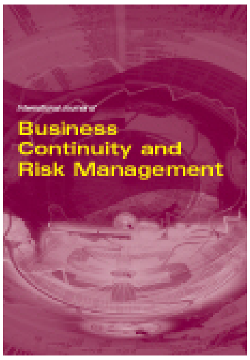


International Journal of Business Continuity and Risk Management

ISSN online: 1758-2172 - ISSN print: 1758-2164
https://www.inderscience.com/ijbcrm

A modelling and management approach to risks in reverse logistics implementation

Himanshu Prajapati, Ravi Kant, Ravi Shankar

DOI: 10.1504/IJBCRM.2023.10055473

Article History:

Received:	18 August 2021
Last revised:	08 February 2022
Accepted:	08 February 2022
Published online:	17 April 2023

A modelling and management approach to risks in reverse logistics implementation

Himanshu Prajapati*

Mechanical Engineering Department,
Sardar Vallabhbhai National Institute of Technology,
Surat, 395007, Gujarat, India
and
Mechanical Engineering Department,
Maharishi Markandeshwar (Deemed to be University),
Mullana-Ambala, 133207, Haryana, India
Email: h14prajapati@gmail.com
*Corresponding author

Ravi Kant

Mechanical Engineering Department,
Sardar Vallabhbhai National Institute of Technology,
Surat, 395007, Gujarat, India
Email: ravi792002@gmail.com

Ravi Shankar

Department of Management Studies,
Indian Institute of Technology Delhi,
New Delhi, 110016, India
Email: ravi1@dms.iitd.ac.in
Email: r.s.research@gmail.com

Abstract: This research aims to identify and model the reverse logistics (RL) risk variables to estimate the risks associated with their deployment. Furthermore, it suggests risk management techniques to execute the RL implementation effectively. The Delphi technique, interpretive structural modelling (ISM), and fuzzy cross-impact matrix multiplication applied to classification (F-MICMAC) create a hybrid research framework in this study. Delphi determines the RL risk factors and ISM creates a structural model to examine the contextual connection between them, followed by F-MICMAC classification. The key risk elements connected with RL implementation include government policy risk and management policy risk. Major RL risk management strategies include collaboration with network partners, risk-sharing with stakeholders, strong mutual trust among collaborators, improved forecasting techniques and continuous information sharing. The current evaluation is extremely beneficial in identifying the driving and dependence power and the efficacy of a certain risk, which helps in segregating them for RL implementation.

Keywords: reverse logistics; risks; reverse supply chain; risk management; Delphi; interpretive structural modelling; ISM; F-MICMAC.

Reference to this paper should be made as follows: Prajapati, H., Kant, R. and Shankar, R. (2023) 'A modelling and management approach to risks in reverse logistics implementation', *Int. J. Business Continuity and Risk Management*, Vol. 13, No. 1, pp.19–48.

Biographical notes: Himanshu Prajapati is a research scholar at the Department of Mechanical Engineering, Sardar Vallabhbhai National Institute of Technology, Surat, India and Assistant Professor at Department of Mechanical Engineering, Maharishi Markandeshwar (Deemed to be University), Mullana-Ambala, India. He has published several research articles in reputed international journals and conferences. His area of interest includes reverse logistics, supply chain management, circular supply chain management and Industry 4.0.

Ravi Kant is an Associate Professor at the Department of Mechanical Engineering, Sardar Vallabhbhai National Institute of Technology, Surat, India. His areas of research interest include operations and supply chain, knowledge management, and Lean and Six Sigma. He has about 12 years of experience in industry, teaching and research. He has co-authored more than 200 research papers in international journals and conferences and three books.

Ravi Shankar is an 'Amar S. Gupta Chair Professor of Decision Science' and Professor of Operations and Supply Chain Management in the Department of Management Studies (DMS), Indian Institute of Technology (IIT) Delhi, India. He is also an Honorary Visiting Professor of Decision Science at the School of Economics and Management, Loughborough University, UK. He has a rich industry and teaching experience of over 37 years. His areas of interest include operations and supply chain management, decision sciences, business analytics and big data, sustainable freight transportation, project management, total quality management and Six Sigma, strategic technology management, etc. He has co-authored more than 400 research papers and six books.

1 Introduction

Reverse logistics (RL) maintains the efficient flow of goods. RL is defined as "The process of planning, implementing and controlling the efficient, cost-effective flow of raw materials, in-process inventory, finished goods and related information from the point of consumption to the point of origin to recapture value or proper disposal" (Rogers and Tibben-Lembke, 2001).

The need for implementing RL arises due to the environmental degradation by enormous waste generation and the product returns in the new world of e-business. E-businesses build customers' trust by allowing product returns that are recycled or refurbished and then resold. The world's largest e-commerce company Amazon said that India has got the highest product return rate in the world compared to all the places they operate (Entrackr, 2018). The total amount of solid waste produced in India is around 62 million tonnes per year (Government, 2020), with this figure anticipated to rise to 165 million tonnes by 2030 (Godrej Industries, 2017). Many countries' governments, including India, have enacted laws and regulations to protect the environment, but their ground implementation is poor. This is demonstrated by the net rise in waste generated each year. RL is one of the critical operational ways to reduce waste, and as a result, the environmental effect. It covers various product recovery procedures such as recycling, reuse, remanufacturing, repair and refurbishment (Prajapati et al., 2019a).

The adoption of RL in a company provides a chance to grow its business. An efficient RL practice increases profitability (Senthil et al., 2018). However, RL implementation is a complicated process. Depending on how a business perceives it, it might damage the firm or a chance for profit (Meng, 2010). The vulnerability in the implementation of RL leads to adverse consequences (Biehl et al., 2007). The RL implementation is complicated, and there are several risks involved. Knowledge of different related risks is critical for effective RL project execution (Dandage et al., 2018). The existence of hazards disrupts the execution of the RL; therefore, a company must have thorough information on the risk elements involved before implementation. Identifying and addressing all of the various RL risk sources helps shape our perceptions towards threats and opportunities (Ward and Chapman, 2003). Risk management often entails identifying, assessing, assigning and controlling risks. Risk identification is usually the foundation of all other procedures, and the risk factors are generally not autonomous but interrelated (Han et al., 2019). Therefore, this article aims to the following objectives:

1 Identify the RL risk factors for assessing associated risks during its implementation.
2 Modelling the interrelationships between identified risk factors of RL implementation.
3 Suggest the risk management strategies so that firms can effectively execute the RL implementation.

To fulfil the goal of this research, a two-stage research framework is presented. The first stage is to identify the risk factors associated with RL implementation, and the second is to determine the hierarchical level and interdependence of the identified risk variables. Through literature review, this study creates a list of risks in RL implementation, and with the assistance of the Delphi approach, merges relative risks and adds if overlooked. Interpretive structural modelling (ISM) is used to create a structural model that distinguishes between source, intermediate, and result RL risks and determines the contextual link between the RL implementation risks chosen. ISM, which Warfield developed in 1974, is a systematic, efficient, and straightforward technique of recognising relationships among particular items that describe an issue. It gives results direction and aids in creating an easy-to-understand graphical model (Attri et al., 2013). The fuzzy cross-impact matrix multiplication applied to classification (F-MICMAC) analysis (French acronym: Matriced' Impacts Croise's Multiplication Appliquée a UN Classement; English acronym: cross-impact matrix multiplication applied to classification) is designed to determine the most critical factors within a model among many factors based on its effectiveness. F-MICMAC categorises the selected risks into four groups based on their driving and dependence power. This study also includes risk management techniques as well as managerial implications.

The article is structured as follows: Section 2 summarises the prior literature on RL, particularly related to risk, and frames the research gap and necessity for this study. The suggested framework for this study is described in Section 3. Section 4 describes how the planned research technique was put to use. Section 5 discusses the ISM, and F-MICMAC model results, gives insight into the RL risk management techniques and evaluates the managerial implications. The study's conclusions are presented in Section 6.

2 Literature review

Many studies regarded risks as a negative potential, while others argued about the opportunities they provide (Ward and Chapman, 2003). According to Narkhede et al. (2019), the risk is "the presence of prospective or real threats or opportunities that have an influence on the project's aim during the life cycle." It may provide opportunities and prospects that are beneficial to the organisation (Pfohl et al., 2010). Ward and Chapman (2003) stress the word uncertainty rather than risk. The terms uncertainty, disruption, and disturbance are used interchangeably in the risk literature. Risk identification and subsequent analysis in RL are critical concepts to understand

2.1 RL and risk

RL adoption provides several opportunities, particularly in nations where this technique is still in its early stages (Prajapati et al., 2019a). Agrawal et al. (2015) underlined the need to conduct independent research on RL risk assessment. A systematic review was conducted to identify previous work and research gaps for hazards in RL deployment. Prajapati et al. (2019a) provided the procedures for material selection and refining, which were followed. To get an initial selection of 2,277 articles, the Scopus database was searched using the keywords 'RL' + 'risk' and 'RL' + 'disruption'. After applying different criteria, the list was narrowed down to 92 items. These 92 publications were evaluated using their abstracts and full texts (if needed) to choose papers that focused on hazards in RL implementation. There were 26 publications identified that studied risks in RL.

Most of the articles study RL risk as a factor in their mathematical model such as, risks to population in location inventory model (Rabbani et al., 2020), supplier selection in demand supply risks using conditional value at risk (CVaR) (Rezaei et al., 2020), maximise profit and minimise cost in presence of risks (Gooran et al., 2020), designing a RL network using CVaR (Zamani et al., 2020; Babazadeh et al., 2015; Soleimani and Govindan, 2014), develop sustainable business model using triple bottom line and risk elements (Wit and Pylak, 2020), build RL design to manage end of life returns and associated risks (Krug et al., 2020), multi-period RL network design under uncertainty for construction waste (Rahimi and Ghezavati, 2018) and for the transportation of hazardous material and facility location under risk (Yanik, 2015), multi-product RL network design considering both risk-seeking and risk-averse decision-makers (Gooran et al., 2018; Yu and Solvang, 2017), designing location routing model with inventory risks (Zhao and Ke, 2017), risk-averse multi-echelon multi-product RL model under uncertainty (Yu and Solvang, 2017), designing multi-objective model to identify supplier under demand and supply risk (Moghaddam, 2015), designing forward-reverse network design under partial or complete facility disruption (Hatefi and Jolai, 2015; El-Sayed et al., 2010), and developing RL model to minimise environment risk (Ahluwalia and Nema, 2006).

