Dhamija and Bag 2020). AI enables firms to automate the processes which make accurate forecasting by rapidly sensing customer needs and expectations, optimizing the inventory, resource allocation, route optimization, and delivery of goods (Jabbour et al., 2020). By highlighting potential scenarios and how to respond to them, demand forecasting powered by AI has the potential to lower uncertainty while boosting competitive advantage. AI also brings visibility across the supply chain that helps in managing inventory levels, identifying the risk patterns that may disrupt the operations, and help in identifying the alternative routes for delivery. An AI-enabled supply chain can effectively use the data and analyze the cause and effect of a particular situation, additionally providing an effective solution for the same. Table A lists the key studies that combine artificial intelligence and the supply chain.

Table A- Key studies on Artificial Intelligence(AI) and Supply Chain Resilience (SCR)

1	Artificial intelligence in supply chain management: theory and applications	Min, H. (2010)
2	Mobilizing organizational performance through robotic and artificial intelligence awareness in mediating role of supply chain agility	Panichayakorn and Jermsittiparsert (2019),
3	Artificial intelligence for supply chain resilience: learning from Covid-19	Modgil et al. (2021a)
4	"The role of artificial intelligence in effective business operations during COVID-19",	Chen et al. (2022)
5	AI technologies and their impact on supply chain resilience during COVID-19	Modgil et al. (2021b)
6	Exploring the role of artificial intelligence in managing agricultural supply chain risk to counter the impacts of the COVID-19 pandemic	Nayal et al. (2022)

2.2 Supply Chain Resilience

A resilient supply chain is defined as the ability of a supply network to remain operational despite disturbances (Zhou et al. 2022; Ivanov 2020). According to Yu et al. (2019), firms' ability to adjust to new circumstances and successfully navigate supply network disruptions is referred to as "supply chain resilience". To maintain a competitive edge in business, firms have realized the need for contingency planning to deal with variability in demand and supply (Baz and Ruel, 2021; Singh et al. 2019; Singh and Acharya 2013). supply chain challenges, hazards, and disruptions are being addressed by building supply chain resilience (Zhou et al., 2022). Businesses have realized the importance of resilience due to disruption in the supply chain caused by a variety of factors ranging from natural disasters to man-made disasters (Shivajee et al. 2022; Modgil et al. 2021a; Wamba et al., 2020). Environmental changes disrupt the various nodes of a supply chain which can lead to various economic consequences for the firm (Zhu et al. 2022; Hendricks and Singhal 2005). To mitigate this, it is important to identify the nodes where interruption is likely to happen, resilience enables the system to identify the risks, enhance adaptability, and ability to quickly respond to the situation. Hence the application of AI became more important as at the macro level, AI makes environmental scanning and endurance in supply chains. (Baryannis et al., 2019).

3. Factors of AI enabled resilient supply chain

In this section five factors (Transparency; Personalized Solution, Procurement Strategy, Last mile delivery and Reduced impact of disruption) are discussed in detail.

3.1 Transparency (TR)

The importance of digitization to businesses in the logistics and supply chain management space is expanding (Herold et al., 2021). Massive amounts of data are produced by supply chain networks from constantly changing sources. These data can be used by AI to analyze trends that help to streamline the supply chain operation. Supply chains have a unique opportunity to raise levels of trust and transparency as a result of AI (Modgil et al., 2021a; Singh et al., 2022). An AI-powered supply chain provides end-to-end visibility, stakeholders may receive timely information about the demand patterns, forecasting, delivery schedule, production planning, and maintenance. Organizations may promote product excellence, shorten time to market, and create new goods and services by employing AI to increase supply chain transparency.

3.2 Personalized solution (PS)

Customization is key to success and remaining competitive in today's market. AI can gather data on customers' requirements by using its analytical capability to enable the supply chain to create personalized products to the specific need of the individual user. It can also sense the customer requirement which helps in making the error-free forecast. AI allows for the creation of personalized products in line with customer demands. Brands that tailor and consider client preferences often produce a higher return on investment and higher revenue than non-personalized brands (McKinsey, 2018).

3.3 Procurement strategy (PROC)

The procurement strategy plays a significant part in maintaining the robustness of the supply chain, the personalized solution requires a flexible procurement strategy, identifying alternative suppliers, keeping track of inventory, and minimization of supplier lead time a. Effective procurement strategy can bring down the overall supply chain and inventory cost and enhance optimal utilization of resources (Knudsen, 2003). Using intelligent computer algorithms, AI-enabled supply chains handle complicated challenges more quickly or successfully by providing solutions for spend analysis, contract management, and strategic sourcing

3.4 Last mile delivery (LMD)

The last stage of the supply chain is known as last-mile delivery (LMD), during which the delivery partner delivers the goods to the final consumer. (Aljohani and Thompson, 2020). AI enhances customer experiences by offering customized delivery solutions, flexible delivery dates, and using diverse delivery modes to reach the customer as per their requirements (Modgil et al., 2021b). Technology provides a solution to track the shipments using virtual chat boats, customer can ask their queries about the shipment, exact delivery date and time, and current status of their delivery. In a nutshell, digital communication improves the last-mile delivery customer experience and assists organizations to improve delivery planning.

3.5 Reduce disruption impact (RDI)

Supply chain disruptions are bound to happen due to a variety of controllable or uncontrollable reasons i.e., economic crisis, natural disasters, terrorist attacks, labour strikes, etc. Finding potential hazards is the key to reducing the impact of disruption. A resilient supply chain can mitigate most of the risks by its ability to resist and adapt and recover. AI can identify the supply chain segments where disruption will have the biggest impact using its powerful, predictive analytics. Disruption risk can be reduced by identifying the supply chain's weak link and making appropriate plans and making the supply chain robust and resilient.

4. Research Design

A mixed-method approach is adopted that includes identification of AI-enabled supply chain resilient capabilities, building the level hierarchy using interpretive structural modelling (ISM), and then applying total interpretive structural modelling (TISM) to understand the causal relationships and direct-indirect linkages amongst constructs, before undertaking a quantitative study to validate the hierarchal model and hypotheses. Alvesson & Sandberg (2011) also advocate the interpretive logic and generating research questions through problematization. While interviewing the respondents for the TISM model, first they have been briefed about the objective of the study. The characteristics of a resilient supply chain are discussed and explained to each respondent. The contextual relationship through the VAXO matrix is determined between the different characteristics. Once VAXO matrix is developed, then structural self-interaction matrix is developed followed by initial and final reachability matrix. Further the driver dependence power matrix is developed for classifying the characteristics leading to the development of the TISM Model. The multi-method approach is preferred due to reason that it enhances the robustness of study findings (Dubey et al., 2015; Shibin et al., 2018). This study adopts the basic model presented by Modgil et al. (2021) for supply chain resilience, wherein in-depth interviews are conducted to understand the supply disruptions and how AI can assist in preventing such disruptions. The model is developed using thematic analysis to elucidate appropriate insights. Furthermore, a three-step coding approach was taken, namely open, axial and selective coding to build constructs and sub-constructs. The present study is the extension of this prior study, building the hierarchal model based on the constructs and sub-constructs proposed. The results presented in this study empirically validate the model using survey research. Fig.1 depicts the research design used in this study.

