Chapter 7

I4.0 ADOPTION: FLEXIBILITY, RESILIENCE, AND SUSTAINABILITY

7.1 Introduction

Supply chains all around the globe have experienced unprecedented disruptions such as the COVID-19 pandemic, extreme weather events, industrial mishaps, political conflicts, and war. In response to these disruptions, supply chains have implemented various strategies. However, as the global supply chain industry encompasses a wide range of activities and forms complex networks these strategies need to be more flexible for effective implementation to fulfill consumer demand under various global challenges. Flexible practices can significantly reduce the response time to disruptions and play a pivotal role in bolstering resilience and sustainability aspects of processes especially when they are assisted with industry 4.0 technologies. The seamless integration of flexible supply chain processes with Industry 4.0 technologies forms a powerful alliance that fosters resilience and sustainability. The synergized capabilities of industry 4.0 technologies and flexibility can empower supply chains to navigate uncertainties and withstand disruptions.

The use of I4.0 for supply chain flexibility is a new field and the available research on flexibility in the supply chain using I4.0 is limited. Most of the studies discuss concepts, practices, and dimensions however, how to enhance flexibility using I4.0 and analyzing its impact on resilience and sustainability is sparse. The research gap in this study is addressed by using the Interpretive Structural Modelling (ISM) approach to systematically understand the enabler's interrelationships and to develop a conceptual model. Further, to address the uncertainties and to assess the behavior in various scenarios fuzzy Adaptive Neuro-Fuzzy Inference System (ANFIS) is used. ISM's qualitative insights and fuzzy ANFIS' quantitative modeling capabilities create a more robust and accurate model. To handle imprecise or uncertain data and learn from experience, making it useful in decision-making situations to identify significant I4.0 adoption enablers for supply chain flexibility and develop strategies to adopt them.

The Research Questions (RQs) discussed in this study are:

RQ 1: What are the significant I4.0 adoption enablers for flexibility in the supply chains?

RQ 2: What are the effects of I4.0 adoption enablers on flexibility dimensions in the supply chain and their impact on resilience and sustainability?

RQ 3: Which I4.0 adoption enablers for flexibility should be implemented first, and in which flexibility dimension?

7.2 Methodology

The adoption of I4.0 for flexibility in supply chains is a relatively new field, and the combination of ISM and fuzzy ANFIS approaches to assess its effectiveness is a novel approach that integrates two different methodologies to address a complex problem-making a novel contribution to this area.

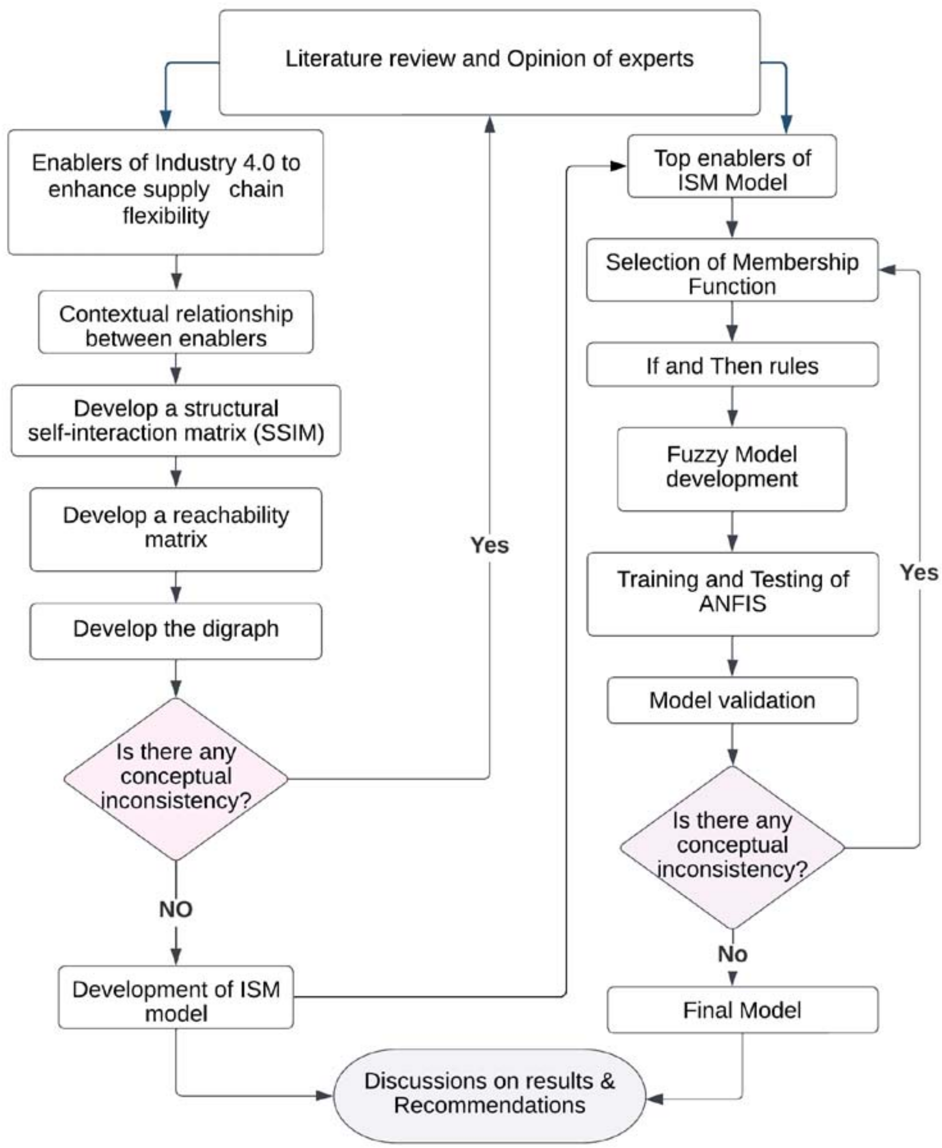


Figure 13: Hybrid flow diagram for ISM and Fuzzy-ANFIS approach

ISM is a qualitative technique that offers a systematic approach to comprehending the relationships between elements. The novelty of ISM lies in its ability to identify the driving and dependent powers of enablers, as well as the hierarchical structure of relationships between them. Using ISM, it is possible to create a conceptual model that depicts the relationships between the diverse I4.0 adoption enablers for various flexibility dimensions. Fuzzy ANFIS, on the other hand, is a quantitative method that combines the power of fuzzy logic and neural networks. It enables the modeling of complicated systems with uncertainties and nonlinearity. Using fuzzy ANFIS, it is possible to create a predictive model that can be used to evaluate the system's behavior under various scenarios. Combining qualitative insights from ISM with the quantitative modeling capabilities of fuzzy ANFIS allows for the development of a more robust and accurate model. To handle imprecise or uncertain data and to learn from experience, making it particularly useful in decision-making situations to identify the critical factors that affect flexibility in supply chains, and to develop strategies to improve them using I4.0. Fig 13 shows the hybrid flow diagram of the ISM and Fuzzy ANFIS approach**.** A questionnaire is distributed via digital medium for the screening of enablers, and 240 responses are received, with 210 of them being considered. Table 31 presents the specification of experts for the questionnaire and contextual relation among enablers.

Table 31: Expert specifications

Types of Respondents	Respondents (for screening of enablers)	Work Experience (in Years)	Experts (for contextual relation among enablers)	Work Experience (in Years))
Experts from Industry	29	5.0	3	6.0
Academicians	78	4.5	5	6.5
Research Scholar	110	1.5	-	-

The selection of 18 I4.0 adoption enablers is conducted through the distribution of a questionnaire via digital medium, as well as a comprehensive review of relevant literature. In the subsequent phase, 16 I4.0 adoption enablers are chosen to utilize the Delphi technique and categorized into three dimensions of flexibility: logistics flexibility, manufacturing flexibility, and operations and decision-making flexibility (as shown in Table 32). Moreover, the Delphi method is utilized to ascertain the contextual relationship among enablers. The Delphi method is a structured communication procedure employed to gather the thoughts and perceptions of a group of subject-matter experts on a specific subject. It is frequently employed when there is a need to collect multiple perspectives on a complicated issue or when there is a lack of a clear consensus. A group of experts with expertise and experience in related areas is chosen to apply the Delphi technique for obtaining the contextual relationship among enablers. In the first round, these experts are requested to select and categorize I4.0 adoption enablers under three dimensions of flexibility and to provide their perspectives on the contextual relationships between enablers. These viewpoints are gathered and analyzed, and a summary of the responses is given to the experts in subsequent rounds. The experts are requested to review the summary of responses and provide additional feedback and opinions in each succeeding round. This procedure was repeated until the experts reached an agreement on the contextual relationships between I4.0 adoption enablers (Table 33).