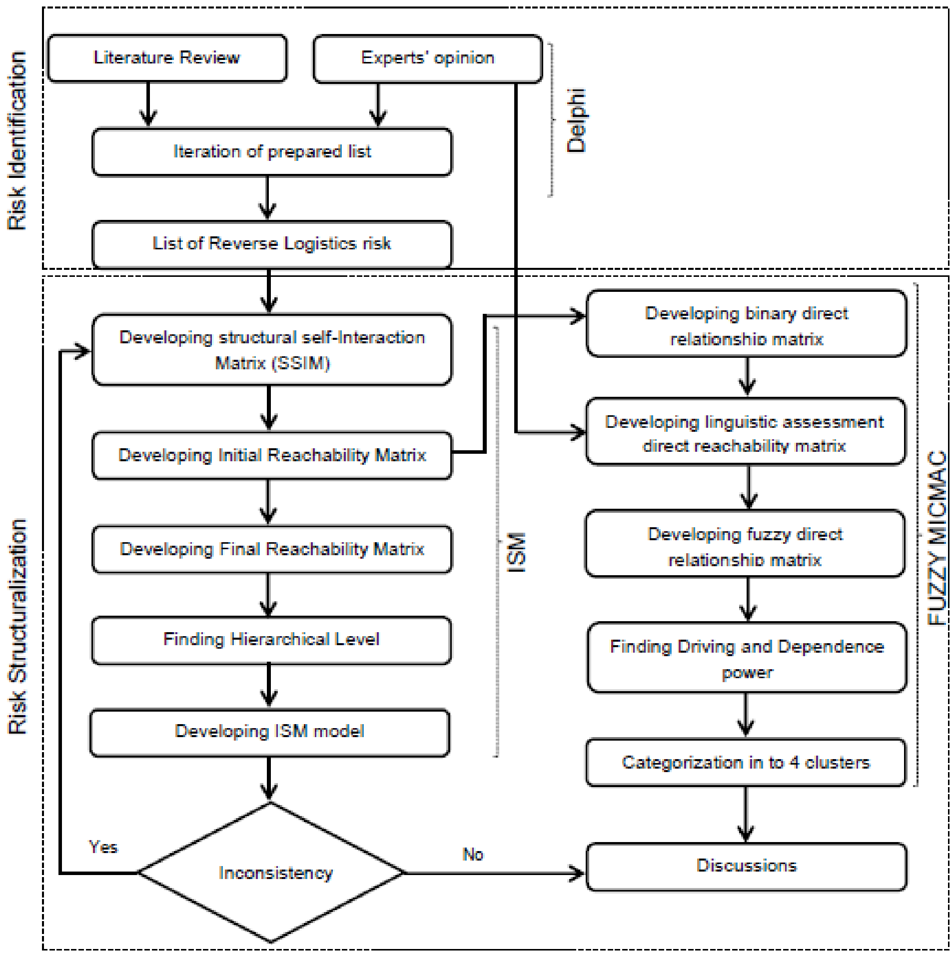
Few authors have considered MCDM-based frameworks for studying RL risks are, prioritising the risks in RL network (Senthil et al., 2018), evaluation and selection of third party RL provider (Zarbakhshnia et al., 2018), considering sustainable and risk factors to evaluate and select sustainable third party RL provider (Mavi et al., 2017), assess optimal downstream collection strategy for RL using the related benefits, opportunities, costs and risks (BOCR) criteria and sub-criteria (Hsueh and Lin, 2017), and construct a network

BOCR model (Hsueh and Lin, 2015). Panjehfouladgaran and Lim (2020) studied RL risk management clustering and mitigation strategies. Several risks factor such as financial and economic risks, inventory risks, disruption risks, data management risks, and return product quantity risks are pretty common in RL literature. Financial risks encompass all monetary risks (operational, market, liquidity, etc.) associated with the industry's investment in RL implementation. Inventory risk is related to the management and storage of returns. The risk of return product quantity is associated with the variable amount of returns. Several risks factors such as process design risk, information and communication risks (ICT), strategy risk, return forecasting risk, return product quality risk, and social risks are quite less reported in the literature. Process design risk is related to a process's design to manage a wide range of returns and quality. ICT and risk forecasting are inextricably intertwined since effective ICT leads to a reliable forecast. End-of-life returns always include a quality risk since they define the remaining value in the product. The return handling agency must directly carry the risk of return product quality and is inextricably tied to gatekeeping design risk. We select 19 RL implementation risks for this study, which will be described later.

Table 1 Review of risk management strategies in literature

Reference	*Outcome*
Ghadge et al. (2012)	Risk sharing, multi-sourcing, risk sharing, vendor managed inventory, incentive contracts, product variety, delivery management, postponement, real time coordination, agility in options, strategic management, supply chain rebuilding, proper resource management, rerouting, dynamic pricing.
Wang and Yang (2012)	Merge managerial flexibility/agility with the research project for risk management.
Singhal et al. (2011)	Proper capacity and inventory management, reliability, relate demand to supply, outsourcing, information sharing and forecasting, risk calculation, assessment of risk, developing collaborative performance index, maintaining optimal inventory.
Tang and Musa (2011)	Multiple sourcing, resilience supply chain, outsourcing, dependable partners, supplier involvement, in-house manufacturing, hedging, postponement, better information technology, lean manufacturing.
Wang et al. (2010)	Synchronise corporate strategy with risk, align performance measurement system with risk.
Pfohl et al. (2010)	Capital market theory, new institutional economics theory for base of supply chain risk management, also they put other 17 principle for risk management.
Manuj and Mentzer (2008)	Avoidance, postponement, control, transfer, security, hedging, supply chain flexibility, set desired cost saving.
Kwak and Dixon (2008)	Use flexible and analytical tool for risk management, design risk averse decision making model, involve stakeholders, outsourcing, follow regulations, take help from risk experts, benchmark, merge risk with project timeline.
Tang (2006)	Information sharing, vendor managed inventory, collaborative forecasting, robust product management strategy, robust demand management strategy, robust information management strategy.
Jüttner et al. (2003)	Avoidance, control, cooperation, flexibility.

Figure 1 Proposed research methodology



Although there are numerous publications in the literature on RL's mathematical modelling for diverse activities with risk as one of its components. Senthil et al. (2018) use analytical hierarchy process (AHP) coupled with the fuzzy technique for order preference by similarity to ideal solution (TOPSIS) and preference ranking organisation method for enrichment evaluations (PROMETHEE) to prioritise the RL network risk. They rank nine RL risks depending on a few parameters. Although they looked at nine risk variables, there are many more. Furthermore, research on the interconnectivity of risk in RL implementation is still lacking. Therefore, there is a need to investigate various risk variables in RL implementation and understand their interdependence.

The literature was also searched for studies on RL risk management strategies, but only one paper was found. The scope of the search was broadened to include supply chain management and green supply chain management. Table 1 lists a few publications that only cover the risk management approach.

3 The proposed framework

This study provides a two-step approach for risk identification and risk structuralisation. The method for identifying and selecting hazards is referred to as risk identification. The Delphi technique is used in this study to determine the hazards associated with RL implementation. The method for organising risk variables into a well-defined framework is risk structuralisation. Due to its appropriateness, ISM-F-MICMAC is used to determine an identified risk's interrelationship, driving and dependency power. The suggested research framework for this project is depicted in Figure 1.

4 Application of the proposed research framework

4.1 Risk identification

The risks in RL implementation are identified with the help of the Delphi method.

4.1.1 The Delphi method

The Delphi method is one of the oldest techniques for administrative decision-making that takes into account the opinions of a panel of experts. It was created in the 1950s by the RAND Corporation in the USA (Han et al., 2019). Delphi is a structured group discussion technique used to manage (or solve) a complicated issue (Okoli and Pawlowski, 2004). It eliminates face-to-face squabbling amongst experts (Barrios et al., 2021). Previously, the Delphi approach has been used in studies on healthcare research (Nasa et al., 2021), solar energy in smart cities (Ghadami et al., 2021), Industry 4.0 (Culot et al., 2020), information systems (Lee and Park, 2020), Brownfield (Han et al., 2018, 2019), e-commerce (Okoli and Pawlowski, 2004), forest management (Filyushkina et al., 2018), sustainable ecotourism (Ocampo et al., 2018) and in many others. The five step Delphi method is as follows:

Step 1 *Factor selection:* A list of semi-structured criteria is prepared based on existing literature.

Step 2 *Remove duplicates:* The prepared list is rechecked to remove the duplicates present if any.

Step 3 *Selection of experts:* A group of experts is chosen from a target system for this study. The number of experts in Delphi is not limited and can be chosen based on the study aim (Nasa et al., 2021). An expert panel in this research consists of ten professionals, two of whom are academics with extensive experience in supply chain management and RL research, three consultants dealing with RL implementation, and five industry experts from an Indian electrical manufacturing company that is already implementing RL in their organisation. These experts assist in the identification of RL risk factors and the following iterations.