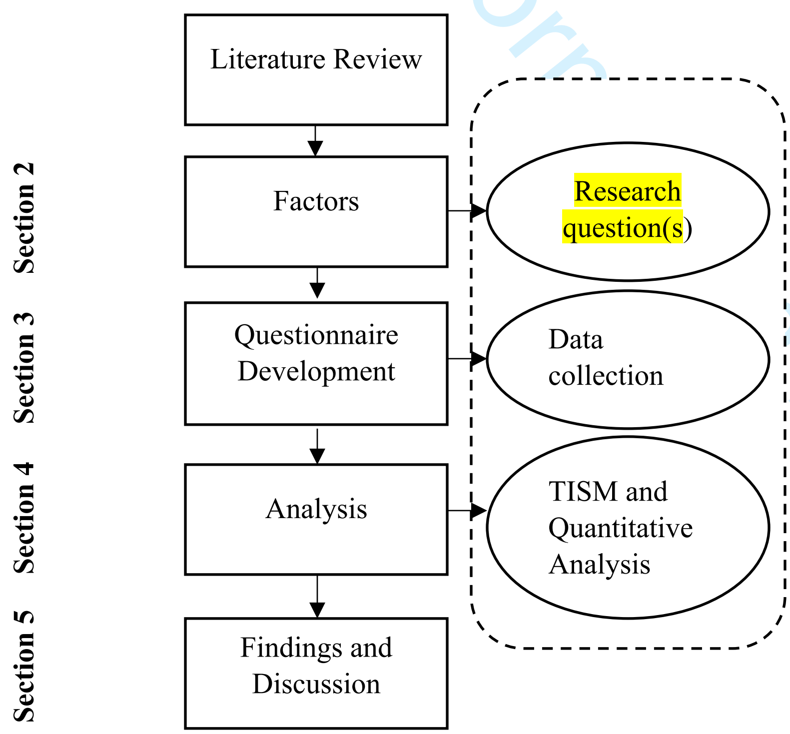

Figure1 Research Design for the study

4.1 Data Collection

Organizations across the world are experiencing supply chain disruption in ways that are challenging to analyze and evaluate. It seems certain that the impact will spread to many businesses and industries. Understanding how global manufacturers are handling supply chain disruptions and how to organize their reactions can help organizations. Firms are using digital ways to predict and prevent disruptions. To understand what AI can offer to the supply chain and how firms can install AI capabilities, 27 professionals were interviewed who have adequate knowledge of supply chain and digital capabilities. Based on the input received, a TISM framework was constructed. Further, survey research was conducted for scale development and to test the developed hypothetical model. A survey instrument was designed after an extensive literature survey by identifying appropriate measures. The questionnaire was sent to 350 supply chain professionals, from which 247 responses were received. 231 responses were considered for further analysis based on the completeness of the survey. Elimination occurred where responses were not received from executives working in the supply chain domain, or where responses had insufficiently complete information.

5. Analysis

The analysis is conducted in two phases: in phase one 27 supply chain professionals are interviewed to understand the interaction amongst variables and further developed the TISM model. In phase 2 a survey-based questionnaire is developed, and responses are collected for further analysis that leads to testing the model and hypothetical framework developed through TISM.

5.1 Phase I: Total Interpretive Structural model (TISM)

The interpretive structural model (ISM) was developed by Prof. John N. Warfield in 1974. It can be used in defining the relationship among variables and developing a process hierarchy. More recently, operations management academics have been paying increased attention to TISM as an improved approach (Anbarasan and Sushil, 2018; Shibin et al. 2018; Sushil, 2017). ISM is used to map the complex relationships among variables as well as to understand the behavior of variables with respect to other present variables. The TISM model excels in capturing the causal ties or transitive links between the model's constructs, giving it an edge over ISM (Shibin et al., 2018). The idea behind TISM is to use experts' insights and experience on subject matter to understand the complex system by dividing it into small parts and developing a structural model.

5.1.2 Development of the TISM Model

The first step to develop the TISM framework is to identify the dimensions that have been adopted. The interpretive knowledge base was then developed to record expert opinion. This study involved experts in the supply chain domain who have either knowledge of technology-enabled supply chain or have implemented it in their work domain. The experts involved have on an average 7 years of experience with supply chain systems and their opinions are sought for building the TISM model. Following expert verification, data was collected for the TISM process.

The steps involved in developing an interpretive model are the following:

Step 1: Identification/adaptation of variables of AI-enabled resilient supply chain through literature review and further verified through experts' opinions.

Step 2: A relationship among all the variables of AI-enabled supply chain resilience is established.

Step 3: Constructing a structural self-interaction matrix (SSIM), a pairwise comparison among AI-enabled supply chain resilience variables is made to develop SSIM. In the form of V, A, X, and O, the pairwise relationship is described where:

V: variable CD_i influences CD_j.

A: variable CD_j influences CD_i.

X: variable CD_i and CD_j influences each other, and,

O: variable CD_i and CD_j are not related.

(Where CD_i and CD_j are two variables)

Step 4: Developing a reachability Matrix by converting SSIM into a binary matrix

Symbol used	Conversion in the initial reachability matrix
V	In the event that the SSIM entry (i, j) is V, the entry (i, j) in the initial reachability matrix entry changes to 1 and the entry (j, i) to 0.
A	In the event that the SSIM entry (i, j) is A, the entry (i, j) in the initial reachability matrix entry changes to 0 and the entry (j, i) to 1
X	In the event that the SSIM entry (i, j) is X, the entry (i, j) in the initial reachability matrix entry changes to 1 and the entry (j, i) to 1
O	In the event that the SSIM entry (i, j) is O, the entry (i, j) in the initial reachability matrix entry changes to 0 and the entry (j, i) to 0

Step 5: After checking for transitivity in the reachability matrix, the development of a final reachability matrix is performed.

Step 6: Develop the level hierarchy/level portioning after a series of iterations.

Step 7: Construct the level hierarchy in diagram form.

5.1.3 Data Analysis

The contextual matrix was developed amongst variables after receiving the initial feedback from industry practitioners, leading to the emergence of a structured self-interaction matrix (SSIM) as shown in Table 1

Table 1 SSIM Matrix of AI-enabled SCR variables

Variables	LMD	RDI	PROC	PS	TR	SCR
LMD		V	A	O	A	O
RDI			A	O	O	V
PROC				A	O	O
PS					A	O
TR						O
SCR						

The SSIM is then converted into the Reachability matrix (Table-2) as explained in Step 4.

Table 2 Reachability Matrix of AI-enabled SCR variables

Variables	**LMD**	**RDI**	**PROC**	**PS**	**TR**	**SCR**
LMD	1	1	0	0	0	0
RDI	0	1	0	0	0	1
PROC	1	1	1	0	0	0
PS	0	0	1	1	0	0
TR	1	0	0	1	1	0
SCR	0	0	0	0	0	1

Next, the Final reachability matrix was developed using the principle of transitivity as proposed by Farris and Sage (1975) and further used and explained in the works of Sushil (2015), and Vivek et al. (2008). The logic of the transitivity principle is as follows: if x leads to y and y leads to z, then x must lead to z. Based on the same logic, the final reachability matrix is prepared as shown in Table 3.

Table 3 Final Reachability Matrix

Variables	LMD	RDI	PROC	PS	TR	SCR	Driving Power
LMD	1	1	0	0	0	1*	3
RDI	0	1	0	0	0	1	2
PROC	1	1	1	0	0	1*	4
PS	1*	1*	1	1	0	0	4
TR	1	1*	1*	1	1	0	5
SCR	0	0	0	0	0	1	1
Dependence	4	5	3	2	1	4	

Level Partitioning (LP): The process of dividing up multiple variables into their respective levels is referred to as level partitioning. The calculation of reachability and antecedent sets from Table 1 is the first step in determining the levels of variables (Warfield, 1974; Purohit et al., 2016). In the process, iteration keeps on happening until the reachability set itself becomes the intersection set as shown in Table 4 to Table 8.