Table 32: Flexibility Dimensions and I4.0 Adoption Enablers

Flexibility Dimensions	Sl. No.	I4.0 adoption enablers for flexibility	Description	References
Flexibility in logistics	1	Traceability tools (TT)	Traceability tools can help with documentation, monitoring of items, enabling process improvements, better decision-making, and identifying & tracking problematic products swiftly so that managers can be notified right away.	(Aung & Chang, 2014; Bevilacqua et al., 2009; Dabbene et al., 2014)
	2	Storage optimization (SO)	Storage optimization, if not done correctly, can lead to wasted time, money, and loss of productivity due to clogged aisles, missing inventory, and decreased output. This is largely avoidable with the use of I4.0 technologies.	(Andiyappillai, 2020; Bányai, 2018; Choudhury et al., 2021a)
	3	Warehouse optimization (WO)	The moving of items into the best storage location is known as warehouse optimization. However, because of things like quick expansion, high seasons, and sluggish sales, warehouses frequently run out of storage capacity. WO	(Andiyappillai, 2020; Bányai, 2018; Choudhury et al., 2021a)

			guarantees the best possible use of every square foot of warehouse space while maintaining order and productivity.	
	4	Decision-making tools-scheduling, routing, etc. (LDM)	LDM can greatly improve the process of planning out the precise routes that vehicles will take to accomplish logistics processes and establishing time slots for when and by whom deliveries will be made.	(Bányai, 2018; Choudhury et al., 2021)
Flexibility in manufacturing	5	Planning & Scheduling tools (PS)	Planning and scheduling tools coordinate and allocate resources in a way that optimizes the flow of information, commodities, and services from supplier to consumer while balancing supply and demand.	(Bányai, 2018; Choudhury et al., 2021a; Marchi & Zanoni, 2017)
	6	Smart manufacturing (SM)	To optimize the manufacturing processes, smart manufacturing uses digital technologies manufacturing operations within. It integrates smart technology components into the conventional production process.	(Choudhury et al., 2021; Marchi & Zanoni, 2017)
	7	Energy management tools (EM)	Energy management tools are responsible for converting, deploying, and tracking energy use. It actively controls current energy consumption and use.	(Bányai, 2018; Marchi & Zanoni, 2017; Safarzadeh et al., 2020)
	8	Inventory management (IM)	Inventory management makes it easier to manage finished goods, works-in-progress, maintenance, repairs, and operations.	(Holmström et al., 2019; Marchi & Zanoni, 2017; Ngai, 2010)
	9	Material movement systems (MM)	Material movement systems facilitate material handling of the supply chain and are responsible for the movement of products and raw materials.	(Andiyappillai, 2020; Marchi & Zanoni, 2017; Sarc et al., 2019)

Flexibility in operations & decision making	10	Energy-efficient processes (EEP)	Energy-efficient processes require less energy to carry out the same function or achieve the same outcome. For instance, it uses less energy to heat, cool, and run machines, and to produce goods.	(Bányai, 2018; Haraldsson & Johansson, 2019; Marchi & Zanoni, 2017; Shah et al., 2022)
	11	Performance measurement systems (PMS)	The processes of the supply chain will benefit from performance measurement systems, and the effectiveness of each process can be evaluated in terms of reliability, flexibility, responsiveness, cost, and quality.	(Andiyappillai, 2020; Marchi & Zanoni, 2017)
	12	Efficient communication (EC)	Good client relationships, better inventory management, timely deliveries, and revenue increases can all be facilitated by efficient communication between stakeholders.	(Bányai, 2018; Gebhardt et al., 2022)
	13	Real-time analysis of key processes (RTA)	It can help in identifying the bottleneck points and provide valuable feedback to enhance the flexibility of the supply chain.	(Bányai, 2018; Ngai, 2010)
	14	Predictive Analysis tools (PA)	By spotting patterns and trends across the supply chain, Predictive Analysis tools can help identify both existing risks and potential future risks, thereby improving the accuracy of planning.	(Schoenherr & Speier-Pero, 2015; Bányai, 2018; Jeble et al., 2018; Yeboah-Ofori et al., 2021)
	15	Customer data processing and analysis (CDA)	A company can improve demand forecasting by processing and analyzing customer data. By better comprehending the risks, it facilitates an organization in developing a lean supply chain and in getting ready for the future.	(Choudhury et al., 2021a; Jeble et al., 2018; Sahoo, 2022; Schoenherr & Speier-Pero, 2015)

	16	Smart ordering (SMO)	Smart ordering offers a straightforward and effective platform so that various parties from various businesses can take part in multi-party transactions. It offers a unified platform for all participants, including buyers, sellers, movers, shippers, and service providers.	(Bányai, 2018; Choudhury et al., 2021b; Schoenherr & Speier-Pero, 2015; Zhu et al., 2022)

7.2.1 Interpretive Structural Modelling (ISM)

Contextual interrelationships among the enablers of an occurrence can be extracted using ISM, which can take into account theoretical, subjective, computational, and even anecdotal evidence. With ISM, experts can provide their views about a phenomenon of interest dynamically and systematically, with the added benefit of being able to modify their initial inputs as new information becomes available (Ghobakhloo & Fathi, 2021). It transforms the relations among elements into a well-defined interpretive structural model and provides a clear structural map by establishing a directional order of interactions among the system's elements.

ISM model development steps

Step 1: Identification of I4.0 adoption enablers for supply chain flexibility

Th I4.0 adoption enablers for supply chain flexibility are identified based on a literature review and the opinion of experts.

Step 2: The Structural Self-Interaction Matrix (SSIM)

The SSIM is developed by establishing the contextual relationship among identified enablers (Table 33). The following terminology is used to describe the connections:

For any two enablers ‘m’ and ‘n’

V: Enabler m influences enabler n

A: Enabler m influences enabler n

X: m and n mutual influence

O: No relation between m and n

*Table 33**:** SSIM (Structural Self Interaction Matrix)*

Enablers		SMO 16	CDA 15	PA 14	RTA 13	EC 12	PMS 11	EEP 10	MM 9	IM 8	EM 7	SM 6	PS 5	LDM 4	WO 3	SO 2	TT 1
TT	1	V	V	V	V	O	V	V	V	V	O	O	X	V	V	V	X
SO	2	A	O	A	A	O	A	O	X	O	O	O	A	O	O	X	
WO	3	X	O	A	A	X	A	A	V	O	O	O	A	A	X		
LDM	4	V	A	O	X	O	V	X	V	V	V	O	A	X			
PS	5	V	X	V	O	O	V	V	V	V	V	V	X				
SM	6	O	O	O	A	A	A	A	V	X	X	X					
EM	7	O	O	O	A	A	A	A	V	X	X						
IM	8	A	A	A	A	A	A	A	V	X							
MM	9	A	O	O	A	A	A	A	X								
EEP	10	V	O	O	X	O	O	X									
PMS	11	V	O	X	A	O	X										
EC	12	X	O	O	O	X											
RTA	13	V	A	V	X												
PA	14	O	A	X													
CDA	15	V	X														
SMO	16	X															

Step 3: Initial Reachability Matrix (IRM)

After establishing the SSIM, IRM is developed by converting the information into binary form using the following rules.

1. In the Initial Reachability Matrix, (m, n) becomes 1 if the SSIM value is V, and (n, m) becomes 0. In addition, (m, n) becomes 0, and (n, m) becomes 1 if the SSIM value is A.

2. In the Initial Reachability Matrix, (m, n) and (n, m) become 1 if the SSIM value is X, and (m, n) and (n, m) become 0 if the SSIM value is O (Table 34).

*Table 34**:** IRM (Initial Reachability Matrix)*

Enablers		SMO 16	CDA 15	PA 14	RTA 13	EC 12	PMS 11	EEP 10	MM 9	IM 8	EM 7	SM 6	PS 5	LDM 4	WO 3	SO 2	TT 1
TT	1	1	1	1	1	0	1	1	1	1	0	0	1	1	1	1	1
SO	2	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0

WO	3	1	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0
LDM	4	1	0	0	1	0	1	1	1	1	1	0	0	1	1	0	0
PS	5	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1
SM	6	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0
EM	7	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0
IM	8	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0
MM	9	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0
EEP	10	1	0	0	1	0	0	1	1	1	1	1	0	1	1	0	0
PMS	11	1	0	1	0	0	1	0	1	1	1	1	0	0	1	1	0
EC	12	1	0	0	0	1	0	0	1	1	1	1	0	0	1	0	0
RTA	13	1	0	1	1	0	1	1	1	1	1	1	0	1	1	1	0
PA	14	0	0	1	0	0	1	0	0	1	0	0	0	0	1	1	0
CDA	15	1	1	1	1	0	0	0	0	1	0	0	1	1	0	0	0
SMO	16	1	0	0	0	1	0	0	1	1	0	0	0	0	1	1	0

Step 4: Final Reachability Matrix (FRM)

An FRM is developed from IRM by eliminating multiple indirect linkages by considering transitivity. The transitivity concept states that if m is linked to n and n is linked to p then it may be inferred that m is linked to p. Table 35 shows the Final Reachability Matrix after taking into account the transitivity among enablers in IRM.