Table 2 RL risks

S. no.	*Risk*	*Code*	*Description*	*References*
1	Financial and economic risk	R1	Risks associated with the improper investment. It also includes currency inflation, exchange rates, operation cost overrun and sources of funds collection.	De Oliveira et al. (2021), Gooran et al. (2020), Yazdani et al. (2019), Zarbakhshnia et al. (2018), Mavi et al. (2017)
2	Network design risk	R2	Risk occurs due to the imprecise network structure of RL. This may lead to operation failure.	Zamani et al. (2020), Babazadeh et al. (2015), Soleimani and Govindan (2014)
3	Inventory and capacity design risk	R3	Risks involved with the design of storage and capacity of reprocessing centres.	Rabbani et al. (2020), Senthil et al. (2018), Zhao and Ke (2017)
4	Process design risk	R4	The demand for more comprehensive products leads to complex product design, thereby creating the risk of handling returns and designing an efficient process for handling returns.	Krug et al. (2020), Gooran et al. (2018)
5	Gatekeeping design risk	R5	Risks associated with the improper investigation of returns.	Senthil et al. (2018), Yu and Solvang (2017)
6	Information and communication technology (ICT) risk	R6	Tracing of end-of-life/end-of-use products largely depends upon ICTs. A good ICT will help in proper forecasting of RL inventory, which in turn helps management to formulate proper capacity planning.	Expert opinion
7	Management policy risk	R7	Represents risk at management end which includes supervision risk, insufficient control potential risk, policy failure risk and risk of manager's quality and ability.	De Oliveira et al. (2021), Senthil et al. (2018), Mavi et al. (2017), Yanik (2015)
8	Strategy risk	R8	Includes errors related to the proper strategic planning for implementing RL.	De Oliveira et al. (2021), Rezaei et al. (2020), Zarbakhshnia et al. (2018), Hatefi and Jolai (2015)
9	Machine/facility failure risk	R9	Failure of machine/facility leading to disruption in the RL process and its effectiveness.	Yazdani et al. (2019), Zarbakhshnia et al. (2018)
10	Return forecasting risk	R10	Error in predicting returns leading to few returns (wastage of man and machine time) or excessive returns (handling and managing issues).	Alshamsi and Diabat (2015)

Table 2 RL risks (continued)

S. no.	*Risk*	*Code*	*Description*	*References*
11	Information flow and data managing risk	R11	Company's internal and external flow of goods and finances are closely interrelated with the accuracy of information. Failure of information flow may cause excessive damage.	De Oliveira et al. (2021), Senthil et al. (2018)
12	Outsourcing risk	R12	Outsourcing of any activity involves sharing of company's data with an outsourced vendor. The consequence may be data leakage, indistinct responsibility and insufficient control potential. Also, the performance of the vendor will largely affect RL performance.	Gooran et al. (2018), Senthil et al. (2018), Zarbakhshnia et al. (2018), Alshamsi and Diabat (2015)
13	Return product quality risk	R13	The products acquired from consumers will not have the same quality. The variation in the quality of returned products requires individual attention which affects the net profitability from RL.	Yazdani et al. (2019), Gooran et al. (2018), Zarbakhshnia et al. (2018)
14	Return product quantity risk	R14	The quantity of returns is always indeterminate, leaving RL vulnerable for inventory and capacity planning.	Gooran et al. (2018), Senthil et al. (2018) , Zarbakhshnia et al. (2018)
15	Scarcity of skilled labour risk	R15	There is a lack of qualified and skilled manpower for RL implementation in the countries where it is newly born.	Senthil et al. (2018)
16	Government policy risk	R16	It includes challenges associated with the management of local government and authorities. An unstable government, investment policies, taxation policies largely affects RL implementation.	Yazdani et al. (2019), Rahimi and Ghezavati (2018)
17	Regulation and legality risk	R17	Possibility of legal actions taken against the company due to its activities, inaction, products and services.	Yazdani et al. (2019)
18	Social risk	R18	This includes inadequate knowledge of benefits due to product returns and the process of return. Also, there is a culture difference between two states which need to be understood.	De Oliveira et al. (2021), Krug et al. (2020), Senthil et al. (2018)
19	Market demand risk	R19	The acceptance of refurbished and remanufactured products into the market is also a major risk.	Gooran et al. (2018), Senthil et al. (2018), Zarbakhshnia et al. (2018)

Step 4 *Iteration of pre-prepared list:* The semi-structured list is distributed to each expert, who updates it based on their knowledge. The replies are gathered, ideas are combined, and the second set of criteria is created. It is forwarded to the same experts for revisions and recommendations. The procedures can be continued until a state of shared consciousness is attained.

Step 5 *Finalisation of factors:* A completed set of criteria is created for future study based on the replies gathered and iterations performed.

The extensive literature analysis finds 22 risk variables for RL. The expert panel combines four RL risk variables and recommends one new RL risk factor. As a result, this study highlights 19 risk factors for RL adoption for future investigation. Table 2 contains a full list of the RL risk variables, along with a definitive description based on the Delphi approach.

4.2 Risk structuralisation

Risk structuralisation involves the evaluation of interrelationship between the risk, its driving and dependence power and dividing it into the four clusters of driving, dependent, linkage and autonomous variables.

4.2.1 Interpretive structural modelling

The ISM is the most commonly utilised structural analysis method (Han et al., 2019). The ISM model includes level-by-level information for locating a criterion (Trivedi et al., 2021). Its basic idea is to leverage experts' relevant knowledge and information to break down a complicated framework into a few sub-components and build a multilayer model (Kumar et al., 2021). The ISM approach transforms vague and ineffectively articulated frameworks into a clear and well-defined framework (Shanker and Barve, 2021). ISM is deployed in many research areas such as supply chain management (Gorane and Kant, 2015; Shanker and Barve, 2021), inland waterways as a sustainable transportation mode (Trivedi et al., 2021), Industry 4.0 and circular economy (Kumar et al., 2021), green supply chain management (VenkatesaNarayanan and Thirunavukkarasu, 2021), supply chain performance measurement (Katiyar et al., 2018) and many more. ISM typically causes managers to reconsider obvious demands and enhance their understanding of the relationships between critical elements (Mishra et al., 2017).

Step 1 *Identification of criteria:* Table 1 shows the criteria for which the interrelationship is to be modelled.

Step 2 *Finding contextual relationship:* A brainstorming session was held among the experts (described in Section 4.1.1) to discover a contextual link between criteria and to create a structural self-interaction matrix (SSIM) based on pairwise comparisons. The comparison is based on qualitative ratings expressed as V, A, X and O, where

V indicates i^{th} criterion influence j^{th} criterion and not vice-versa

A indicates j^{th} criterion influence i^{th} criterion and not vice-versa

X indicates i^{th} criterion and j^{th} criterion influence each other

O indicates i^{th} criterion and j^{th} criterion are unrelated.

The SSIM for risks in RL implementation is developed using the response from the experts (Table 3).

Table 3 Structural self-interaction matrix

	19	*18*	*17*	*16*	*15*	*14*	*13*	*12*	*11*	*10*	*9*	*8*	*7*	*6*	*5*	*4*	*3*	*2*
R1	A	A	A	A	A	A	A	A	A	A	A	A	O	A	A	A	A	A
R2	V	X	X	A	V	V	V	V	V	V	V	A	A	X	V	V	V	
R3	X	A	A	A	A	X	V	A	A	A	A	A	A	A	X	A		
R4	V	A	A	A	X	V	V	O	O	O	X	A	A	A	V			
R5	X	A	A	A	A	X	V	A	A	A	A	A	A	A				
R6	V	X	X	A	V	V	V	V	V	V	V	A	A					
R7	V	V	V	X	V	V	V	V	V	V	V	V						
R8	V	V	V	A	V	V	V	V	V	V	V							
R9	V	A	A	A	X	V	V	O	O	O								
R10	V	A	A	A	O	V	V	X	X									
R11	V	A	A	A	O	V	V	X										
R12	V	A	A	A	O	V	V											
R13	A	A	A	A	A	A												
R14	X	A	A	A	A													
R15	V	A	A	A														
R16	V	V	V															
R17	V	X																
R18	V																	

Table 4 Initial reachability matrix

	1	*2*	*3*	…	…	*17*	*18*	*19*
R1	1	0	0	…	…	0	0	0
R2	1	1	1	…	…	1	1	1
R3	1	0	1	…	…	0	0	1
…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…
R17	1	1	1	…	…	1	1	1
R18	1	1	1	…	…	1	1	1
R19	1	0	1	…	…	0	0	1

Step 3 *Develop initial reachability matrix:* The SSIM is converted to a binary digit matrix known as initial reachability matrix (Table 4) by replacing the above qualitative terms (V, A, X and O) to binary numbers (0 and 1) according to the following rule:

- If i to j value is V, replace (i, j) to 1 and (j, i) to 0.
- If i to j value is A, replace (i, j) to 0 and (j, i) to 1.
- If i to j value is X, replace both (i, j) and (j, i) to 1.

- If *i* to *j* value is O, replace both (*i*, *j*) and (*j*, *i*) to 0.

Step 4 *Convert initial reachability matrix to final reachability matrix:* The transitivity rule transforms the initial reachability matrix to the final reachability matrix, which states that if a criteria *P* is linked to a criterion *Q* and a criterion *Q* is connected to a criterion *R*, then *P* must be connected to *R*.

This matrix also displays the driving and dependence power of each RL risk variable. The driving force of a variable reflects the number of elements (including self) that may aid in achieving a goal. The driving power is determined by summing the entries in the final reachability matrix's rows. The dependence power reflects the number of elements (including self) that may aid to achieve it. The dependence power is calculated by adding the entries in the columns of the final reachability matrix. Table 5 presents the final reachability matrix.

Step 5 *Finding the hierarchical level of criterion:* The levels of each criterion are determined through several iterations based on reachability and antecedent set through level partitioning. The final reachability matrix leads to the development of reachability and antecedent set for each risk factor. The reachability set $M(x_i)$ of the variable x is the set of variables defined in the columns that contained 1 in row x_i. Similarly, the antecedent set $N(x_i)$ of the variable x_i is the set of variables defined in the rows that contained 1 in column x_i (Mishra et al., 2017). The intersections of these sets are found for each risk variable. Those variables which have the same reachability and intersection set are assigned top-level in the ISM model. The top-level variables would not impact the other variables below in the hierarchy. Now, the variables which are assigned at some level are removed, and the next iterations are performed to find out the prominence for other variables.

In the present research, six iterations were performed to find the level of selected 19 RL risk variables. In Table 6, risk variables R1 and R13 have the same reachability and intersection set; therefore, they are assigned level 1 in the ISM model.

Now, level 1 is not carried for further iterations and is discarded. In the second iteration (Appendix: Table A2), the risk variables R3, R5, R14, and R19 are assigned at the second level in the ISM model. Similarly, the process of removing the variables (assigned levels) and performing the iterations is repeated to assign the level to each variable in the system. In third iteration (Appendix: Table A3), variables R4, R9, R10, R11, R12, and R15 are assigned at level 3. In the fourth iteration (Appendix: Table A4), variables R2, R6, R17, and R18 are assigned at level 4. In fifth iteration (Appendix: Table A5), variable R8 is assigned at level 5. In the sixth iteration, variables R7 and R16 are assigned the bottom level, i.e., level 6 (Appendix: Table A6). The bottom level variables are the key drivers of the system that changes in these have an overall impact on the entire system.