Table 4 LP of AI enabled SCR variable- Iteration 1

Elements	Reachability set (RS)	Antecedent set (AS)	Intersection set (IS)	Level
LMD	1,2,6	1,3,4,5	1	
RDI	2,6	1,2,3,4,5	2	
PROC	1,2,3,6	3,4,5	3	
PS	1,2,3,4	4,5	4	
TR	1,2,3,4,5	5	5	
SCR	6	1,2,3,4,5,6	6	Level 1

Table 5: LP of AI enabled SCR Variable-Iteration 2

Elements	RS	AS	IS	Level
LMD	1,2	1,3,4,5	1	
RDI	2	1,2,3,4,5	2	**Level II**
PROC	1,2,3	3,4,5	3	
PS	1,2,3,4	4,5	4	
TR	1,2,3,4,5	5	5	

Table 6: LP of AI enabled SCR Variable-Iteration 3

Elements	RS	AS	IS	Level
LMD	1	1,3,4,5	1	**Level III**
PROC	1,3	3,4,5	3	
PS	1,3,4	4,5	4	
TR	1,3,4,5	5	5	

Table 7: LP of AI enabled SCR Variable- Iteration 4

Elements	RS	AS	IS	Level
PROC	3	3,4,5	3	**Level** IV
PS	3,4	4,5	4	
TR	3,4,5	5	5	

Table 8: LP of AI enabled SCR Variable-Iteration 5

Elements	RS	AS	IS	Level
PS	4	4,5	4	**Level V**
TR	4,5	5	5	**Level VI**

Figure 2 and Table 8 are the final outputs of the TISM process, which clearly shows the interaction among variables. The dotted lines in Figure 2 depict the transitive relationship while the solid lines depict the direct relationship based on the feedback received from the experts.

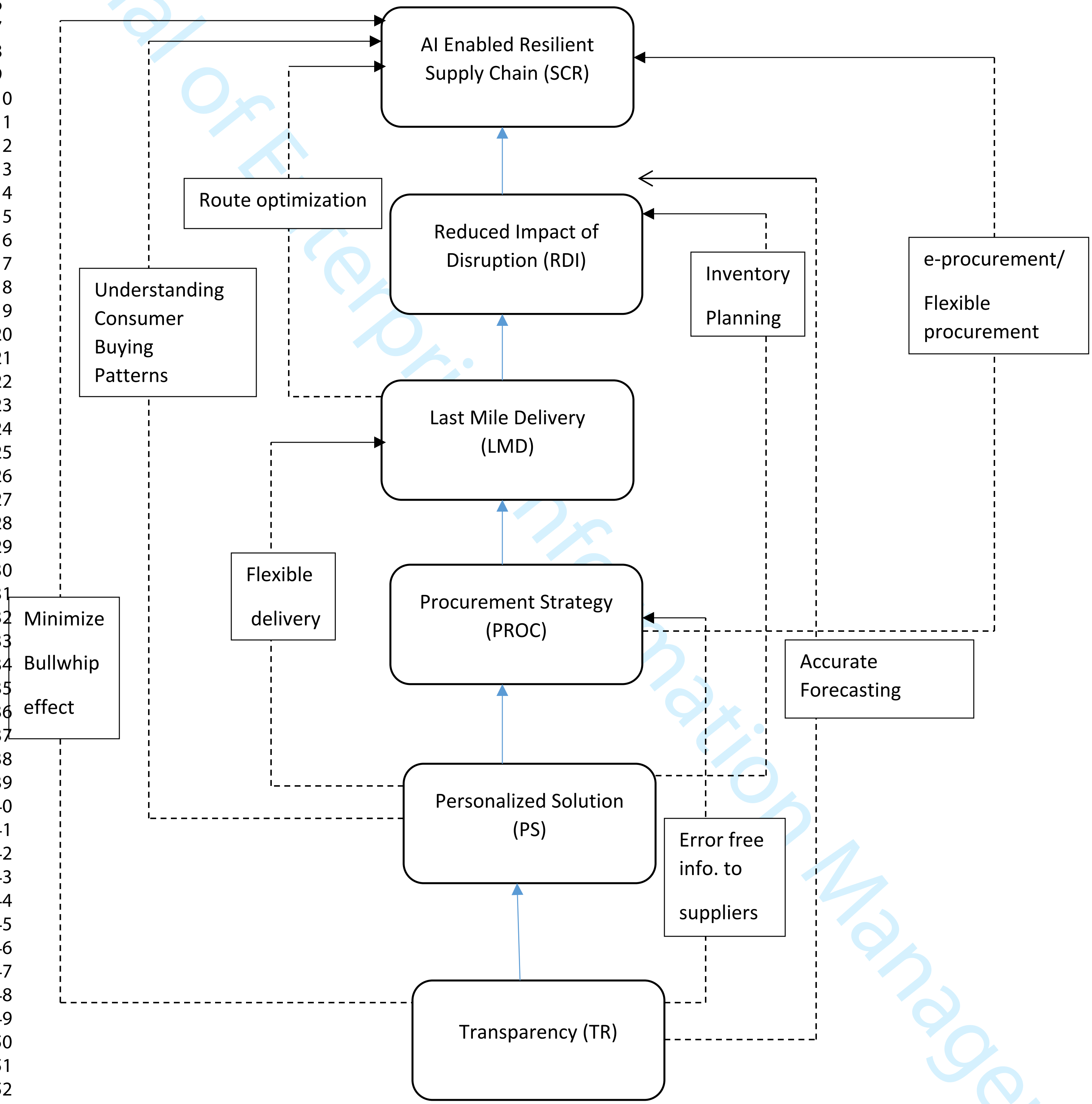

Figure 2 TISM Model of "Artificial intelligence enabled supply chain resilience"

Table 8 Summary of transitive links

Variables	LMD	RDI	PROC	PS	TR	SCR
LMD						Route optimization, traffic analysis
RDI						
PROC						e-procurement and flexible procurement
PS	Flexible delivery	Inventory Planning				Understanding consumer buying patterns
TR		accurate forecasting	Error-free information to suppliers			Minimizes bullwhip effect
SCR						

It can be inferred from Fig.2 that transparency creates the base to achieve resilience in the supply chain. When consumers buy something from a merchant, they expect transparency and trust, and managing these demands is challenging. Transparency throughout the supply chain is necessary for resilience. Planning for upcoming disruptions is simpler when suppliers' relationships are better understood. End-to-end visibility of supply chain activities enable the firm to pass on error-free information to stakeholders efficiently which will lead to minimizing the bullwhip effects in the supply chain. Transparency also enables making accurate forecasts and intuiting the accurate customer demand which leads to providing a personalized experience to the customer.

Accurate forecasts lead to better procurement strategies, inventory planning and minimizing the inventory costs. Forecast helps firm to strategies and re-strategise their inventory planning and overall procurement strategies. Firms may opt for flexible strategy and place inventory at pre identified points in supply chain as safety stock in order to avoid any disruption. Firms may also opt for multiple suppliers in order to increase flexibility in procurement process that will lead to increase resilience in supply chain. It also assists in understanding buying patterns and fixing the delivery mode to create a better end consumer experience.