*Table 35**:** Final Reachability Matrix (FRM)*

Enablers		SMO	CDA	PA	RTA	EC	PMS	EEP	MM	IM	EM	SM	PS	LDM	WO	SO	TT	Driving power
		16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	
TT	1	1	1	1	1	0	1	1	1	1	0	0	1	1	1	1	1	13
SO	2	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	2
WO	3	1	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	4
LDM	4	1	0	0	1	0	1	1	1	1	1	0	0	1	1	0	0	9
PS	5	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	14
SM	6	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	4
EM	7	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	4
IM	8	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	4
MM	9	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	2
EEP	10	1	0	0	1	0	0	1	1	1	1	1	0	1	1	0	0	9
PMS	11	1	0	1	0	0	1	0	1	1	1	1	0	0	1	1	0	9

EC	12	1	0	0	0	1	0	0	1	1	1	1	0	0	1	0	0	7
RTA	13	1	0	1	1	0	1	1	1	1	1	1	0	1	1	1	0	12
PA	14	0	0	1	0	0	1	0	0	1	0	0	0	0	1	1	0	5
CDA	15	1	1	1	1	0	0	0	0	1	0	0	1	1	0	0	1*	7
SMO	16	1	0	0	0	1	0	0	1	1	0	0	0	0	1	1	0	6
Dependence power		10	3	6	5	3	6	5	14	13	9	8	3	6	10	8	2	111/111

Step 5: Hierarchical partitioning

The Final Reachability Matrix yields the reachability and antecedent set. The reachability set includes enabler m and others influenced by it. The antecedent set includes enabler n and others that influence it. After finding reachability and antecedent, the intersection set is formed from their common elements. The ISM hierarchy prioritizes enablers with the same reachability and intersection sets and removes enablers from all sets. Repeat until all levels are identified. The level partitioning based on reachability and antecedent set along with the hierarchical levels is shown in Table 36

*Table 36**:** Hierarchical levels of I4.0 adoption enablers for flexibility in the supply chain*

Enabler	Reachability Set	Antecedent Set	Intersection Set	Level
1	1,2,3,4,5,8,9,10,11,13,14,15,16	1,5,15	1,5,15	VI
2	2,9	1,2,5,9,11,13,14,16	2,9	I
3	3,9,12,16	1,3,4,5,10,11,12,13,14,16	3,12,16	III
4	3,4,7,8,9,10,11,13,16	1,4,5,10,12,13,15	4,10,13	V
5	1,2,3,4,5,6,7,8,9,10,11,14,15,16	1,5,15	1,5,15	VI
6	6,7,8,9	5,6,7,8,10,11,12,13	6,7,8	II
7	6,7,8,9	4,5,6,7,8,10,11,12,13	6,7,8	II
8	6,7,8,9	1,4,5,6,7,8,10,11,12,13,14,15,16	6,7,8	II
9	2,9	1,2,3,4,5,6,7,8,9,10,11,12,13,16	2,9	I
10	3,4,6,7,8,9,10,13,16	1,4,5,10,11,13	4,10,13	V
11	2,3,6,7,8,9,11,14,16	1,4,5,11,13,14	11,14	IV
12	3,6,7,8,9,12,16	3,12,16	3,12,16	III
13	2,3,4,6,7,8,9,10,11,13,14,16	1,4,10,13,15	4,10,13	V
14	2,3,8,11,14	1,5,11,13,14,15	11,14	IV
15	1,4,5,8,13,14,15,16	1,5,15	1,5,15	VI
16	2,3,8,9,12,16	1,3,4,5,10,11,12,13,15,16	3,12,16	III

Step 6: Conical Matrix

By grouping enablers at the same level across the rows and columns of the final reachability matrix, a conical matrix can be created (Table 37). The driving power can be computed by adding the ones in the rows, and dependency power by adding the ones in the columns. The driving and dependence powers of the enablers are then ranked; the higher the rank, the more ones there are.

*Table 37***:** *Conical Matrix*

Enabler		SO	MM	SM	EM	IM	WO	EC	SMO	PMS	PA	LDM	EEP	RTA	TT	PS	CDA	Driving power
		2	9	6	7	8	3	12	16	11	14	4	10	13	1	5	15	
SO	2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
MM	9	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
SM	6	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	4
EM	7	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	4
IM	8	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	4
WO	3	0	1	0	0	0	1	1	1	0	0	0	0	0	0	0	0	4
EC	12	0	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	7
SMO	16	1	1	0	0	1	1	1	1	0	0	0	0	0	0	0	0	6
PMS	11	1	1	1	1	1	1	0	1	1	1	0	0	0	0	0	0	9
PA	14	1	0	0	0	1	1	0	0	1	1	0	0	0	0	0	0	5
LDM	4	0	1	0	1	1	1	0	1	1	0	1	1	1	0	0	0	9
EEP	10	0	1	1	1	1	1	0	1	0	0	1	1	1	0	0	0	9
RTA	13	1	1	1	1	1	1	0	1	1	1	1	1	1	0	0	0	12
CDA	15	0	0	0	0	1	0	0	1	0	1	1	0	1	1*	1	1	7
TT	1	1	1	0	0	1	1	0	1	1	1	1	1	1	1	1	1	13
PS	5	1	1	1	1	1	1	0	1	1	1	1	1	0	1	1	1	14
Dependence power		8	14	8	9	13	10	3	10	6	6	6	5	5	2	3	3	111/111

Step 7: Preparation of digraph and ISM model

An initial digraph with transitivity connections is produced using the conical matrix, and after the indirect links are eliminated, a final digraph is made. The enablers are positioned in this digraph following the levels discovered during iteration. As can be seen in Fig 14, the digraph is transformed as an ISM model by substituting the nodes with the titles of enablers.