Table 5 Final reachability matrix

	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*	*18*	*19*	*DrP*
R1	1	0	0	0	0	0	0	0	0	0	0	0	1T	0	0	0	0	0	0	2
R2	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1	0	1	1	1	16
R3	1	0	1	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	1	6
R4	1	0	1	1	1	0	0	0	1	0	0	0	1T	1T	1	0	0	0	1T	9
R5	1	0	1	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	1	6
R6	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1T	0	1	1	1	16
R7	1T	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	19
R8	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	1	1	1	17
R9	1	0	1	1	1T	0	0	0	1	0	0	0	1	1T	1	0	0	0	1T	9
R10	1	0	1	0	1	0	0	0	0	1	1	1	1	1	0	0	0	0	1	9
R11	1	0	1	0	1	0	0	0	0	1	1	1	1	1	0	0	0	0	1	9
R12	1	0	1	0	1	0	0	0	0	1	1	1	1	1	0	0	0	0	1	9
R13	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	2
R14	1	0	1	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	1	6
R15	1	0	1	1	1	0	0	0	1	0	0	0	1	1	1	0	0	0	1	9
R16	1	1	1	1	1	1	1	1	1	1	1	1	1T	1	1	1	1	1	1	19
R17	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1	0	1	1	1	16
R18	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1	0	1	1	1	16
R19	1	0	1	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	1	6
DeP	19	7	17	10	17	7	2	3	10	10	10	10	19	17	10	2	7	7	17	

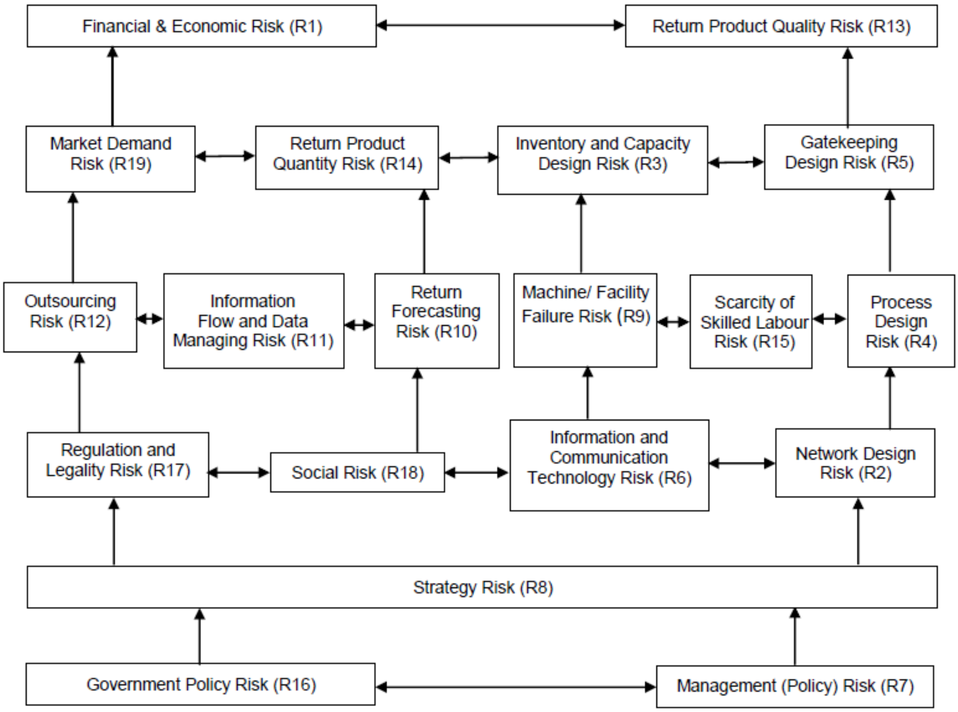
Note: DrP: driving power and DeP: dependence power.

Table 6 Level partition of levels of RL risk – first iteration

	Reachability set	*Antecedent set*	*Intersection set*	*Level*
R1	1, 13	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19	1, 13	1
R2	1, 2, 3, 4, 5, 6, 9, 10, 11, 12, 13, 14, 15, 17, 18, 19	2, 6, 7, 8, 16, 17, 18	2, 6, 17, 18	
R3	1, 3, 5, 13, 14, 19	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17, 18, 19	3, 5, 14, 19	
R4	1, 3, 4, 5, 9, 13, 14, 15, 19	2, 4, 6, 7, 8, 9, 15, 16, 17, 18	4, 9, 15	
R5	1, 3, 5, 13, 14, 19	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17, 18, 19	3, 5, 14, 19	
R6	1, 2, 3, 4, 5, 6, 9, 10, 11, 12, 13, 14, 15, 17, 18, 19	2, 6, 7, 8, 16, 17, 18	2, 6, 17, 18	
R7	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19	7, 16	7, 16	
R8	1, 2, 3, 4, 5, 6, 8, 9, 10, 11, 12, 13, 14, 15, 17, 18, 19	7, 8, 16	8	
R9	1, 3, 4, 5, 9, 13, 14, 15, 19	2, 4, 6, 7, 8, 9, 15, 16, 17, 18	4, 9, 15	
R10	1, 3, 5, 10, 11, 12, 13, 14, 19	2, 6, 7, 8, 10, 11, 12, 16, 17, 18	10, 11, 12	
R11	1, 3, 5, 10, 11, 12, 13, 14, 19	2, 6, 7, 8, 10, 11, 12, 16, 17, 18	10, 11, 12	
R12	1, 3, 5, 10, 11, 12, 13, 14, 19	2, 6, 7, 8, 10, 11, 12, 16, 17, 18	10, 11, 12	
R13	1, 13	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19	1, 13	*1*
R14	1, 3, 5, 13, 14, 19	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17, 18, 19	3, 5, 14, 19	
R15	1, 3, 4, 5, 9, 13, 14, 15, 19	2, 4, 6, 7, 8, 9, 15, 16, 17, 18	4, 9, 15	
R16	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19	7, 16	7, 16	
R17	1, 2, 3, 4, 5, 6, 9, 10, 11, 12, 13, 14, 15, 17, 18, 19	2, 6, 7, 8, 16, 17, 18	2, 6, 17, 18	
R18	1, 2, 3, 4, 5, 6, 9, 10, 11, 12, 13, 14, 15, 17, 18, 19	2, 6, 7, 8, 16, 17, 18	2, 6, 17, 18	
R19	1, 3, 5, 13, 14, 19	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17, 18, 19	3, 5, 14, 19	

Step 6 *Developing the ISM model:* Now, with the help of the levels assigned to each RL risk variables, the ISM model is developed. A six level ISM model is given in Figure 2. The risks in RL implementation are arranged according to the levels assigned in Step 5. The variables R7 and R16 acquiring level 6 is kept at the bottom of the model while the variables R1 and R13 acquiring level 1 is kept at the top.

Figure 2 The ISM model



4.2.2 Fuzzy cross-impact matrix multiplication applied to classification

The F-MICMAC analysis aids in determining the degree of connection between the criteria. The MICMAC approach, created in 1973 by Duperrin and Godet, is an aberrant grouping technique that evaluates the degree of each ISM criteria (Raval et al., 2018). The MICMAC examines the criterion in terms of its driving power (the number of criteria it may affect) and dependency power (i.e., the number of criteria that can influence it) (Shanker and Barve, 2021). The requirements are divided into four groups: autonomous (weak driving – weak dependency), dependent (weak driving – strong dependence), linkage (strong driving – high dependence), and driver (strong driver – weak dependence). A driver-dependence matrix is formed to present all the criteria at a place. To show all of the requirements in one location, a driver-dependence matrix is created. The MICMAC technique only examines binary digits to identify the relationship, i.e., a ‘0’ indicates no link and a ‘1’ indicates a relationship between the two variables. It never demonstrates the quality of the link between the variables (Abbas et al., 2021). The F-MICMAC analysis handles this shortcoming by classifying the connection as having no impact, very low influence, low influence, medium influence, high influence, very high influence and complete influence. The F-MICMAC additionally improves the MICMAC analysis’s sensitivity (Ramos et al., 2021). The F-MICMAC technique is described in detail below:

Step 1 *Developing the binary direct reachability matrix (BDRM):* The BDRM is developed from the final reachability matrix by making all the diagonal elements 0 and removing all the transitivity in it (Table 7).

Table 7 The BDRM

	1	*2*	*3*	…	…	*17*	*18*	*19*
R1	0	0	0	…	…	0	0	0
R2	1	0	1	…	…	1	1	1
R3	1	0	0	…	…	0	0	1
…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…
R17	1	1	1	…	…	0	1	1
R18	1	1	1	…	…	1	0	1
R19	1	0	1	…	…	0	0	0

Step 2 *Developing fuzzy direct reachability matrix (FDRM):* The triangular fuzzy set is defined by a set (i, j, k), where i is the lower limit and k is the upper limit. The value j is such that, $i < j < k$ and is valued between [0, 1]. The F-MICMAC analyses the interrelationships between the variable by using the linguistic scale. First, the linguistic assessment direct reachability matrix (LADRM) is developed (Table 8) from the BDRM matrix by rating the quality of the relationship between the two variables on a linguistic scale (Appendix: Table A1).

Table 8 The LADRM

	1	*2*	*3*	…	…	*17*	*18*	*19*
R1	O	O	O	…	…	O	O	O
R2	H	O	H	…	…	H	M	VL
R3	H	H	O	…	…	O	O	L
…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…
R17	M	H	L	…	…	O	H	L
R18	L	M	L	…	…	H	O	H
R19	H	O	H	…	…	O	O	O

Again, the judgement of the same experts as in ISM was taken to rate the relationship between two variables using the linguistic scale. Using the best non-fuzzy performance value, the fuzzy values are defuzzified to crisp values for further calculations [equation (1)] (Bhosale and Kant, 2016).

$$\textit{Best non-fuzzy performance value}\ (BNP) = \frac{[(k-i)+(j-i)]}{3} + i \tag{1}$$

The FDRM matrix (Table 9) is obtained from the LADRM by replacing the linguistics values by the respective quantitative term.

Table 9 The FDRM

	1	*2*	*3*	…	…	*17*	*18*	*19*
R1	0	0	0	…	…	0	0	0
R2	0.7	0	0.7	…	…	0.7	0.5	0.1
R3	0.7	0	0	…	…	0	0	0.3
…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…
R17	0.5	0.7	0.3	…	…	0	0.7	0.3
R18	0.3	0.5	0.3	…	…	0.7	0	0.7
R19	0.7	0	0.7	…	…	0	0	0

Step 3 *Obtaining fuzzy stabilised matrix:* After obtaining the FDRM, the multiplication concept of the fuzzy set theory is utilised to get the stabilised matrix (Table 10) (Mishra et al., 2017). The matrix multiplication follows the following rule [equation (2)]:

$$X = A.B = \max k\left[\min\left(a_{ik}; b_{kj}\right)\right] \text{ where } A = \left[a_{ik}\right] \text{ and } B = \left[b_{ik}\right] \tag{2}$$

The driving and dependence power of each risk variable is obtained by adding the rows and columns entries separately.