The major objective behind having alternative delivery modes and routes to analyze the traffic patterns using AI finally leads to route optimization. All of this will lessen the impact of disruption on the supply chain and foster overall supply chain resilience. The discussion section provides a thorough explanation of the model's analysis.

5.2. Phase II: Quantitative Survey Research:

The hypothetical framework developed from TISM is tested using the survey method. A questionnaire was developed on AI-enabled supply chain resilience variables and their items. As discussed in Section 3.1, executives in the supply chain field are sent a questionnaire who have an understanding of digital technologies in January 2022. This study used SPSS v.21 for the analysis of data. Appendix A contains the respondents' information.

5.2.1 Common Method and Non-Response Bias

To address the problem of common method bias in the study, the respondents are asked not to answer the questionnaire purely on their experience, but also to refer to the minutes and information available on their website and internal system (Guide and Ketokivi, 2015). In empirical research, non-response bias is usually a concern (Chen and Paulraj, 2004). Hence, to validate the non-response bias, the responses are compared in two waves (115 and 116) (Armstrong and Overton, 1977). The t-statistics ($p = 0.08$) indicate that there is no potential concern in the data collected.

5.2.2 Measurement Validation

There is no theoretical groundwork predicting the links among constructs used in this study, as shown in Figure 2, which is derived by interpretive logic. This study considered the reliability of each component. Next, the construct validity is evaluated using convergent validity, composite reliability, and discriminant validity. The findings of the factor loading, composite reliability, and average variance extracted (AVE) have been retrieved and is presented in Table 9. Factor loading value greater than or equal to 0.7 is considered ideal however 0.5 is also acceptable if the AVE value of the construct meets the requirement of 0.5 (Fornell and Larcker, 1981). It is found that the item loadings on their respective structures are higher than 0.7 which is consistent with the works of Tambade et al. (2019) & Kumar and Singh (2021, 2022). The minimum value obtained for loading is 0.807, similarly for SCR it is 0.872 and for AVE it is 0.632. These results led to the conclusion that the scale has convergent validity.

Table 9 Convergent Validity, Scale Composite Reliability (SCR), and Average Variance Extracted (AVE)

Item	Loading	SCR	AVE
TR 1	.905	0.939	0.794
TR 2	.900		
TR 3	.895		
TR 4	0.865		
PS1	0.869	0.918	0.738
PS 2	0.868		
PS 3	0.860		
PS 4	0.839		
PROC 1	0.820	0.872	0.632
PROC 2	0.807		
PROC 3	0.806		
PROC 4	0.746		
LMD1	0.872	0.882	0.845
LMD 2	0.865		
LMD 3	0.798		
RDI 1	0.890	0.863	0.822

RDI 2	0.819		
RDI 3	0.757		
SCR1	0.827	0.849	0.807
SCR 2	0.814		
SCR 3	0.782		

For discriminant validity, the correlation coefficients' absolute values must be lower than the square root of AVE's absolute value. (Fornell and Larcker, 1981). The AVE values shown in Table-10 is greater than 0.5 that is line with the Hair et al. (2006) recommendation. Table 10 represents the result for discriminant validity.

Table 10 Correlation Coefficient amongst variables of AI enabled SCRs

	TR	PS	PROC	LMD	RDI	SCR
TR	**0.794**					
PS	0.312	**0.738**				
PROC	0.3296	0.811	**0.632**			
LMD	0.2339	0.200	0.216	**0.845**		
RDI	0.805	0.415	0.407	0.398	**0.822**	
SCR	0.301	0.810	0.539	0.172	0.385	**0.807**

The hypothesis is tested using regression analysis. Table 11 presents the summary of the hypothesis. The results of the regression analysis demonstrate that each of the theoretical framework's five links has statistical support ($p < .05$). From Table 11 it can be observed that the regression coefficient of path TR→PS is positive. It refers to transparency positively influencing personalized solutions. It guarantees the availability of information on product and service prices and delivery schedules that are reasonable. Such transparency and honesty with clients lead to better customer experience and enhance customer retention.

Table 11 Structural Estimates: Summary of Hypothesis Testing

Effect Of	**Effect On**	**Beta**	**p-value**	**Results**
TR	PS	0.312	***	Supported
PS	PROC	0.415	***	Supported
PROC	LMD	0.407	***	Supported

LMD	RDI	0.216	***	Supported
RDI	AI-SCR	0.172	***	Supported

The regression coefficient for path PS→PROC is positive (0.415), which refers to the strong association between personalized solutions and procurement strategy. The personalized solution would require creating or identifying the customer segment for the product and fetching the customer needs. Customizing goods and services is referred to as personalization, which calls for a flexible buying strategy. Personalization strengthens procurement by enabling it to have multiple suppliers for one product which will allow the firm to manage the lead time and supplier cost as well.

The regression coefficient of path PROC→LMD is positive (0.407) and statistically significant ($p < .05$). Customers' experiences and expectations can be greatly enhanced by ensuring seamless delivery and a successful final delivery leg. The analysis supports the hypothesis that Procurement strategy will positively influence the last mile delivery. The end-to-end supply chain cycle time will be reduced with the right set of procurement strategies. Access to last-mile delivery options is facilitated by AI-enabled systems, which may facilitate capacity procurement.

The regression coefficient for path LMD→RDI comes out to be positive (0.415), referring to last mile delivery positively achieving reduced disruption impact. Investing in creating flexible delivery infrastructure assists by technology will be able to identify the alternative mode of delivery, and routes of delivery to reduce any disruption impact. It will enable firms to offer customized delivery that requires a flexible logistics system and strong warehousing and distribution system. Installing these capacities will enable the organization to minimize the disruption impact.

The regression coefficient for path RDI→AI-SCR is positive (0.172 and strategically significant ($p < 0.05$). The reduced disruption effect is positively associated with artificial intelligence-based supply chain resilience. To install resilience initiatives, businesses need to assess their exposure, vulnerabilities, and potential losses. If the supply chain is able to adapt to the changes due to external disruption, it will be termed a resilient system.

6 Findings and Discussion

This study offers a deeper understanding of artificial intelligence-enabled supply chain towards resilience and how different characteristics of supply chain help to achieve resilience. The motivation for this study is triggered by the increasing disruptive events and rising risks to supply chains across the globe (Baz and Ruel, 2021; Hussain et al., 2022). First the process structure of characteristics of resilient supply chain is not clear from the literature; this study therefore investigates the direct or indirect relationships and influence between different process elements as presented in TISM model. The results from the TISM and empirical analyses indicate the interdependence of supply chain characteristics. Different supply chain characteristics examine the driver-dependent relationship, which is further verified through an empirical analysis. The findings of the study represent an interesting image of association among transparency, personalized solutions, procurement strategy, last-mile delivery and reduced impact of disruption that lead to resilient supply chain. With the inter-connected business activities and continuous data flowing from sensors to machines at manufacturing facilities, and delivery trucks, security systems such as 360-degree cameras can communicate the supply chain status to related stakeholders on real-time basis. Hence, this answers the research question: *How are the key characteristics of an AI-enabled supply chain's resilience related to each other?* With the rise of internet penetration and using AI, supply chains are becoming intelligent with little supervision required. This way AI presents the opportunity for supply chains to achieve greater levels of trust and transparency, which is the key driver making a supply chain resilient enough to handle and thrive in uncertain events. In their recent study, Belhadi et al. (2021) argued and advocated for the role of artificial intelligence in supply chain resilience, how the characteristics of the supply chain are associated in ensuring the supply chain resilience adds another angle to the practice and theory (Whetten, 1989).