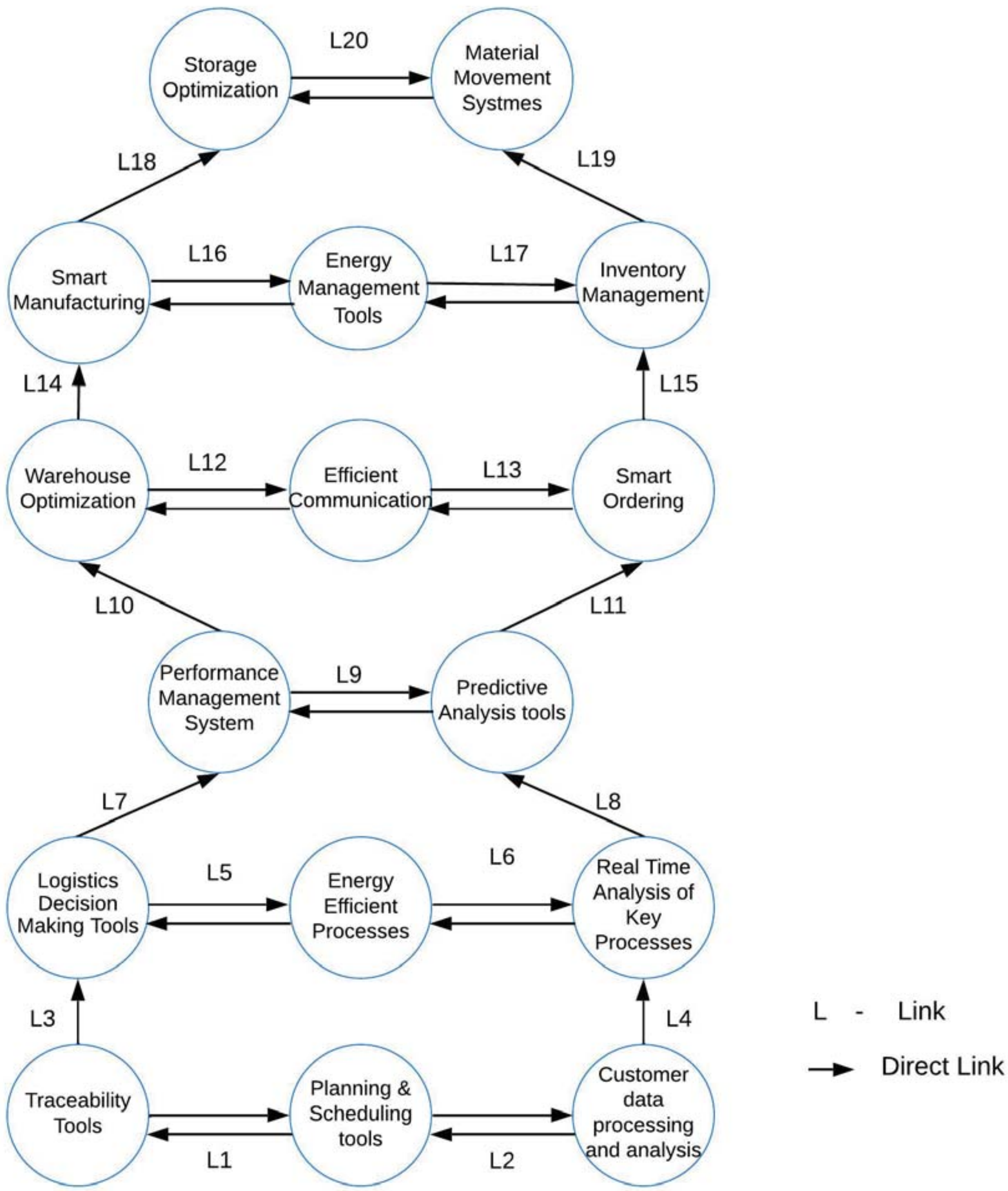


Figure 14: The structural ISM model of enablers for flexibility in the supply chain

Interpretation of Links: In level VI, Links L1 and L2 underscore the significance of traceability tools, planning and scheduling tools, and customer data processing and analysis as drivers for all intermediate and top-level enablers. Additionally, Links L3 and L4 illustrate how traceability tools influence logistics decision-making and how real time analysis of key processes can be facilitated by customer data analysis. Moving to level V, logistics decision-making tools, energy-efficient processes, and real-time analysis of key processes are interconnected through Links L5 and L6. This linkage, as corroborated by level VI, emphasizes that logistics decision-making can be enhanced through real-time analysis while emphasizing energy efficiency.

Levels IV and III, positioned in the intermediate level, signify moderate driving and dependence power. Performance management systems and predictive analysis tools are linked to level V through Links L7 and L8, and they are further interconnected through Link L9. Specifically, L7 demonstrates how logistics decision-making enhances performance management, while L8 highlights how smart ordering is improved by predictive analysis tools. Link L9 signifies the relationship between smart ordering and performance management. Links L10 and L11 connect level IV with level III, where warehouse optimization, efficient communication, and smart ordering are situated. These are interlinked through Links L12 and L13. At the top levels (level I and II), characterized by low driving powers and high dependence, smart manufacturing, energy management tools, and inventory management are interlinked through Links L16 and L17 in level II. The relationship between inventory, energy consumption, and manufacturing is optimized through Links L14 and L15, connecting these aspects with the support of level III. In level I, storage optimization and material movement systems are interlinked through Link L20, supported by level II through Links L18 and L19, respectively.

7.2.2 Fuzzy model for flexibility in the supply chain

In stage II of the study, the top enablers of the ISM model are selected under three dimensions to understand the combined impact of the enablers on the respective dimension. The fuzzy approach is applied using MATLAB R2022b to the flexibility dimensions separately.

A fuzzy set F in S is defined by

$$F \rightarrow \{s, \mu_F(s)/s \ \in S\}, \quad (1)$$

In which $\mu_F(s): S \rightarrow [0,1]$ is called the pertinence function of F and $\mu_F(s)$ is the degree of the pertinence of s in F. The effect of various enablers on flexibility in the supply chain is predicted using the fuzzy model, which is used to simulate various scenarios. Fuzzy models function by giving various variables degrees of membership, which indicate the extent to which those variables belong to a given set or category. It requires fuzzification as the first step which is the conversion of crisp data into fuzzy data or Membership functions. A membership function is a function that gives meaningful values to the discrete values of a variable within its domain of discourse, which corresponds to the range of all possible real values (Fig 15).

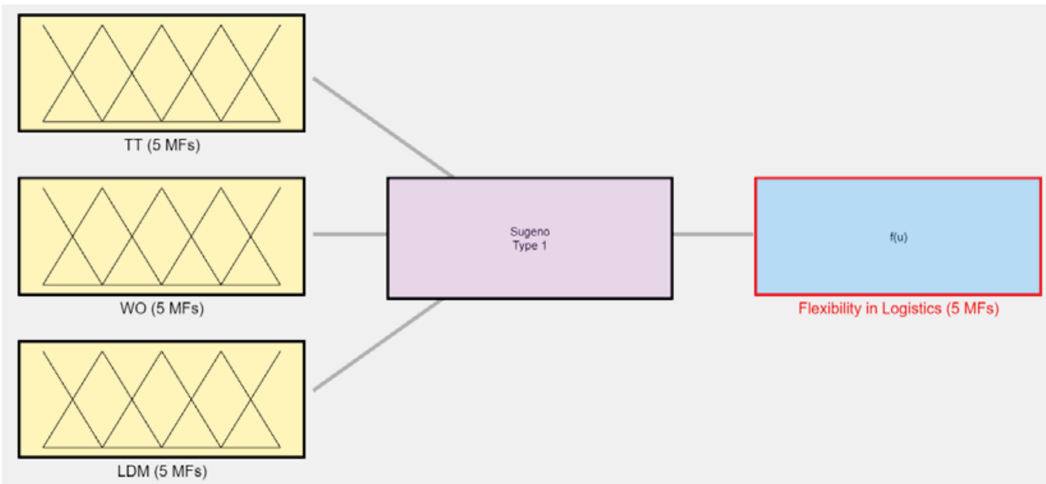
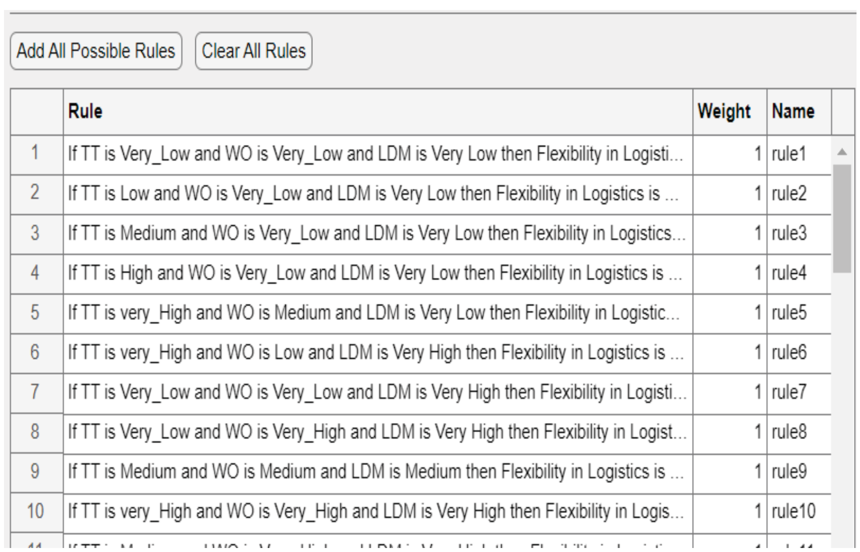


Figure 15: Membership functions

After that, the membership functions are combined with control rules (If- Then) to derive the fuzzy output (Fig 16). In step three defuzzification is performed. Five membership functions are chosen for the present study. Impact levels at different combinations are tested.



Add All Possible Rules | Clear All Rules

	Rule	Weight	Name
1	If TT is Very_Low and WO is Very_Low and LDM is Very Low then Flexibility in Logisti...	1	rule1
2	If TT is Low and WO is Very_Low and LDM is Very Low then Flexibility in Logistics is ...	1	rule2
3	If TT is Medium and WO is Very_Low and LDM is Very Low then Flexibility in Logistics...	1	rule3
4	If TT is High and WO is Very_Low and LDM is Very Low then Flexibility in Logistics is ...	1	rule4
5	If TT is very_High and WO is Medium and LDM is Very Low then Flexibility in Logistic...	1	rule5
6	If TT is very_High and WO is Low and LDM is Very High then Flexibility in Logistics is ...	1	rule6
7	If TT is Very_Low and WO is Very_Low and LDM is Very High then Flexibility in Logisti...	1	rule7
8	If TT is Very_Low and WO is Very_High and LDM is Very High then Flexibility in Logist...	1	rule8
9	If TT is Medium and WO is Medium and LDM is Medium then Flexibility in Logistics is ...	1	rule9
10	If TT is very_High and WO is Very_High and LDM is Very High then Flexibility in Logis...	1	rule10

Figure 16: Control (If-Then) rules

For the supply chain, a linguistic scale (Table 38) is chosen to input the degree of enablers for technology adoption, and the data sets obtained from fuzzy models are used to train and test the ANFIS models.