Step 4 *Classification of categories:* Based on the driving and dependence power of each risk variable, they are classified into four clusters, i.e., autonomous, dependent, linkage and driver variables (Figure 3). A higher value of dependence power shows that many variables are required to be addressed to address a given variable. On the other hand, a higher value of driving power indicates that these variables have to be addressed first compared to others.

- *Autonomous RL risks:* This cluster of risks in RL implementation has a low dependency as well as a low driving power. These hazards are not impacted by other risks and have little impact on other risks. The autonomous hazards are generally detached from the system and are located close to the origin. The lack of components in this category implies that all of the risk factors considered are substantial and have some effect while adopting RL.
- *Dependent RL risks:* The risks in RL implementation, which fall under this cluster, have high dependence and low driving power. These risks are highly dependent on other risks in the system. Financial and economic risk (R1), inventory and capacity design (R3), process design risk (R4), gatekeeping design risk (R5), machine/facility failure risk (R9), returns forecasting risk (R10), return product quality risk (R13), return product quantity risk (R14), scarcity of skilled labour risk (R15), and market demand risk (R19) are in the second cluster of F-MICMAC analysis. Except for R5, the management cannot control the remaining other risks and depend on them.

- *Linkage risks:* The risks falling in this category have high driving and dependence power. These are the most unstable risks as any change in them has a high impact on the system, and they also affect themselves (either positively or negatively). Derived from the driving barrier, the linkage barrier results in an absolute dependent barrier. Information flow and data managing risk (R11) is the only risk in RL implementation that falls in this category. Trust becomes a critical issue when it comes to risks (Khurana et al., 2010). Information flow and data management is the heart of RL management. It smoothen the RL process from the bottom level till the top.
- *Driving risks:* The fourth region belongs to the driving risks, which have low dependence and high driving power. These are the critical risks in the system and generally placed at the ISM model's bottom level. Handling the driving risk factors may help in managing other risk factors in the system as well. Network design risk (R2), information and communication technology risk (R6), management policy risk (R7), strategy risk (R8), outsourcing risk (R12), government policy risk (R16), litigation risk (R17), and social risk (R18) are the risk factors that falls in this category.

Figure 3 Results of F-MICMAC analysis (see online version for colours)

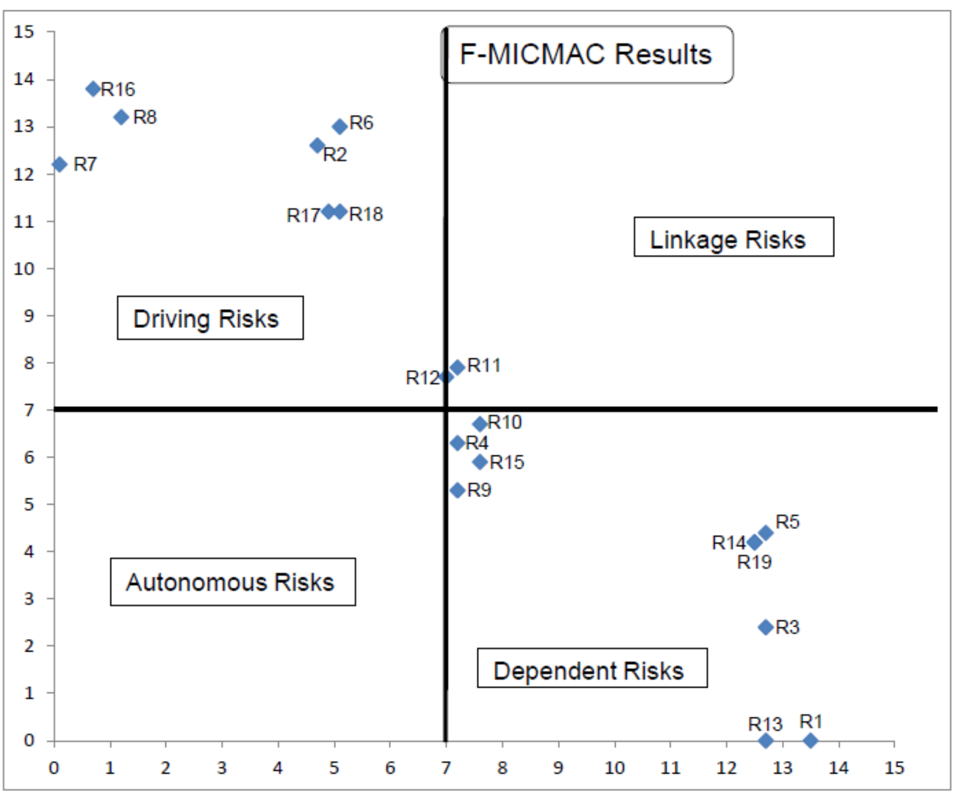


Table 10 The fuzzy stabilised matrix

	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*	*18*	*19*	*DrP*
R1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
R2	0.9	0.7	0.9	0.9	0.9	0.7	0	0	0.9	0.7	0.7	0.7	0.9	0.7	0.9	0	0.7	0.7	0.7	12.6
R3	0.9	0	0.3	0	0.3	0	0	0	0	0	0	0	0.3	0.3	0	0	0	0	0.3	2.4
R4	0.7	0	0.7	0.7	0.7	0	0	0	0.7	0	0	0	0.7	0.7	0.7	0	0	0	0.7	6.3
R5	0.9	0	0.7	0	0.7	0	0	0	0	0	0	0	0.7	0.7	0	0	0	0	0.7	4.4
R6	0.9	0.5	0.9	0.9	0.9	0.7	0	0	0.7	0.9	0.9	0.7	0.9	0.9	0.9	0	0.7	0.7	0.9	13
R7	0.7	0.7	0.7	0.7	0.9	0.7	0.1	0.5	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0	0.7	0.7	0.9	12.2
R8	0.5	0.7	0.9	0.9	0.7	0.9	0	0	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0	0.9	0.9	0.7	13.2
R9	0.7	0	0.7	0.3	0.7	0	0	0	0.7	0	0	0	0.5	0.5	0.7	0	0	0	0.5	5.3
R10	0.9	0	0.9	0	0.9	0	0	0	0	0.5	0.5	0.3	0.9	0.9	0	0	0	0	0.9	6.7
R11	0.9	0	0.9	0	0.9	0	0	0	0	0.9	0.9	0.7	0.9	0.9	0	0	0	0	0.9	7.9
R12	0.9	0	0.9	0	0.9	0	0	0	0	0.9	0.5	0.9	0.9	0.9	0	0	0	0	0.9	7.7
R13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
R14	0.7	0	0.7	0	0.7	0	0	0	0	0	0	0	0.7	0.7	0	0	0	0	0.7	4.2
R15	0.7	0	0.7	0.7	0.5	0	0	0	0.5	0	0	0	0.7	0.7	0.7	0	0	0	0.7	5.9
R16	0.9	0.7	0.9	0.7	0.9	0.7	0	0.7	0.7	0.7	0.7	0.7	0.9	0.9	0.7	0.7	0.7	0.7	0.9	13.8
R17	0.7	0.7	0.7	0.7	0.7	0.7	0	0	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0	0.7	0.7	0.7	11.2
R18	0.9	0.7	0.7	0.7	0.7	0.7	0	0	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0	0.5	0.7	0.7	11.2
R19	0.7	0	0.7	0	0.7	0	0	0	0	0	0	0	0.7	0.7	0	0	0	0	0.7	4.2
DeP	13.5	4.7	12.9	7.2	12.7	5.1	0.1	1.2	7.2	7.6	7.2	7	12.7	12.5	7.6	0.7	4.9	5.1	12.5	

Note: DrP: driving power and DeP: dependence power.

A new ISM-FMICMAC model may be developed by utilising the effectiveness of risks in RL implementation, which is calculated by subtracting the dependence power from the corresponding driving power of the variable (Table 11). Generally, the driving variables have a higher value of effectiveness. The risks having higher effectiveness are placed at the bottom level, while those having lower effectiveness are placed at the top level of this model. Based on the effectiveness, the ranking of the risks in RL implementation is also calculated.

Table 11 Effectiveness, ranking and level of risk variables by F-MICMAC analysis

Risk factor	*Driving power*	*Dependence power*	*Effectiveness*	*Ranking*	*Level*
R1	0	13.5	–13.5	18	1
R2	12.6	4.7	7.9	5	11
R3	2.4	12.7	–10.3	16	3
R4	6.3	7.2	–0.9	11	7
R5	4.4	12.7	–8.3	14	4
R6	13	5.1	7.9	4	11
R7	12.2	0.1	12.1	2	13
R8	13.2	1.2	12	3	12
R9	5.3	7.2	–1.9	13	5
R10	6.7	7.6	–0.9	10	7
R11	7.9	7.2	0.7	8	8
R12	7.7	7	0.7	9	8
R13	0	12.7	–12.7	17	2
R14	4.2	12.5	–8.3	15	4
R15	5.9	7.6	–1.7	12	6
R16	13.8	0.7	13.1	1	14
R17	11.2	4.9	6.3	6	10
R18	11.2	5.1	6.1	7	9
R19	4.2	12.5	–8.3	15	4

5 Discussion

Stringent government laws and regulations and diminishing natural raw material sources have heightened the need for RL implementation. Nonetheless, a significant amount of risk is involved with RL implementation, which the industry must efficiently manage. This study uses the Delphi method, ISM, and F-MICMAC to create a hybrid research framework. The Delphi technique identifies the nineteen RL risk variables, and ISM creates a structural model for each discovered component to examine the contextual connection. However, the model does not offer information on the link between the variables' degree (or quality). Hence, it uses F-MICMAC for categorising RL risk factors, which elements the shortcomings of the ISM model. F-MICMAC organises these RL risk factors into four clusters based on its driving and dependence power. Further, the results of ISM and F-MICMAC are compared to enhance the model's sensitivity.