6.1 Theoretical contributions

The role of artificial intelligence in supporting the supply chain resilience is discussed in the literature (Belhadi et al., 2021; Ivanov et al., 2021). What is less understood is how different characteristics of a supply chain are associated and hardly studies are found in verifying the structure of association through an empirical study. This study contributes in enhancing the understanding of the relationship among supply chain characteristics and how they help in achieving the resilient supply chain. This is achieved in two ways. First, the study reveals process structure, direct and indirect influence among different characteristics through TISM model. For instance, personalized solutions requirement demand companies to opt for flexible delivery system, that in turn ensure different routes and ways for last mile delivery (Purohit et al., 2016). Additionally, offering personalized solutions assists in understanding the buying pattern that help the AI to collect the data and suggest relevant changes in the supply chain operations to have sufficient resilience (Dubey et al., 2019a; Modgil et al., 2021b). Transparency promotes error free information to suppliers influencing the adequate procurement strategy. Further transparency helps in achieving accurate forecasting that avoid any major disruption or reduced impact if a disaster strikes (Li et al., 2022). Second the association emerged from TISM model is further verified through empirical study that supports the findings of TISM model.

Although researchers have different views on achieving resilience among supply chains. Li et al. (2022) advocated using blockchain-supported business models for supply chain resilience, which ultimately helps in organizational performance. Blockchain technology helps reduce the risks often associated among intermediaries, smooth interventions and facilitate contract management to capture the essential components of a resilient supply chain (Min, 2019). However, the focus of Blockchain is on security and shared network (Dutta et al., 2020), whereas the focus of AI is to handle and interpret the large data emitted by supply chains (Belhadi et al., 2021; Bag et al., 2021; Modgil et al., 2021a, b) in the unpredictable business environment and therefore act as an enabler to support the resilience among supply chains. AI enhances the (Dubey et al., 2021) supply chain capability by sensing the business environment and facilitating flexibility among supply chain nodes that help to achieve supply chain resilience (Gupta et al., 2021). With AI, the supply chains are better positioned once they sense the risks associated with certain conditions and prepare the supply chains to avoid and resist first and recover from the disruptive event (Baryannis et al., 2019). In addition, a supply chain that is enabled with AI is helpful not only in making quick decision but also in planning for the continuity of the supply chain in a variety of different circumstances. The study findings further strengthen the association among characteristics to make it AI enabled and resilient supply chain also supported by other studies in the past (Belhadi et al., 2021; Dubey et al., 2022; Modgil et al., 2021a).

6.2 Implications for Practice

There is little doubt that AI offers a promising proposition to enable required resilience among supply chains. Transparency in the supply chain helps to maintain customer and supplier expectations. This study offers useful implications for managers responsible for running supply chains. Today professionals rely on the usage of data to design and develop strategies to tackle any disruption in supply chains. Stated simply, artificial intelligence is the representation of the input data and its training. Supply chain professionals, therefore, need to focus attention on the database that their supply chain is utilizing that can otherwise plague the algorithm of filtering the useful data. The study findings are useful for supply chain managers from different industries in understanding how resilience in the supply chains can be achieved. Before investing in the technologies, however, supply chain professionals need to assess how such technology can create a value for the customers, how the technology can create human and machine balance and help in facilitating the supply chain to deliver higher-margin products closer to the customer.

This study provides the hierarchal approach to bring resilience in supply chain. Supply chain professionals should work towards ensuring end to end visibility in supply chains to bring more transparency. The technology available today i.e., Artificial Intelligence, makes it possible for operations to have complete transparency and can proactively flag any impending or potential disruptions to the supply chain. These disruptions can be caused by anything from severe weather to political unrest. Visibility across supply chain helps in figuring out the consumer buying pattern or exact demand of product in market. Analyzing the behavior of customers is another area where AI can be helpful. Artificial intelligence enables marketers to investigate how customers interact with their businesses. It can provide an understanding of each stage of the customer journey and assist marketers in gaining an understanding of the factors that drive customer behavior. More accurate data about market and consumer will ensure reduced disruption impact that will lead to increased resilience in supply chain.

In the past, organizations have faced disruptive events and many of the supply chains struggled with allocation of appropriate people, having adequate inventories at each node of supply chain and varying service levels during pre and post disruption. Artificial intelligence can be useful in imitating the intelligence of human beings and can continuously monitor the data flowing from upstream and downstream to suggest best strategies for having resilient supply chain referring to the context, region, and country. In this way, supply chain managers can minimize the disruption impact. Furthermore, AI enabled supply chain can help professionals to coordinate better among themselves and tackle challenges with minimal cost. AI enabled supply chains can also be helpful in addressing the authenticity and reliability issue of data being generated, collected, extracted and analyzed. AI enabled supply chains may also be helpful to communicate among different geographical locations in the case of global supply chains.

Managers can employ AI for real-time and quick coordination that enhances participation and build trust among supply chain partners that are needed to work in tandem in the era of uncertainty and for quick recovery in case of a disruptive event. Managers need to employ AI-driven solutions by identifying, evaluating, developing, and testing novel approaches toward supply chain resilience. Managers should further exploit artificial intelligence to develop information processing capabilities of the system that can assess the external elements and mitigate any risks. The sensing of the external environment through artificial intelligence further facilitates managers to execute the procurement and last-mile delivery activities as quickly as possible to ensure minimal impact of the disruption.

7. Conclusion and Future Scope

This study contributes to the literature on supply chain management and information systems management by highlighting the driving and dependence power of supply chain resilience characteristics and how AI enable supply chain resilience. The study also highlights, how different characteristics of supply chain resilience are influenced by each other through empirical analysis, where all the hypotheses are supported. Transparency acts as a pillar and driving force in AI enabled supply chain to have adequate resilience so that it can withstand the disruption with minimal disruption. In the uncertain business environment, AI can facilitate supply chains to respond to rapidly changing business scenarios and address operational challenges. Furthermore, AI is capable of dealing with large data (Bag et al., 2020) flowing from diverse sources and mitigate the risk at different supply chain nodes and create value for the customer. AI can further contribute towards resilience, by simulating rich data and can facilitate real-time monitoring of the scenario. In summary, AI facilitates data governance and enhances the technological capabilities of the supply chain to interact with different stakeholders and collaborate with them during a disruptive event.

Every supply chain has different problems and challenges, though all of the challenges cannot be solved by AI. Further, to strengthen the supply chain resilience, one may need a trusted network to operate, and the security of the transactions may not be addressed by AI. For instance, supply chain collaboration is one of the key aspects of moving towards better resilience, therefore rather than AI and technology like blockchain (Li et al., 2022; Min, 2019), quantum computing (Gupta et al., 2022) can also be considered while considering overall picture of resilience. This study first developed a TISM model to understand the driving and dependent element to gauge the relationship of characteristics. However, future studies can be conducted to further generalize the findings and observe how different characteristics are related. Further, the study has explored the general supply chain resilience, and not the event or severity of event-specific resilience, which can be explored in the future. Sometimes behavioral issues in the workforce also contribute to the poor performance of a supply chain, which has not been considered in this study. Hence, future studies can consider the behavioral characteristics of the workforce and how to integrate them towards supply chain resilience when required. Cross-sectional data are utilized for the empirical analysis in this study. Data collected over time could be used in subsequent research to make the findings more practical to a variety of supply chains.