Table 38: Linguistic scale

Very low	Low	Medium	High	Very high
0-2	3-4	5-6	7-8	9-10

7.2.3 An Adaptive Neuro-Fuzzy Inference System (ANFIS) Model

ANFIS is a machine learning model that uses fuzzy logic and neural networks to improve decision-making. This model optimizes supply chain flexibility using I4.0. The ANFIS model uses fuzzy logic to describe enablers relationships like efficient energy processes, material movement systems, and inventory management. A neural network learns from data and adjusts its fuzzy logic representation to make more precise predictions. After training, the model can simulate and predict the role of different enablers in improving the flexibility of the supply chain. A hybrid learning algorithm that combines gradient descent and least squares techniques is used to build ANFIS models.

The modeling starts with a data set consisting of data obtained from a fuzzy model. It modifies its parameters during training to reduce the discrepancy between the actual and intended output.

To understand, let's suppose that the FIS has one output, O, and two inputs, m, and n. Furthermore, the FIS's rule base includes two fuzzy if-then rules:

1: If m is K_1 and n is L_1 then $O_1 = a_1 m + b_1 n + c_1$ (2)

2: If m is K_2 and n is L_2 then $O_2 = a_2 m + b_2 n + c_2$ (3)

Where a, b, and c are the output parameters.

Figure 17 depicts the ANFIS architecture, in which every node in a layer carries out the same kinds of tasks. The parameter values of a node define its node function if its parameter set is not empty; an adaptive node of this sort is represented by a square.

If, on the other hand, a node has no parameters can be represented by a circle with its function fixed. The following is a description of the ANFIS network's layers:

Fuzzification layer (Layer 1): The node function of node i can be expressed as

$$f_i^1 = \mu_{Ki}(m) \quad (4)$$

where f_i^1 is the membership function of K_i (linguistic label), and m is the input to node i Parameters in this layer are defined as

$$\mu_{Ki}(m) = \exp[-(\frac{m-d_i}{e_i})^2] \quad (5)$$

Where d_i and e_i are the premise parameters. The ANFIS model uses a gradient descent method to define premise parameters in layer 1.

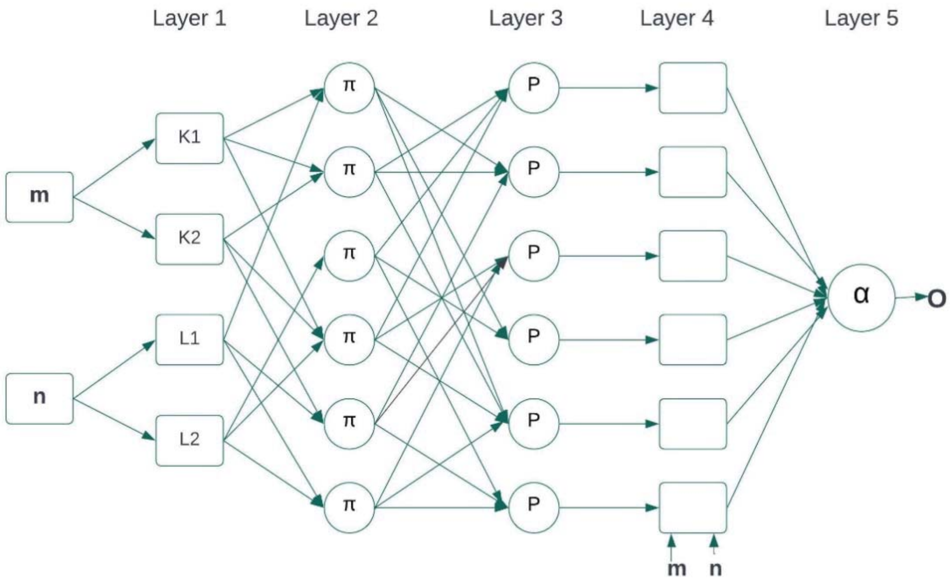


*Figure 17**:** The architecture of an adaptive network-based fuzzy inference system*

Multiplication layer (Layer 2): In this layer, circle nodes multiply input signals and produce the outcome. The least-square technique is used to define the coefficient of output equations in layer 2. This is represented as:

$$\omega_i = \mu_{Ki}(m) \times \mu_{Li}(n), i = 1, 2 \tag{6}$$

Normalization layer (Layer 3): Each node in this layer with the label P. computes the average ratio of the firing intensity of each rule.

$$\overline{\omega_i} = \frac{\omega_i}{\omega_1+\omega_2}, i = 1, 2 \tag{7}$$

Defuzzification layer (Layer 4): The node function of this layer is.

$$f_i^4 = \overline{\omega_i} O_i = \overline{\omega_i}(a_i + b_i + c_i), i = 1,2.. \tag{8}$$

where a_i, b_i, and c_i are called consequent parameters.

Summation layer (Layer 5): One fixed node makes up this layer, which computes the total output as the sum of all incoming signals:

$$Output\ (O) = f_i^5 = \sum_i \overline{\omega_i}\, O_i = \frac{\sum_i \overline{\omega_i} O_i}{\sum_i \overline{\omega_i}} \tag{9}$$

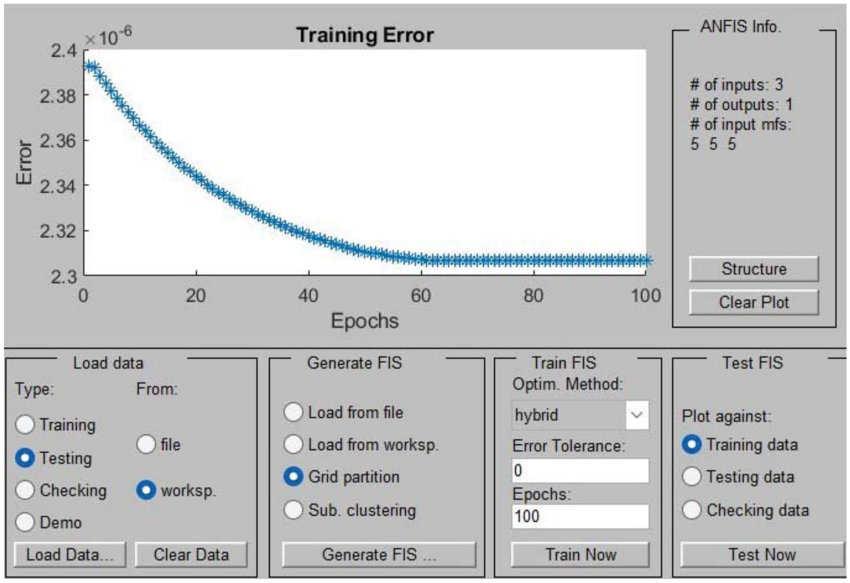


Figure 18: Testing of ANFIS model for flexibility in logistics.

The ANFIS model is developed using the aforementioned steps to predict the enablers' behavior on respective flexibility dimensions. The data set is obtained through a fuzzy model and a training data set is used to obtain the initial premise parameters. To obtain the consequent parameter values least square technique is used and error for the data set is obtained (Fig 18). By using the learning rate, and direction vector ANFIS minimizes the error and gets terminated below the threshold value. After that, the testing dataset is used to compare the model with the actual system. To model the ANFIS MATLAB R2022b software is used which consists of the toolbox with training algorithms. Table 39 shows the training parameters of the ANFIS model.

Table 39: Training parameters of the ANFIS model

Parameters	Type/numbers
Layers	5
Membership functions	Triangular
Number of membership functions	5
Learning rule	Least square method
Epoch	100
Sub models	3
Output	1
Minimal training root mean square error range for all models	2.3×10^{-6} to 2.79×10^{-6}
Input range	0 to 5

7.3 Results

7.3.1 Flexibility in Supply Chain - ISM Model

Matrice d'Impacts Croisés Multiplication Appliquée àun Classement (MICMAC) analysis is carried out to examine the driving and dependence power of the enablers. The MICMAC technique is a structural analysis tool that uses relations between a system's components. It establishes two hierarchies, one based on driving power and the other on dependence power, to investigate. In doing so, the enablers are divided into the following four groups (Fig 19):

a) Autonomous enablers: These enablers fall into the category of autonomous enablers because they lack strong driving and dependencies. They have a lesser degree of system connectivity.
b) Linkage enablers: These enablers fall into the category of linkage enablers because they have strong driving and dependence power. They lack stability as well.
c) Dependent enablers: These enablers belong to the group of dependent enablers because they have weak driving power and strong dependence power.
d) Independent enablers: These enablers belong to the group of independent enablers due to strong driving power and weak dependence.