5.1 The ISM model

The management policy risk (R7) and government policy risk (R16) are at the ISM model's bottom level. The policies are the basis for the initiation of any RL project activity. Every industry planning is required to fulfil the condition of laws stated by the government and follow the industry guidelines. Strategy risk (R8) is at the fifth level in the model, which implies that strategic planning is of utmost importance. Proper strategy planning reduces the impact of other risks present in the system towards minimisation. Network design risk (R2), information and communication technology risk (R6), litigation risk (R17), and social risk (R18) are at the fourth level in the model. A good RL network helps for efficient collection of returns and flow of information. Adoption of relevant technology and processes is required for effective RL deployment. The absence of these influences other RL risk variables such as predicting returns, process design, etc. The lack of customer understanding of return benefits is a social RL risk. It influences the quality and amount of product returns, which in turn has an impact on inventory and capacity planning. The management could do nothing except educate people about the detrimental effects of waste generation, the benefits of RL adoption, and their participation in its effective implementation. The above all are the driving factors in the F-MICMAC analysis, which implies that these risks are to be addressed first before considering other risks. Process design risk (R4), machine/facility failure risk (R9), return forecasting risk (R10), information flow and data managing risk (R11), outsourcing risk (R12), and scarcity of skilled labour risk (R15) are at the third level in the model. These risks are in the dependence cluster but have a reasonably high driving power, impacting the risks at level 1 and level 2 of the ISM model. R10, R11 and R12 are interlinked as valuable data provides better forecasting, which creates more data to be analysed and further enhances the return forecasting values. Outsourcing also offers data to improve the return forecasting further. R4, R9 and R15 are also interrelated.

Machines' life depends upon their proper maintenance and handling, requiring skilled labour. Design the return handling process according to the skills of the available labours. Therefore, the scarcity of skilled labours creates a significant risk to RL implementation. Inventory and capacity design (R3), gatekeeping design risk (R5), return product quantity risk (R14), and market demand risk (R19) is at the second level in the ISM model. The gatekeeping decides the return product quantity, which, in turn, decides the organisation's inventory handling capacity. Senthil et al. (2018) prioritised nine RL risk factors, seven risk factors lies at level 2 or 3 of our ISM model. The other two top-ranking criteria in their findings are consistent with ours and turn out to be critical risks.

Financial and economic risk (R1) and Return product quality risk (R13) are at the top level of the ISM model and is dependent on all the other factors in the system. The quality of returns decides the value (revenue) from the product the organisation will get (Meng et al., 2017). The RL implementation requires a high initial investment, which ultimately creates a financial risk for the organisation implementing it.

5.2 The ISM-F-MICMAC results

The ISM model places the RL risk factors at six different levels. Many risks are at the same level due to the calculation based on binary numbers. It does not show the quality of the relationship the factors have between them. The F-MICMAC analysis enhances the model's sensitivity by rating the quality of the relationship on the seven-point scale.

The placement of risks at a particular level shows its effectiveness, expanding the ISM-FMICMAC model to 14 levels (Table 11). Government policy risk (R16) is at the bottom, acting as the base for the model and is the critical driving risk factor for the RL implementation. All the other things depend on the government's policies to implement RL. Most industries think that implementing RL is an extra burden on the company, but this is not so (Prajapati et al., 2019a). Government policies play a significant role in changing this thinking and promoting RL implementation. Strategy risk (R8) has a higher driving power than management (policy) risk (R7) but has lower effectiveness. Therefore, R7 is at level thirteenth, and R8 is at level 12th in the ISM-F-MICMAC model. Network design risk (R2) and information and communication technology risk (R6) are at the same level, but unlike ISM results, litigation risk (R17) and social risk (R18) are at different levels. Similar is the case with process design risk (R4), machine/facility failure risk (R9), and scarcity of skilled labour risk (R15).

Information flow and data managing risk (R11) and outsourcing risk (R12) are at the eighth level, whereas return forecasting risk (R10) shifts to level 7 of this model. Return forecasting requires proper collection and analysis of past data. R11 and R12 bring together accurate data from the market, which helps in precise returns forecasting. Gatekeeping design risk (R5), return product quantity risk (R14), and market demand risk (R19) stay at the fourth level similar to the ISM model, but Inventory and capacity design (R3) shifts to the third level. RL risk factors R5, R14 and R19, will collectively decide the organisation's capacity design; hence, R3 is dependent on these factors. Financial and economic risk (R1) is the only risk at the top level of the ISM-F-MICMAC model as it is the ultimately driven variable in the system. Any change in the system's risk factor affects the organisation's financial status.

5.3 RL risk management strategies

Risk management is a collaborative effort by stakeholders to detect and communicate concerns to eliminate data inconsistencies and avoid negative repercussions for company performance. The following steps should be included in risk management: identification, assessment, mitigation methods and control of risks (Pfohl et al., 2010). There are two types of risk mitigation strategies: proactive and reactive risk mitigation. The decision to select the appropriate risk strategy is essential, and it is widely seen as being driven by the decision-makers behavioural side. Discussion with our experts reveal that major RL risk management strategies includes collaboration with network partners, risk sharing with stakeholders, strong mutual trust among collaborators, improved forecasting technique, continuous information sharing, considering sustainability factors while designing RL network and Integrating product life cycle with RL network. Tang (2006) suggested the risks management strategies, namely information sharing, vendor managed inventory, and collaborative forecasting as the measures to tackle supply chain risks, are equally applicable to manage RL risks. Few risk mitigation strategies such as strong mutual trust among collaborators (Ghadge et al., 2012), integrated management of RL and its risks, prioritising risks rank, quantifying risk factors, developing risk averse RL network (Singhal et al., 2011), avoidance and dodging, and developing new theories, found from the literature were approved by the experts to tackle various risk in RL implementation.

5.4 Managerial implications

RL will play a crucial part in achieving the goals of the Indian Government's initiatives such as 'Clean India, Green India', 'Swachh Bharat Mission' and others. The government has established several rules and ordinances that compel industries to adopt RL in their present supply chain (Prajapati et al., 2019b). The application of RL may help society maintain cleanliness by reducing trash going to landfills, limiting the usage of virgin raw materials, and financially benefiting industries. It is difficult for management to identify the risks connected with RL deployment and the relationships between them. The current study reveals many risk variables related to RL adoption. There is a contextual connection between the RL risk variables. As a result, this study aims to discover the link that exists between the risk variables. The present study shows that all 19 RL risks are substantial; hence, management must manage each risk throughout RL implementation. Understanding the driving and reliance power and the efficacy of a specific risk factor aids in separating the variables that demand prompt attention. To ease RL implementation, the ABC analysis may also be performed based on the efficacy of the risk variables. This research provides valuable information and helps set the guidelines for the industries willing to implement RL.

6 Conclusions

The advantages of the reverse supply chain are offset by the various risks and uncertainties that a company may encounter during implementation. Understanding hazards and managing them in the reverse supply chain is critical, and it is a primary focus for both academics and business. A business must view risk management as an integrated management strategy to be successful. The Delphi approach was used in this study to determine the 19 most relevant hazards in RL deployment. To select the contextual connection among the risks, a six-level ISM model was constructed. The ISM model was validated using F-MICMAC analysis based on its driving and dependent power. The strength of the link between the components and its new levels was also calculated based on the effectiveness of individual risks. The risk variables were classified into four groups depending on their driving and dependent power. There are no risk variables in the autonomous risk cluster, ten risk factors in the dependent risk cluster, one risk in the linkage risk cluster, and eight risk factors in the driving risk cluster. The ISM-MICMAC and ISM-F-MICMAC findings were compared in order to get insight into the efficacy of particular risk factors during RL implementation. Finally, the understanding of RL risk management techniques and managerial implications were explored to control the risks associated with RL deployment.

The current investigation is quite beneficial for identifying risks in RL deployment and understanding the relative efficacy of various hazards. On the other hand, the developed model is a hypothetical model produced by requesting expert advice and conducting a literature review. ISM provides an organised, directed model for complicated situations and reasonably represents the risk variables involved, but the model's accuracy suffers as the number of variables increases. The model is subjective and solely based on the expert's opinion. A more significant number of experts may result in disagreements (arguments) that impact model building. Statistical analysis might be used to test the ISM-F-MICMAC model for real-world applications. Structural equation modelling (SEM) or system dynamics (SD) modelling might be utilised to validate the proposed model further. The analytic hierarchy process, analytic network process, and step-wise weight assessment ratio analysis methods might be used to quantitatively assess the variables.

To summarise, the current study effectively offers companies preliminary guidelines for assessing risks associated with RL adoption. This research assists companies in taking preventative actions to avoid becoming trapped in some issues during RL implementation. This research also aids in the formulation of management (strategic) policies by taking into account the different risks involved with execution.

References

Abbas, H., Asim, Z., Ahmed, Z. and Moosa, S. (2021) 'Exploring and establishing the barriers to sustainable humanitarian supply chains using fuzzy interpretive structural modeling and fuzzy MICMAC analysis', *Social Responsibility Journal*, DOI [online] https://doi.org/10.1108/SRJ-12-2020-0485.

Agrawal, S., Singh, R.K. and Murtaza, Q. (2015) 'A literature review and perspectives in reverse logistics', *Resources, Conservation and Recycling*, Vol. 97, pp.76–92.

Ahluwalia, P.K. and Nema, A.K. (2006) 'Multi-objective reverse logistics model for integrated computer waste management', *Waste Management & Research*, Vol. 24, No. 6, pp.514–527.

Alshamsi, A. and Diabat, A. (2015) 'A reverse logistics network design', *Journal of Manufacturing Systems*, Vol. 37, pp.589–598.

Attri, R., Dev, N. and Sharma, V. (2013) 'Interpretive structural modelling (ISM) approach: an overview', *Research Journal of Management Sciences*, Vol. 2319, No. 2, p.1171.

Babazadeh, R., Jolai, F. and Razmi, J. (2015) 'Developing scenario-based robust optimization approaches for the reverse logistics network design problem under uncertain environments', *International Journal of Services and Operations Management*, Vol. 20, No. 4, pp.418–440.

Barrios, M., Guilera, G., Nuño, L. and Gómez-Benito, J. (2021) 'Consensus in the Delphi method: what makes a decision change?', *Technological Forecasting and Social Change*, Vol. 163, p.120484.

Bhosale, V.A. and Kant, R. (2016) 'An integrated ISM fuzzy MICMAC approach for modelling the supply chain knowledge flow enablers', *International Journal of Production Research*, Vol. 54, No. 24, pp.7374–7399.

Biehl, M., Prater, E. and Realff, M.J. (2007) 'Assessing performance and uncertainty in developing carpet reverse logistics systems', *Computers & Operations Research*, Vol. 34, No. 2, pp.443–463.

Culot, G., Orzes, G., Sartor, M. and Nassimbeni, G. (2020) 'The future of manufacturing: a Delphi-based scenario analysis on Industry 4.0', *Technological Forecasting and Social Change*, Vol. 157, p.120092.