References

Aljohani, K. and Thompson, R.G. (2020a), "Receivers-led delivery consolidation policy: estimating the characteristics of the most interested businesses to participate", Research in Transportation Economics. doi: https://doi.org/10.1016/j.retrec.2019.100808

Alvesson, M., & Sandberg, J. (2011), "Generating research questions through problematization", Academy of Management Review, Vol. 36 No.2, pp. 247-271.

Ambulkar, S., Blackhurst, J. and Grawe, S. (2015), "Firm's resilience to supply chain disruptions: scale development and empirical examination", Journal of Operations Management, Vol. 33-34, pp. 111-122.

Anbarasan, P. and Sushil (2018), "Stakeholder Engagement in Sustainable Enterprise: Evolving a Conceptual Framework, and a Case Study of ITC", Business Strategy and the Environment, Vol. 27 No.3, pp.282-299.

Annarelli, A., Battistella, C., Nonino, F., Parida, V., & Pessot, E. (2021), "Literature review on digitalization capabilities: Co-citation analysis of antecedents, conceptualization and consequences", Technological Forecasting and Social Change. doi: https://doi.org/10.1016/j.techfore.2021.120635

Armstrong, J.S. and Overton, T.S. (1977), "Estimating nonresponse bias in mail surveys", Journal of Marketing Research, Vol. 14 No. 3, pp. 396-402.

Astill, J., Dara, R. A., Campbell, M., Farber, J. M., Fraser, E. D., Sharif, S., & Yada, R. Y. (2019), "Transparency in food supply chains: A review of enabling technology solutions", Trends in Food Science & Technology, Vol. 91, pp. 240-247.

Bag, S., Dhamija, P., Luthra, S., & Huisingh, D. (2021), "How big data analytics can help manufacturing companies strengthen supply chain resilience in the context of the COVID-19 pandemic", The International Journal of Logistics Management. doi: https://doi.org/10.1108/IJLM-02-2021-0095.

Bag, S., Gupta, S., & Wood, L. (2020), "Big data analytics in sustainable humanitarian supply chain: Barriers and their interactions", Annals of Operations Research. doi: 10.1007/s10479-020-03790-7

Baryannis, G., Validi, S., Dani, S. and Antoniou, G. (2019), "Supply chain risk management and artificial intelligence: state of the art and future research directions", International Journal of Production Research, Vol. 57 No. 7, pp. 2179-2202.

Bawack, R. E., Fosso Wamba, S., & Carillo, K. D. A. (2021), “A framework for understanding artificial intelligence research: insights from practice”, Journal of Enterprise Information Management, Vol. 34 No.2 pp. 645-678.

Baz, J. and Ruel, S. (2021), “Can supply chain risk management practices mitigate the disruption impacts on supply chains’ resilience and robustness? Evidence from an empirical survey in a COVID-19 outbreak era”, International Journal of Production Economics. doi: https://doi.org/10.1016/j.ijpe.2020.107972

Belhadi, A., Kamble, S., Fosso Wamba, S., & Queiroz, M. M. (2021), “Building supply-chain resilience: an artificial intelligence-based technique and decision-making framework”, International Journal of Production Research, Vol. 60 No.14, pp.4487-4507.

Cetindamar Kozanoglu, D. and Abedin, B. (2021), "Understanding the role of employees in digital transformation: conceptualization of digital literacy of employees as a multi-dimensional organizational affordance", Journal of Enterprise Information Management, Vol. 34 No. 6, pp. 1649-1672.

Chen, I.J. and Paulraj, A. (2004), “Towards a theory of supply chain management: the constructs and measurements”, Journal of Operations Management, Vol. 22 No. 2, pp. 119-150.

Chen, Y., Biswas, M.I. and Talukder, M.S. (2022), "The role of artificial intelligence in effective business operations during COVID-19", International Journal of Emerging Markets, https://doi.org/10.1108/IJOEM-11-2021-1666

Cui, y and Idota H (2018), “Improving Supply Chain Resilience with Establishing A Decentralized Information Sharing Mechanism” MISNC '18: Proceedings of the 5th Multidisciplinary International Social Networks Conference, DOI: doi.org/10.1145/3227696.3227723

de Lima, F.R.P., Da Silva, A.L., Godinho Filho, M. and Dias, E.M. (2018), “Systematic review: resilience enablers to combat counterfeit medicines”, Supply Chain Management: An International Journal, Vol. 12 No. 3, pp. 117-135.

Dhamija, P. and Bag, S. (2020), "Role of artificial intelligence in operations environment: a review and bibliometric analysis", The TQM Journal, Vol. 32 No. 4, pp. 869-896.

Dubey, R., Bryde, D. J., Dwivedi, Y. K., Graham, G., & Foropon, C. (2022), “Impact of artificial intelligence-driven big data analytics culture on agility and resilience in humanitarian supply chain: A practice-based view”, International Journal of Production Economics. doi: https://doi.org/10.1016/j.ijpe.2022.108618.

Dubey, R., Gunasekaran, A., Childe, S.J., Fosso Wamba, S., Roubaud, D. and Foropon, C. (2019a), “Empirical investigation of data analytics capability and organizational flexibility as complements to supply chain resilience”, International Journal of Production Research, Vol.59 No.1, pp.110-128.

Dubey, R., Gunasekaran, A., Childe, S.J., Roubaud, D., Wamba, S.F., Giannakis, M. and Foropon, C. (2019b), "Big data analytics and organizational culture as complements to swift trust and collaborative performance in the humanitarian supply chain", International Journal of Production Economics, Vol. 210, pp. 12-136.

Dubey, R., Gunasekaran, A., Papadopoulos, T., & Childe, S. J. (2015), "Green supply chain management enablers: Mixed methods research", Sustainable Production and Consumption, 4, 72-88.

Dutta, P., Choi, T. M., Somani, S., & Butala, R. (2020), "Blockchain technology in supply chain operations: Applications, challenges and research opportunities", Transportation Research Part E: Logistics and Transportation Review. doi: https://doi.org/10.1016/j.tre.2020.102067

Farris, D. R., and Sage, A. P. (1975), "On the use of interpretive structural modeling for worth assessment", Computers and Electrical Engineering, Vol.2 No.2, pp.149–174

Forbes (2021), "In A World Of Rising Risks, AI Offers Supply Chain Resilience And Reward", available at https://www.forbes.com/sites/forbestechcouncil/2021/07/21/in-a-world-of-rising-risks-ai-offers-supply-chain-resilience-and-reward/?sh=f01cd6e2d1df (Accessed on 11th September 2022)

Fornell, C. and Larcker, D.F. (1981), "Evaluating structural equation models with unobservable variables and measurement error", Journal of Marketing Research, Vol. 18 No. 1, pp. 39-50.

Fu J. and Fu Y. (2015), "An adaptive multi-agent system for cost collaborative management in supply chains" Engineering Applications of Artificial Intelligence Vol. 44, PP. 91-100

Gardner, T. A., Benzie, M., Börner, J., Dawkins, E., Fick, S., Garrett, R., ... & Wolvekamp, P. (2019), "Transparency and sustainability in global commodity supply chains", World Development, Vol. 121, pp. 163-177.