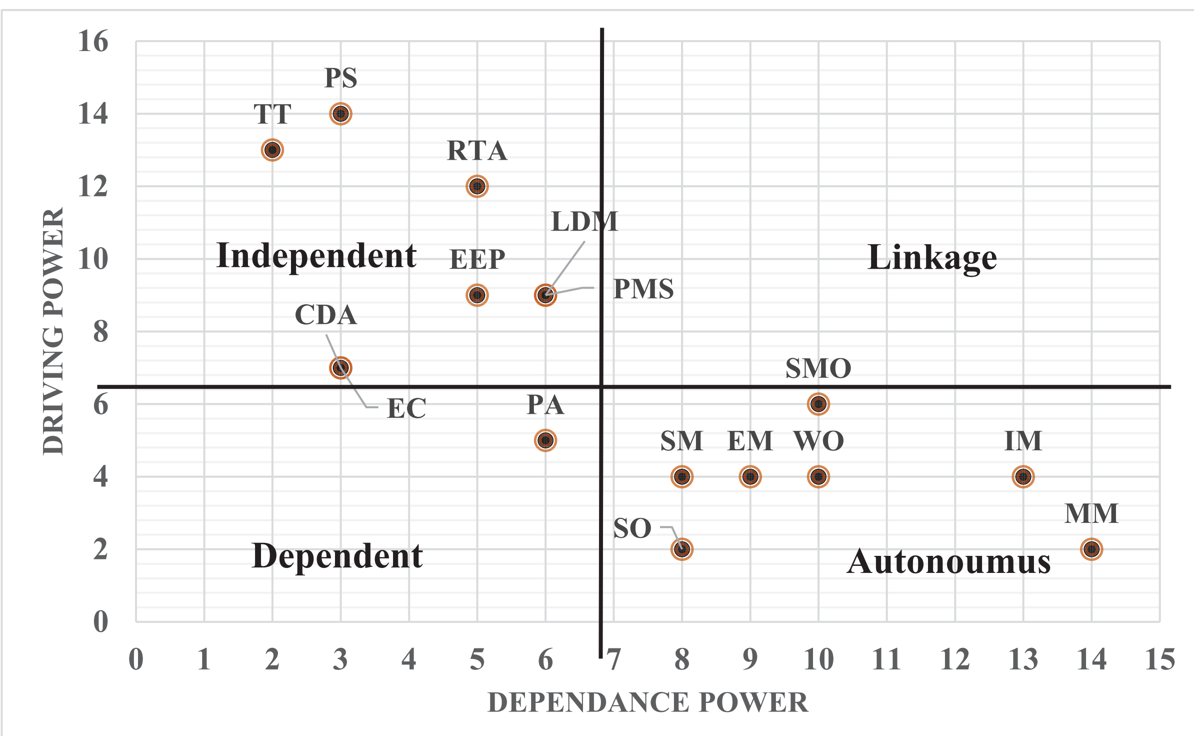


Figure 19: Driving and dependence power diagram

The term "key enablers " refers to enablers that have a very high drive power and fall under the independent or linkage group. A diagram of driving power and dependency power is then created (Fig 19). This diagram consists of four groups. The first group contains "autonomous enablers," the second group "dependent enablers," the third group "linkage enablers," and the fourth group "independent enablers ". The driving and dependency power of each enabler determines where it is located.

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7.3.2 Flexibility in Supply Chain- Fuzzy Model

To understand the effects of these enablers over the flexibility for I4.0 adoption fuzzy model is developed. Ten enablers under three flexibility dimensions flexibility in logistics, flexibility in manufacturing, and flexibility in operations & decision-making, out of sixteen are further selected. The results show that the enablers responsible for flexibility in logistics include LDM, TT, and WO. The function of these enablers is to provide flexibility in logistics by enhancing logistics decision-making through traceability and warehouse optimization. It can enhance the utilization of resources and reduce its impact on the environment. The results obtained are presented in Fig 20 and show the effect of enablers on flexibility in logistics. As the effect of LDM and TT decreases the flexibility in logistics also decreases. It shows that the highest level of flexibility in logistics can be achieved by extending the use of traceability tools and using them in decision-making. It also enhances the performance of warehouses. In the second model, the effects of enablers on flexibility in manufacturing are shown in Fig 21. It shows that planning and scheduling and smart manufacturing in combination with energy management can enhance flexibility in manufacturing.

The results show that the enablers responsible for flexibility in manufacturing include EM, PS, and SM. The function of these enablers is to provide flexibility in manufacturing by incorporating smart manufacturing practices, informed planning and scheduling, and energy management. It can reduce energy consumption and wastage of resources thus enhancing resilience and sustainability. The results of flexibility in Operations & decision-making are