Dandage, R., Mantha, S.S. and Rane, S.B. (2018) 'Ranking the risk categories in international projects using the TOPSIS method', *International Journal of Managing Projects in Business*, Vol. 11, No. 2, pp.317–331.

De Oliveira, U.R., Neto, L.A., Abreu, P.A.F. and Fernandes, V.A. (2021) 'Risk management applied to the reverse logistics of solid waste', *Journal of Cleaner Production*, Vol. 296, p.126517.

El-Sayed, M., Afia, N. and El-Kharbotly, A. (2010) 'A stochastic model for forward-reverse logistics network design under risk', *Computers & Industrial Engineering*, Vol. 58, No. 3, pp.423–431.

Entrackr (2018) [online] https://entrackr.com/2018/12/amazon-product-return-rate-india/ (accessed 8 January 2022).

Filyushkina, A., Strange, N., Löf, M., Ezebilo, E.E. and Boman, M. (2018) 'Applying the Delphi method to assess impacts of forest management on biodiversity and habitat preservation', *Forest Ecology and Management*, Vol. 409, pp.179–189.

Ghadami, N., Gheibi, M., Kian, Z., Faramarz, M.G., Naghedi, R., Eftekhari, M., Tian, G. et al. (2021) 'Implementation of solar energy in smart cities using an integration of artificial neural network, photovoltaic system and classical Delphi methods', *Sustainable Cities and Society*, Vol. 74, p.103149.

Ghadge, A., Dani, S. and Kalawsky, R. (2012) 'Supply chain risk management: present and future scope', *The International Journal of Logistics Management*, Vol. 23, No. 3, pp.313–339.

Godrej Industries (2017) *A Collaborative Solution to Manage India's Solid Waste Challenge* [online] http://www.godrejindustries.com/media/news/253-a-collaborative-solution-to-manage-indias-solid-waste-challe.aspx (accessed 8 August 2019).

Gooran, A., Rafiei, H. and Rabani, M. (2018) 'Modeling risk and uncertainty in designing reverse logistics problem', *Decision Science Letters*, Vol. 7, No. 1, pp.13–24.

Gooran, A.N., Rafiei, H. and Rabbani, M. (2020) 'Evaluation and designing reverse logistics for risk-neutral and risk-seeking decision makers', *International Journal of Operational Research*, Vol. 39, No. 1, pp.24–49.

Gorane, S.J. and Kant, R. (2015) 'Modelling the SCM implementation barriers: an integrated ISM-fuzzy MICMAC approach', *Journal of Modelling in Management*, Vol. 10, No. 2, pp.158–178.

Government (2020) *Government Notifies New Solid Waste Management Rules* [online] https://www.downtoearth.org.in/news/waste/solid-waste-management-rules-2016-53443 (accessed 25 April 2020).

Han, Q., Zhu, Y., Ke, G.Y. and Hipel, K.W. (2018) 'An ordinal classification of Brownfield remediation projects in China for the allocation of government funding', *Land Use Policy*, Vol. 77, pp.220–230.

Han, Q., Zhu, Y., Ke, G.Y. and Hipel, K.W. (2019) 'Public private partnership in Brownfield remediation projects in China: identification and structure analysis of risks', *Land Use Policy*, Vol. 84, pp.87–104.

Hatefi, S.M. and Jolai, F. (2015) 'Reliable forward-reverse logistics network design under partial and complete facility disruptions', *International Journal of Logistics Systems and Management*, Vol. 20, No. 3, pp.370–394.

Hsueh, J.T. and Lin, C.Y. (2015) 'Constructing a network model to rank the optimal strategy for implementing the sorting process in reverse logistics: case study of photovoltaic industry', *Clean Technologies and Environmental Policy*, Vol. 17, No. 1, pp.155–174.

Hsueh, J.T. and Lin, C.Y. (2017) 'Integrating the AHP and TOPSIS decision processes for evaluating the optimal collection strategy in reverse logistic for the TPI', *International Journal of Green Energy*, Vol. 14, No. 14, pp.1209–1220.

Jüttner, U., Peck, H. and Christopher, M. (2003) 'Supply chain risk management: outlining an agenda for future research', *International Journal of Logistics: Research and Applications*, Vol. 6, No. 4, pp.197–210.

Katiyar, R., Barua, M.K. and Meena, P.L. (2018) 'Analysing the interactions among the barriers of supply chain performance measurement: an ISM with fuzzy MICMAC approach', *Global Business Review*, Vol. 19, No. 1, pp.48–68.

Khurana, M.K., Mishra, P.K., Jain, R. and Singh, A.R. (2010) 'Modeling of information sharing enablers for building trust in Indian manufacturing industry: an integrated ISM and fuzzy MICMAC approach', *International Journal of Engineering Science and Technology*, Vol. 2, No. 6, pp.1651–1669.

Krug, Z., Guillaume, R. and Battaïa, O. (2020) 'Exploring the opportunities in establishing a closed-loop supply chain under uncertainty', *International Journal of Production Research*. DOI: 10.1080/00207543.2020.1808259.

Kumar, S., Raut, R.D., Nayal, K., Kraus, S., Yadav, V.S. and Narkhede, B.E. (2021) 'To identify Industry 4.0 and circular economy adoption barriers in the agriculture supply chain by using ISM-ANP', *Journal of Cleaner Production*, Vol. 293, p.126023.

Kwak, Y.H. and Dixon, C.K. (2008) 'Risk management framework for pharmaceutical research and development projects', *International Journal of Managing Projects in Business*, Vol. 1, No. 4, pp.552–565.

Lee, Y. and Park, S. (2020) 'An audit method on information system audit using Delphi method-based on hyperledger fabric', *Journal of Software Engineering Society*, Vol. 29, No. 2, pp.7–12.

Manuj, I. and Mentzer, J.T. (2008) 'Global supply chain risk management strategies', *International Journal of Physical Distribution & Logistics Management*, Vol. 38, No. 3, pp.192–223.

Mavi, R.K., Goh, M. and Zarbakhshnia, N. (2017) 'Sustainable third-party reverse logistic provider selection with fuzzy SWARA and fuzzy MOORA in plastic industry', *The International Journal of Advanced Manufacturing Technology*, Vol. 91, Nos. 5–8, pp.2401–2418.

Meng, K., Lou, P., Peng, X. and Prybutok, V. (2017) 'Quality-driven recovery decisions for used components in reverse logistics', *International Journal of Production Research*, Vol. 55, No. 16, pp.4712–4728.

Meng, X.R. (2010) 'The risk analysis of reverse logistics outsourcing based the fuzzy comprehensive analysis method', *Advanced Materials Research*, Vol. 108, pp.1113–1118.

Mishra, N., Singh, A., Rana, N.P. and Dwivedi, Y.K. (2017) 'Interpretive structural modelling and fuzzy MICMAC approaches for customer centric beef supply chain: application of a big data technique', *Production Planning & Control*, Vol. 28, Nos. 11–12, pp.945–963.

Moghaddam, K.S. (2015) 'Fuzzy multi-objective model for supplier selection and order allocation in reverse logistics systems under supply and demand uncertainty', *Expert Systems with Applications*, Vol. 42, Nos. 15–16, pp.6237–6254.

Narkhede, B.E., Ghadage, Y.D., Raut, R.D. and Luthra, S. (2019) 'Study of implication of qualification and experience in perception of risks and barriers for innovative projects', *International Journal of Mathematical, Engineering and Management Sciences*, Vol. 4, No. 2, pp.289–305.

Nasa, P., Jain, R. and Juneja, D. (2021) 'Delphi methodology in healthcare research: how to decide its appropriateness', *World Journal of Methodology*, Vol. 11, No. 4, p.116.

Ocampo, L., Ebisa, J.A., Ombe, J. and Escoto, M.G. (2018) 'Sustainable ecotourism indicators with fuzzy Delphi method – a Philippine perspective', *Ecological Indicators*, Vol. 93, pp.874–888.

Okoli, C. and Pawlowski, S.D. (2004) 'The Delphi method as a research tool: an example, design considerations and applications', *Information & Management*, Vol. 42, No. 1, pp.15–29.

Panjehfouladgaran, H. and Lim, S.F.W. (2020) 'Reverse logistics risk management: identification, clustering and risk mitigation strategies', *Management Decision*, Vol. 58, No. 7, pp.1449–1474.

Pfohl, H.C., Köhler, H. and Thomas, D. (2010) 'State of the art in supply chain risk management research: empirical and conceptual findings and a roadmap for the implementation in practice', *Logistics Research*, Vol. 2, No. 1, pp.33–44.

Prajapati, H., Kant, R. and Shankar, R. (2019a) 'Bequeath life to death: state-of-art review on reverse logistics', *Journal of Cleaner Production*, Vol. 211, pp.503–520.

Prajapati, H., Kant, R. and Shankar, R. (2019b) 'Prioritizing the solutions of reverse logistics implementation to mitigate its barriers: a hybrid modified SWARA and WASPAS approach', *Journal of Cleaner Production*, Vol. 240, p.118219.

Rabbani, M., Sadati, S.A. and Farrokhi-Asl, H. (2020) 'Incorporating location routing model and decision making techniques in industrial waste management: application in the automotive industry', *Computers & Industrial Engineering*, Vol. 148, p.106692.

Rahimi, M. and Ghezavati, V. (2018) 'Sustainable multi-period reverse logistics network design and planning under uncertainty utilizing conditional value at risk (CVaR) for recycling construction and demolition waste', *Journal of Cleaner Production*, Vol. 172, pp.1567–1581.

Ramos, E., Pettit, T.J., Habib, M. and Chavez, M. (2021) 'A model ISM-MICMAC for managing risk in agri-food supply chain: an investigation from the Andean region of Peru', *International Journal of Value Chain Management*, Vol. 12, No. 1, pp.62–85.

Raval, S.J., Kant, R. and Shankar, R. (2018) 'Lean Six Sigma implementation: modelling the interaction among the enablers', *Production Planning & Control*, Vol. 29, No. 12, pp.1010–1029.

Rezaei, S., Ghalehkhondabi, I., Rafiee, M. and Namdar Zanganeh, S. (2020) 'Supplier selection and order allocation in CLSC configuration with various supply strategies under disruption risk', *Opsearch*, Vol. 57, No. 3, pp.908–934.