Gartner (2020), "Six strategies for more resilient supply chains" available at https://www.gartner.com/smarterwithgartner/6-strategies-for-a-more-resilient-supply-chain (accessed on 14 may 2022)

Guide, V.D.R. and Ketokivi, M. (2015), "Notes from the editors: redefining some methodological criteria for the journal", Journal of Operations Management, Vol. 37 No. 1, pp. 5-8

Gupta, S., Modgil, S., Bhatt, P. C., Jabbour, C. J. C., & Kamble, S. (2022), "Quantum computing led innovation for achieving a more sustainable Covid-19 healthcare industry", Technovation. doi: https://doi.org/10.1016/j.technovation.2022.102544

Gupta, S., Modgil, S., Bhattacharyya, S., & Bose, I. (2021), "Artificial intelligence for decision support systems in the field of operations research: review and future scope of research", Annals of Operations Research. doi: https://doi.org/10.1007/s10479-020-03856-6

Hair.Jr., J. F., Black., W. C., Babin., B. J., Anderson., R. E., & L.Tatham., R. (2006), Multivariate Data Analysis. 6th Edition, Pearson Prentice Hall, Upper Saddle River.

Hendricks, K.B. and Singhal, V.R. (2005), “Association between supply chain glitches and operating performance”, Management Science, Vol. 51 No. 5, pp. 695-711

Hendricks, K.B. and Singhal, V.R. (2005), “Association between supply chain glitches and operating performance”, Management Science, Vol. 51 No. 5, pp. 695-711

Herold, D.M., Ćwiklicki, M., Pilch, K. and Mikl, J. (2021), "The emergence and adoption of digitalization in the logistics and supply chain industry: an institutional perspective", Journal of Enterprise Information Management, Vol. 34 No. 6, pp. 1917-1938.

Hussain, G., Nazir, M.S., Rashid, M.A. and Sattar, M.A. (2022), "From supply chain resilience to supply chain disruption orientation: the moderating role of supply chain complexity", Journal of Enterprise Information Management. doi: https://doi.org/10.1108/JEIM-12-2020-0558

Islam, M. H., Sarker, M. R., Hossain, M. I., Ali, K., & Noor, K. A. (2020), “Towards sustainable supply chain management (SSCM): A case of leather industry”, Journal of Operations and Strategic Planning, 3(1), 81-98.

Ivanov, D. (2020), “Viable supply chain model: integrating agility, resilience and sustainability perspectives – lessons from and thinking beyond the COVID-19 pandemic”, Annals of Operations Research. doi: 10.1007/s10479-020-03640-6.

Ivanov, D., Blackhurst, J. and Das, A. (2021), "Supply chain resilience and its interplay with digital technologies: making innovations work in emergency situations", International Journal of Physical Distribution & Logistics Management, Vol. 51 No. 2, pp. 97-103.

Jabbour, C.J.C., Fiorini, P.D.C., Ndubisi, N.O., Queiroz, M.M. and Piato, E.L. (2020), “Digitally-enabled sustainable supply chains in the 21st century: a review and a research agenda”, Science of the Total Environment. doi: 10.1016/j.scitotenv.2020.138177.

Knudsen, D. (2003), “Aligning corporate strategy, procurement strategy and e-procurement tools”, International Journal of Physical Distribution and Logistics Management, Vol. 33 No. 8, pp. 720-734.

Kumar A. and Singh R.K. (2021), "Does a retailer’s performance depend on CSR practices? A stakeholder theory perspective from developing economy" Benchmarking: An International Journal. doi: 10.1108/BIJ-07-2021-0384

Kumar A. and Singh R.K. (2022), “Supply chain management practices, retail outlets attributes and organisational performance: A case study of organised food retailers in India” Journal of Global Operations and Strategic Sourcing. doi:10.1108/JGOSS-12-2021-0107

Kumar, A., Singh R.K. and Modgil S. (2020), “Exploring the Relationship between ICT, SCM Practices and Organisational Performance in agrifood Supply Chain”, Benchmarking: An International Journal, Vol. 27 No. 3 pp.1003-1041.

Kumar, A., Singh R.K. and Modgil S. (2021), “Influence of data-driven supply chain quality management on organizational performance: evidences from retail industry”, The TQM Journal, doi: 10.1108/TQM-06-2020-0146

Li, G., Xue, J., Li, N., & Ivanov, D. (2022), "Blockchain-supported business model design, supply chain resilience, and firm performance", Transportation Research Part E: Logistics and Transportation Review. doi: https://doi.org/10.1016/j.tre.2022.102773

Li, J., Saide, S., Ismail, M.N. and Indrajit, R.E. (2022), "Exploring IT/IS proactive and knowledge transfer on enterprise digital business transformation (EDBT): a technology-knowledge perspective", Journal of Enterprise Information Management, Vol. 35 No. 2, pp. 597-616

Mathrani, S., Mathrani, A. and Viehland, D. (2013), "Using enterprise systems to realize digital business strategies", Journal of Enterprise Information Management, Vol. 26 No. 4, pp. 363-386.

McCarthy, J., Minsky, M.L., Rochester, N. and Shannon, C.E. (2006), "A proposal for the dartmouth summer research project on artificial intelligence (August 31, 1956)", AI Magazine, Vol. 27 No. 4, p. 12

McKinsey (2018), "Thinking inside the subscription box: new research on e-commerce consumers", available at: https://www.mckinsey.com/industries/technology-media-and-telecommunications/ our-insights/thinking-inside-the-subscription-box-new-research-on-ecommerce-consumers# (accessed 1st April 2022).

Mikalef, P., & Gupta, M. (2021), "Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance", Information & Management, Vol. 58 No.3, 1-20.

Min, H. (2019), "Blockchain technology for enhancing supply chain resilience", Business Horizons, Vol.62 No.1, pp.35-45.

Min, H. (2010), "Artificial intelligence in supply chain management: theory and applications", International Journal of Logistics Research and Applications, Vol. 13 No. 1, pp. 13-39

Modgil S., Singh R.K. and Agrawal S (2022), " Developing Human Capabilities for Digital Transformation in Supply Chains: An Industry 5.0 perspective" Annals of Operations Research, DOI: 10.1007/s10479-023-05245-1

Modgil, S., Gupta, S., Stekelorum, R. and Laguir, I. (2021b), "AI technologies and their impact on supply chain resilience during COVID-19", International Journal of Physical Distribution & Logistics Management, Vol. 52 No. 2, pp. 130-149.

Modgil, S., Singh, R.K. and Hannibal, C. (2021a), "Artificial intelligence for supply chain resilience: learning from Covid-19", The International Journal of Logistics Management, Vol. 33 No.4, pp.1246-1268.

Nayal, K., Raut, R., Priyadarshinee, P., Narkhede, B.E., Kazancoglu, Y. and Narwane, V. (2022), "Exploring the role of artificial intelligence in managing agricultural supply chain risk to counter the impacts of the COVID-19 pandemic", The International Journal of Logistics Management, Vol. 33 No. 3, pp. 744-772

Panichayakorn, T. and Jermsittiparsert, K. (2019), “Mobilizing organizational performance through robotic and artificial intelligence awareness in mediating role of supply chain agility”, International Journal of Supply Chain Management, Vol. 8 No. 5, pp. 757-768

Purohit, J. K., Mittal, M. L., Mittal, S., and Sharma, M. K. (2016), “Interpretive structural modeling based framework for mass customisation enablers: an Indian footwear case”, Production Planning and Control, Vol. 21 No. 9, pp. 774-786.

Queiroz, M. M., & Fosso Wamba, S. (2021), “A structured literature review on the interplay between emerging technologies and COVID-19 – insights and directions to operations fields”, Annals of Operations Research. doi: https://doi.org/10.1007/s10479-021-04107-y.