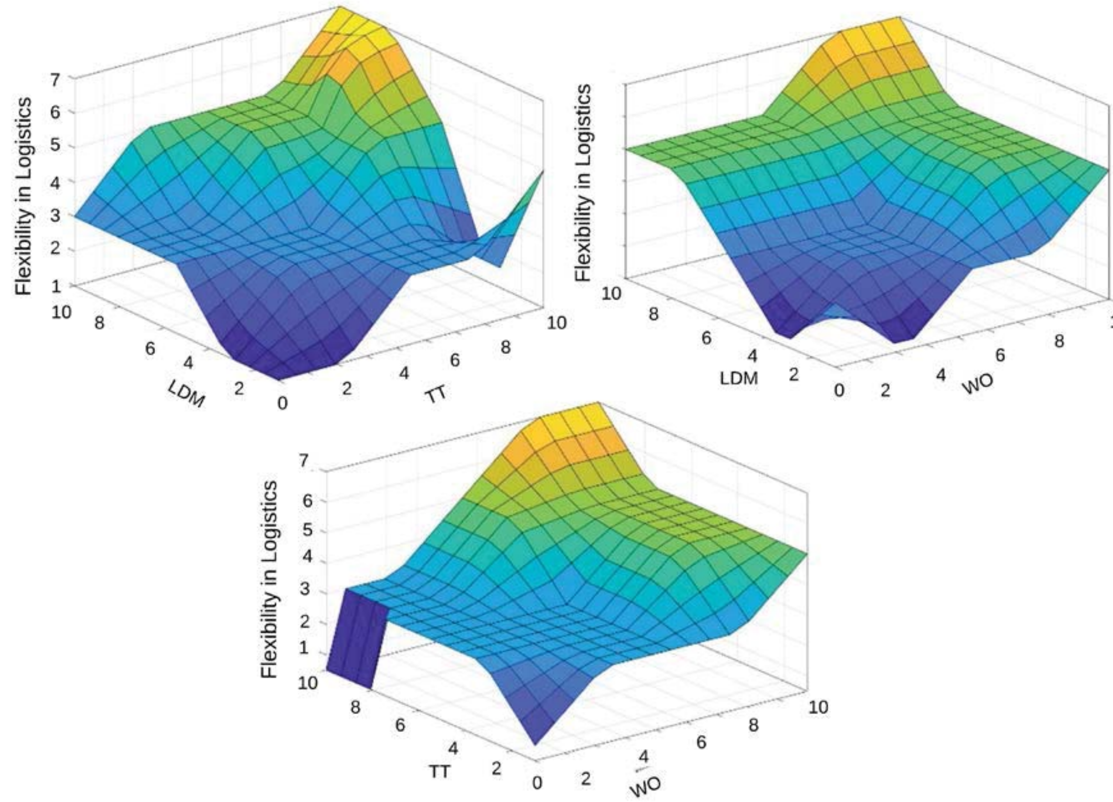

*Figure 20***:** *Flexibility in logistics*

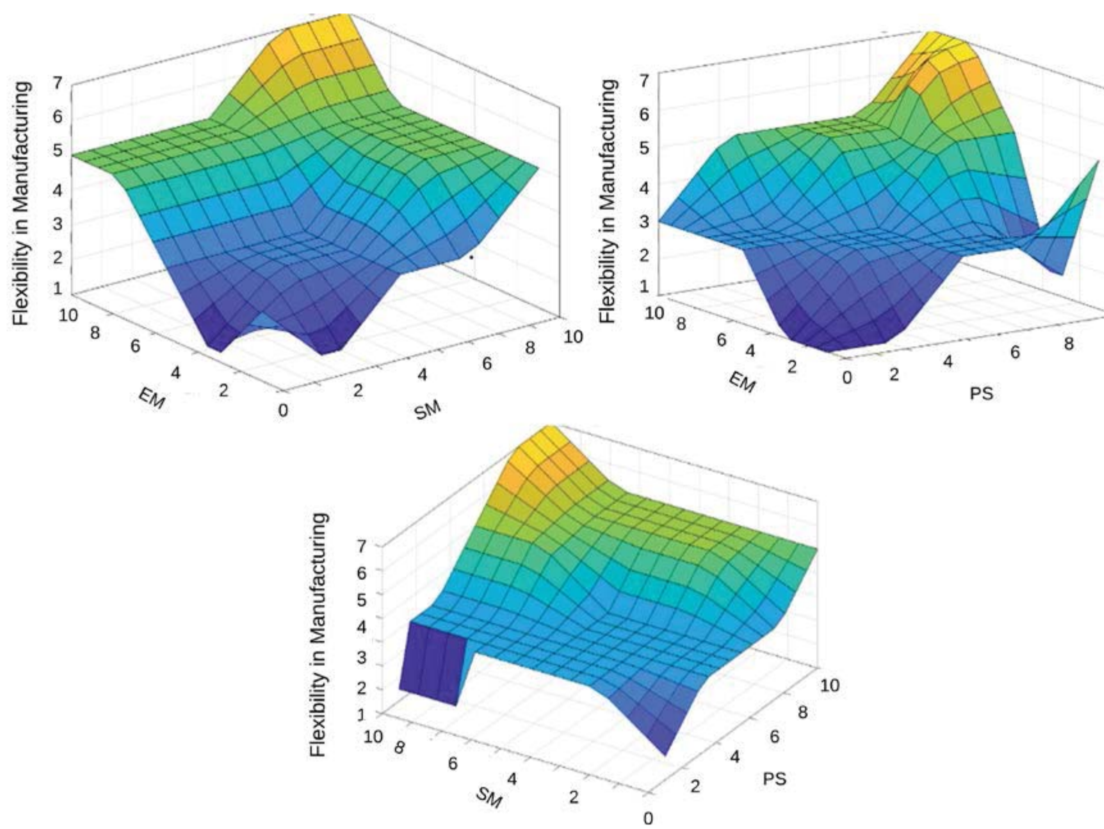

*Figure 21***:** *Flexibility in Manufacturing*

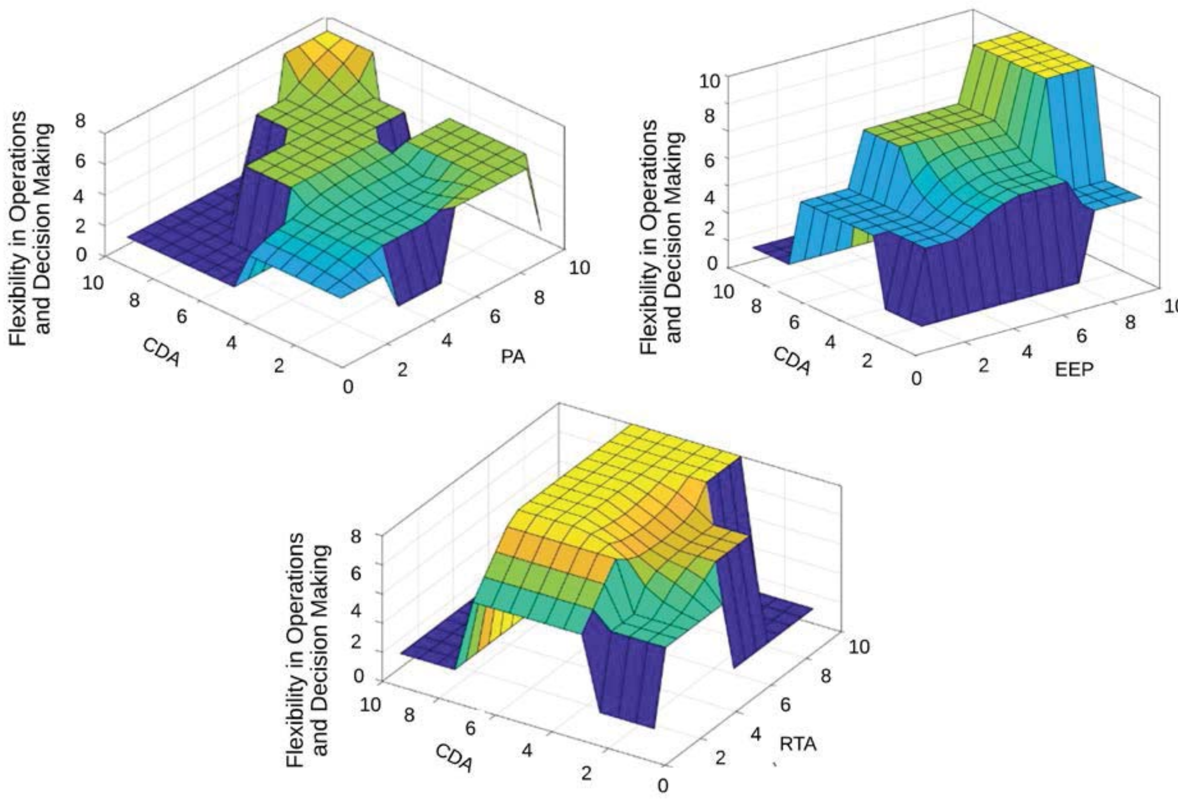

Figure 22: Flexibility in Operations and Decision Making

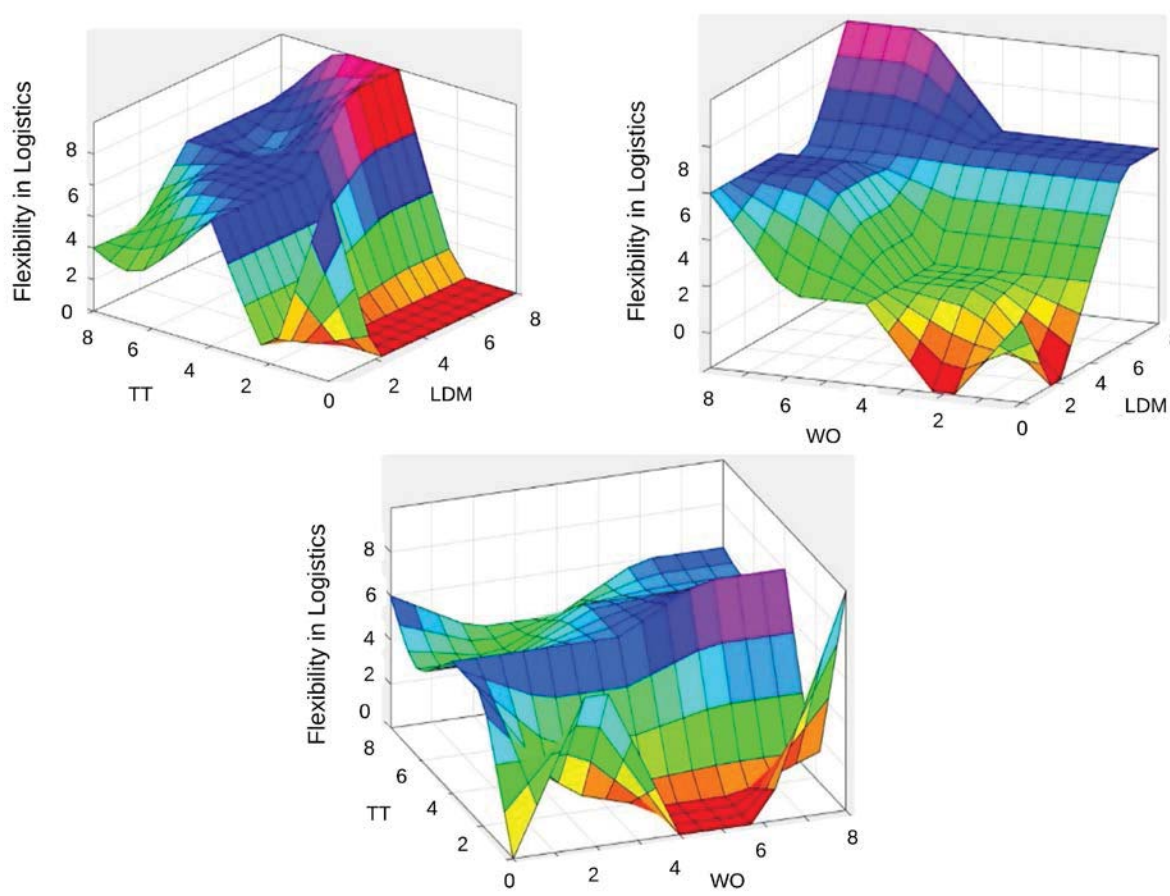

Figure 23: ANFIS model of flexibility in logistics

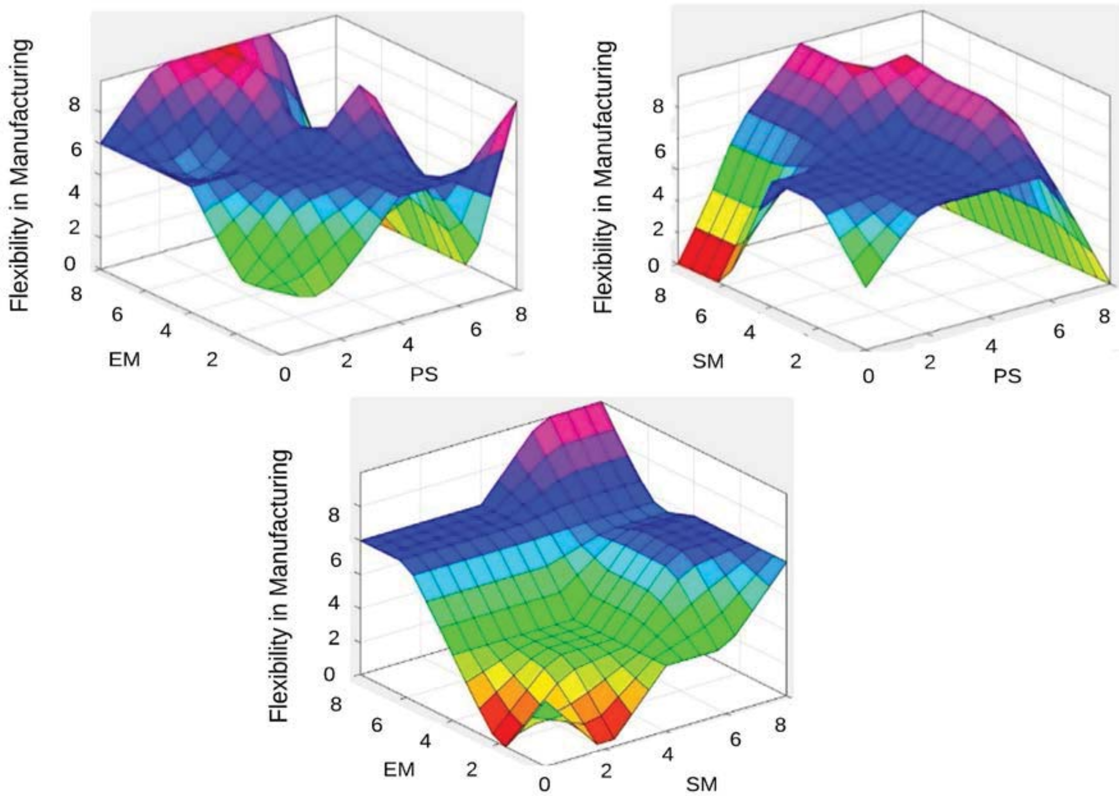

Figure 24: ANFIS model of flexibility in Manufacturing

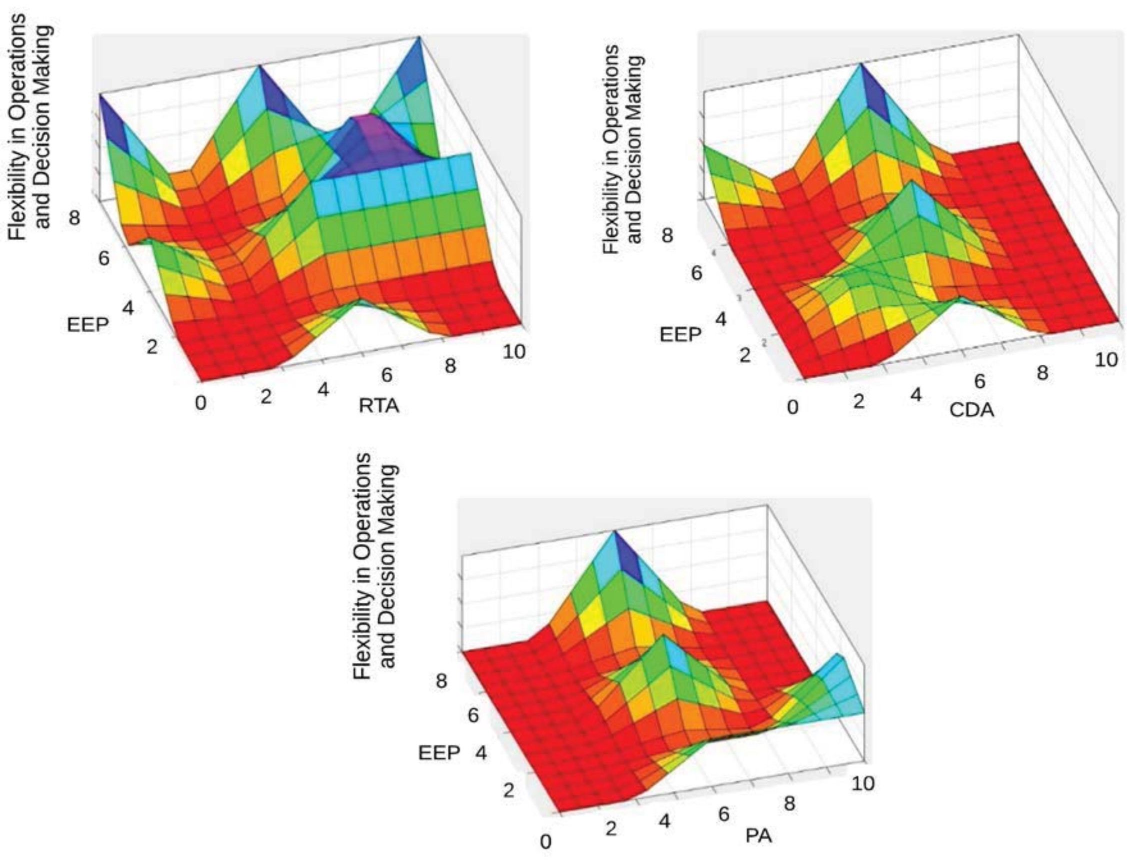

Figure 25: ANFIS model of flexibility in Operations and decision-making

shown in Fig 22. It shows that customer data analysis has a low impact on flexibility however when it is done with real time analysis of key processes it enhances flexibility in Operations & decision-making in a better way. Similarly, predictive analysis plays a crucial role in enhancing flexibility.

7.3.3 Flexibility in the Supply Chain ANFIS model

The developed ANFIS models of flexibility in logistics are shown in Fig 23 and they support the results obtained in the fuzzy model. It shows that flexibility in logistics can be enhanced by the use of traceability tools and warehouse optimization. Fig 24 shows the ANFIS model of flexibility in manufacturing. It supports the findings of the fuzzy model and highlights the importance of smart manufacturing, energy management, and planning and scheduling tools.

Flexibility in operations and decision-making is shown in Fig 25. It shows the relationship between energy efficient processes, predictive analysis, and customer data analysis. These results validate the results obtained in the fuzzy model and show the importance of these tools in enhancing flexibility in operations and decision-making. The obtained results from the ANFIS model validate the results obtained from the fuzzy models with the root mean square error in the range of 2.3×10^{-6} to 2.79×10^{-6}.