Rogers, D.S. and Tibben-Lembke, R. (2001) 'An examination of reverse logistics practices', *Journal of Business Logistics*, Vol. 22, No. 2, pp.129–148.

Senthil, S., Murugananthan, K. and Ramesh, A. (2018) 'Analysis and prioritisation of risks in a reverse logistics network using hybrid multi-criteria decision making methods', *Journal of Cleaner Production*, Vol. 179, pp.716–730.

Shanker, S. and Barve, A. (2021) 'Analysing sustainable concerns in diamond supply chain: a fuzzy ISM-MICMAC and DEMATEL approach', *International Journal of Sustainable Engineering*, Vol. 14, No. 5, pp.1269–1285.

Singhal, P., Agarwal, G. and Mittal, M.L. (2011) 'Supply chain risk management: review, classification and future research directions', *International Journal of Business Science & Applied Management (IJBSAM)*, Vol. 6, No. 3, pp.15–42.

Soleimani, H. and Govindan, K. (2014) 'Reverse logistics network design and planning utilizing conditional value at risk', *European Journal of Operational Research*, Vol. 237, No. 2, pp.487–497.

Tang, C.S. (2006) 'Perspectives in supply chain risk management', *International Journal of Production Economics*, Vol. 103, No. 2, pp.451–488.

Tang, O. and Musa, S.N. (2011) 'Identifying risk issues and research advancements in supply chain risk management', *International Journal of Production Economics*, Vol. 133, No. 1, pp.25–34.

Trivedi, A., Jakhar, S.K. and Sinha, D. (2021) 'Analyzing barriers to inland waterways as a sustainable transportation mode in India: a DEMATEL-ISM based approach', *Journal of Cleaner Production*, Vol. 295, p.126301.

VenkatesaNarayanan, P.T. and Thirunavukkarasu, R. (2021) 'Indispensable link between green supply chain practices, performance and learning: an ISM approach', *Journal of Cleaner Production*, Vol. 279, p.123387.

Wang, J. and Yang, C-Y. (2012) 'Flexibility planning for managing R&D projects under risk', *International Journal of Production Economics*, Vol. 135, No. 2, pp.823–831.

Wang, J., Lin, W. and Huang, Y-H. (2010) 'A performance-oriented risk management framework for innovative R&D projects', *Technovation*, Vol. 30, Nos. 11/12, pp.601–611.

Ward, S. and Chapman, C. (2003) 'Transforming project risk management into project uncertainty management', *International Journal of Project Management*, Vol. 21, No. 2, pp.97–105.

Wit, B. and Pylak, K. (2020) 'Implementation of triple bottom line to a business model canvas in reverse logistics', *Electronic Markets*, Vol. 30, No. 4, pp.679–697.

Yanık, S. (2015) 'Reverse logistics network design under the risk of hazardous materials transportation', *Human and Ecological Risk Assessment: An International Journal*, Vol. 21, No. 5, pp.1277–1298.

Yazdani, M., Chatterjee, P., Pamucar, D. and Abad, M.D. (2019) 'A risk-based integrated decision-making model for green supplier selection: a case study of a construction company in Spain', *Kybernetes*, Vol. 49, No. 4, pp.1229–1252.

Yu, H. and Solvang, W.D. (2017) 'A carbon-constrained stochastic optimization model with augmented multi-criteria scenario-based risk-averse solution for reverse logistics network design under uncertainty', *Journal of Cleaner Production*, Vol. 164, pp.1248–1267.

Zamani, M., Abolghasemi, M., Hosseini, S.M.S. and Pishvaee, M.S. (2020) 'Considering pricing and uncertainty in designing a reverse logistics network', *International Journal of Industrial and Systems Engineering*, Vol. 35, No. 2, pp.158–182.

Zarbakhshnia, N., Soleimani, H. and Ghaderi, H. (2018) 'Sustainable third-party reverse logistics provider evaluation and selection using fuzzy SWARA and developed fuzzy COPRAS in the presence of risk criteria', *Applied Soft Computing*, Vol. 65, pp.307–319.

Zhao, J. and Ke, G.Y. (2017) 'Incorporating inventory risks in location-routing models for explosive waste management', *International Journal of Production Economics*, Vol. 193, pp.123–136.

Appendix

Table A1 Fuzzy linguistic scale

Linguistic value	*Fuzzy value*
No influence (O)	(0, 0, 0)
Very low influence (VL)	(0, 0.1, 0.3)
Low influence (L)	(0.1, 0.3, 0.5)
Medium influence (M)	(0.3, 0.5, 0.7)
High influence (H)	(0.5, 0.7, 0.9)
Very high influence (VH)	(0.7, 0.9, 1.0)
Complete influence (C)	(1.0, 1.0, 1.0)

Table A2 Level partition of levels of RL risk – second iteration

	Reachability set	*Antecedent set*	*Intersection set*	*Level*
R2	2, 3, 4, 5, 6, 9, 10, 11, 12, 14, 15, 17, 18, 19	2, 6, 7, 8, 16, 17, 18	2, 6, 17, 18	
R3	3, 5, 14, 19	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17, 18, 19	3, 5, 14, 19	*2*
R4	3, 4, 5, 9, 14, 15, 19	2, 4, 6, 7, 8, 9, 15, 16, 17, 18	4, 9, 15	
R5	3, 5, 14, 19	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17, 18, 19	3, 5, 14, 19	*2*
R6	2, 3, 4, 5, 6, 9, 10, 11, 12, 14, 15, 17, 18, 19	2, 6, 7, 8, 16, 17, 18	2, 6, 17, 18	
R7	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17, 18, 19	7, 16	7, 16	
R8	2, 3, 4, 5, 6, 8, 9, 10, 11, 12, 14, 15, 17, 18, 19	7, 8, 16	8	

Table A2 Level partition of levels of RL risk – second iteration (continued)

	Reachability set	*Antecedent set*	*Intersection set*	*Level*
R9	3, 4, 5, 9, 14, 15, 19	2, 4, 6, 7, 8, 9, 15, 16, 17, 18	4, 9, 15	
R10	3, 5, 10, 11, 12, 14, 19	2, 6, 7, 8, 10, 11, 12, 16, 17, 18	10, 11, 12	
R11	3, 5, 10, 11, 12, 14, 19	2, 6, 7, 8, 10, 11, 12, 16, 17, 18	10, 11, 12	
R12	3, 5, 10, 11, 12, 14, 19	2, 6, 7, 8, 10, 11, 12, 16, 17, 18	10, 11, 12	
R14	3, 5, 14, 19	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17, 18, 19	3, 5, 14, 19	*2*
R15	3, 4, 5, 9, 14, 15, 19	2, 4, 6, 7, 8, 9, 15, 16, 17, 18	4, 9, 15	
R16	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17, 18, 19	7, 16	7, 16	
R17	2, 3, 4, 5, 6, 9, 10, 11, 12, 14, 15, 17, 18, 19	2, 6, 7, 8, 16, 17, 18	2, 6, 17, 18	
R18	2, 3, 4, 5, 6, 9, 10, 11, 12, 14, 15, 17, 18, 19	2, 6, 7, 8, 16, 17, 18	2, 6, 17, 18	
R19	3, 5, 14, 19	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17, 18, 19	3, 5, 14, 19	*2*

Table A3 Level partition of levels of RL risk – third iteration

	Reachability set	*Antecedent set*	*Intersection set*	*Level*
R2	2, 4, 6, 9, 10, 11, 12, 15, 17, 18	2, 6, 7, 8, 16, 17, 18	2, 6, 17, 18	
R4	4, 9, 15	2, 4, 6, 7, 8, 9, 15, 16, 17, 18	4, 9, 15	*3*
R6	2, 4, 6, 9, 10, 11, 12, 15, 17, 18	2, 6, 7, 8, 16, 17, 18	2, 6, 17, 18	
R7	2, 4, 6, 7, 8, 9, 10, 11, 12, 15, 16, 17, 18	7, 16	7, 16	
R8	2, 4, 6, 8, 9, 10, 11, 12, 15, 17, 18	7, 8, 16	8	
R9	4, 9, 15	2, 4, 6, 7, 8, 9, 15, 16, 17, 18	4, 9, 15	*3*
R10	10, 11, 12	2, 6, 7, 8, 10, 11, 12, 16, 17, 18	10, 11, 12	*3*
R11	10, 11, 12	2, 6, 7, 8, 10, 11, 12, 16, 17, 18	10, 11, 12	*3*
R12	10, 11, 12	2, 6, 7, 8, 10, 11, 12, 16, 17, 18	10, 11, 12	*3*
R15	4, 9, 15	2, 4, 6, 7, 8, 9, 15, 16, 17, 18	4, 9, 15	*3*
R16	2, 4, 6, 7, 8, 9, 10, 11, 12, 15, 16, 17, 18	7, 16	7, 16	
R17	2, 4, 6, 9, 10, 11, 12, 15, 17, 18	2, 6, 7, 8, 16, 17, 18	2, 6, 17, 18	
R18	2, 4, 6, 9, 10, 11, 12, 15, 17, 18	2, 6, 7, 8, 16, 17, 18	2, 6, 17, 18	

Table A4 Level partition of levels of RL risk – fourth iteration

	Reachability set	*Antecedent set*	*Intersection set*	*Level*
R2	2, 6, 17, 18	2, 6, 7, 8, 16, 17, 18	2, 6, 17, 18	*4*
R6	2, 6, 17, 18	2, 6, 7, 8, 16, 17, 18	2, 6, 17, 18	*4*
R7	2, 6, 7, 8, 16, 17, 18	7, 16	7, 16	
R8	2, 6, 8, 17, 18	7, 8, 16	8	
R16	2, 6, 7, 8, 16, 17, 18	7, 16	7, 16	
R17	2, 6, 17, 18	2, 6, 7, 8, 16, 17, 18	2, 6, 17, 18	*4*
R18	2, 6, 17, 18	2, 6, 7, 8, 16, 17, 18	2, 6, 17, 18	*4*

Table A5 Level partition of levels of RL risk – fifth iteration

	Reachability set	*Antecedent set*	*Intersection set*	*Level*
R7	7, 8, 16	7, 16	7, 16	
R8	8	7, 8, 16	8	*5*
R16	7, 8, 16	7, 16	7, 16	

Table A6 Level partition of levels of RL risk – sixth iteration

	Reachability set	*Antecedent set*	*Intersection set*	*Level*
R7	7, 16	7, 16	7, 16	*6*
R16	7, 16	7, 16	7, 16	*6*