Richards, G., Yeoh, W., Chong, A.Y.L. and Popovic, A. (2019), “Business intelligence effectiveness and corporate performance management: an empirical analysis”, Journal of Computer Information Systems, Vol. 59 No. 2, pp. 188-196.

Scholten, K., Scott, P.S. and Fynes, B. (2014), “Mitigation processes–antecedents for building supply chain resilience”, Supply Chain Management: An International Journal, Vol. 19 No. 2, pp. 211-228.

Shibin, K.T. and Dubey, Rameshwar and Gunasekaran, Angappa and Luo, Zongwei and Papadopoulos, Thanos and Roubaud, David (2018), “Frugal Innovation for Supply Chain Sustainability in SMEs: Multi-method Research Design” Production Planning and Control, Vol. 29, No. 1, pp. 908-927.

Shivajee, V., Singh, R.K. and Rastogi, S. (2022), "Procurement system for resilient supply chain amid the COVID-19 pandemic: systematic literature review", Journal of Global Operations and Strategic Sourcing. doi: https://doi.org/10.1108/JGOSS-04-2022-0029

Silva N., Ferreira LMDF, Silva C., Magalhães V and Neto P. (2017), “Improving Supply Chain Visibility With Artificial Neural Networks” Procedia Manufacturing, Vol.11, pp. 2083-2090

Singh R.K., Modgil, S. and Acharya P (2019), “Assessment of flexible supply chain using system dynamics modelling: A case of Indian soap manufacturing firm” Global Journal of Flexible System Management, Vol. 20 No.1, pp. 39-63

Singh R.K., Modgil, S. and Acharya P (2020a), “Identification and Causal Assessment of Supply Chain Flexibility” Benchmarking: An International Journal, Vol. 27 No. 2 pp.517-549

Singh R.K., Modgil, S. and Acharya P (2020b), “A Template Based Approach to Measure Supply Chain Flexibility: A case study of Indian Soap Manufacturing firm” Measuring Business Excellence, Vol. 24 No. 2, pp. 161-181

Singh, R.K. and Acharya P. (2013), “Supply Chain Flexibility: A Framework of Research Dimensions” Global Journal of Flexible System Management, Vol. 14 No.3, pp.157-166

Siurdyban A. and Møller C. (2012), “Towards Intelligent Supply Chains: A Unified Framework for Business Process Design” International Journal of Information Systems and Supply Chain Management, Vol. 5 No. 1 pp.1-19

Sulemana, A., Donkor, E.A., Forkuo, E.K. and Oduro-Kwarteng, S. (2019), "Effect of optimal routing on travel distance, travel time and fuel consumption of waste collection trucks", Management of Environmental Quality, Vol. 30 No. 4, pp. 803-832.

Sushil (2015), “Strategic flexibility: The evolving paradigm of strategic management,” Global Journal of Flexible Systems Management, Vol.16 No.2, pp.113–114.

Sushil. (2017), “Multi-criteria valuation of flexibility initiatives using integrated TISM–IRP with a big data framework”, Production Planning & Control, Vol. 28 No. (11-12), pp.999-1010.

Vivek, S. D., Banwet, D. K., & Shankar, R. (2008), “Analysis of interactions among core, transaction and relationship-specific investments: The case of offshoring”, Journal of Operations Management, Vol.26 No.2, pp.180-197.

Wamba, S. F. (2022), “Impact of artificial intelligence assimilation on firm performance: The mediating effects of organizational agility and customer agility”, International Journal of Information Management. doi: https://doi.org/10.1016/j.ijinfomgt.2022.102544

Wamba, S. F., Dubey, R., Gunasekaran, A., & Akter, S. (2020), “The performance effects of big data analytics and supply chain ambidexterity: The moderating effect of environmental dynamism”, International Journal of Production Economics. doi: https://doi.org/10.1016/j.ijpe.2019.09.019

Wamba, S.F. and Akter, S. (2019), “Understanding supply chain analytics capabilities and agility for data-rich environments”, International Journal of Operations and Production Management, Vol. 39 Nos 6-8, pp. 887-912.

Warfield, J. N. (1974), “Toward interpretation of complex structural models. IEEE Transactions on Systems”, Man and Cybernetics, Vol.5, pp.405–417.

Whetten, D. A. (1989), “What constitutes a theoretical contribution?”, Academy of Management Review, 14(4), 490-495.

Yu, W., Jacobs, M.A., Chavez, R. and Yang, J. (2019), “Dynamism, disruption orientation, and resilience in the supply chain and the impacts on financial performance: a dynamic capabilities perspective”, International Journal of Production Economics, Vol. 218 No. 11, pp. 352-362.

Zhou, J., Hu, L., Yu, Y., Zhang, J.Z. and Zheng, L.J. (2022), "Impacts of IT capability and supply chain collaboration on supply chain resilience: empirical evidence from China in COVID-19 pandemic", Journal of Enterprise Information Management. doi: https://doi.org/10.1108/JEIM-03-2022-0091.

Appendix

Appendix A Respondent Profile

	Phase-I (TISM)	Percentage	Phase-II-(SEM)	Percentage
Type	Frequency		Frequency	
Male	22	81%	192	83%
Female	5	19%	39	17%
Age				
20-30	2	7%	14	6%
31-40	8	30%	86	37%
41-50	13	48%	87	38%
51-60	3	11%	29	13%
60+	1	4%	15	6%
Education				
Graduate	15	56%	157	68%
Post-Graduate	11	41%	70	30%
PhD	1	4%	4	2%
Designation				
Director/CEO	2	7%	7	3%
VP/EVP	4	15%	34	15%
Sr. Manager/GM	10	37%	72	31%
Manager/Dy. Manager	8	30%	105	45%
Executive/Officer	3	11%	13	6%
Work Experience				
1-3 years	3	11%	33	14%
3 to 5 years	7	26%	67	29%
5 to 10 years	11	41%	109	47%
10+ year	6	22%	22	10%

Appendix B Scale and Items

Scale	Items
Transparency	Transparent system supports in fetching error free demand at retailers end
	Transparency in the system assist significantly in demand management
	Billing or Invoicing with digital transparent system create trust among supply chain partners
	Customer feels elated when they can track the live shipment status
Personalized Solution	Installing virtual chat boats and other digital communication medium assists in fetching customer requirement

	Study of consumer buying patterns leads to provide customized solution to individual customers
	Inventory planning based on customer demand will make process quick and smoothen
	AI helps to understand market tendencies, which improves supply chain planning.
Procurement Strategy	Spend analysis reduces costs and saves time, boosting productivity and speed or procurement process
	Resilience in the procurement is a result of effective vendor management (vendor assessment, audit support, credit management, etc.).
	Transparency and efficient procurement are facilitated by risk identification and reduction.
	Effective contract management improves and stabilizes the collaboration between supply chain parties.
Last Mile Delivery	Route planning is made easier and faster using a predictive analytic algorithm.
	Workforce management guarantees resource availability and prompt delivery.
	A paperless process accelerates delivery and saves time.
Reduced Disruption Impact	Automation increases the effectiveness of warehouse management, which lowers human error and strengthens the process against any disruption
	Robotic automation increases the speed and effectiveness of the process by making it shock free against any disturbance
	Flexible supply chains can better withstand disturbances.
Supply Chain Resilience	Customer centric customization, flexible delivery schedule, procurement solutions are outcome of resilient supply chain
	The results of an interruption will be less severe if the supply chain is robust.
	The application of artificial intelligence makes it possible for supply networks to become more resilient.