7.4 Discussions

7.4.1 Summary of results

By addressing enablers for I4.0 adoption relevant to flexibility throughout the supply chain in sufficient depth and breadth across three flexibility dimensions, this study aims to close the research gap. The findings provide support to identify the significant I4.0 adoption enablers for flexibility and its impacts on resilience and sustainability. The study also categorizes different I4.0 adoption enablers for flexibility under three flexibility dimensions for better management and managerial understanding. Further, it suggests the priority, in which I4.0 adoption enablers for flexibility should be implemented first, and in which dimension of the supply chain. The ISM model and driving power and dependency power are shown in Fig 3 and 8 respectively. Fig 8 shows the I4.0 adoption enablers under four groups, independent, dependent, linkage, and autonomous. The enablers in the independent group have capabilities to directly affect the I4.0 adoption for flexibility in the supply chain. Many other enablers responsible for flexibility depend on these independent enablers. Thus, the enablers with high driving power need to be addressed first as they will facilitate other enablers to perform better. Planning and scheduling tools (PS) have the highest driving power followed by traceability tools (TT) thus they can be considered the key enablers for I4.0 adoption.

The results of the fuzzy model of flexibility in logistics (Fig 9) show that the effect of WO is limited on flexibility in logistics even though it works at maximum capacity. However, TT and LDM have better-optimizing capabilities to enhance flexibility in logistics. The obtained results are validated by the ANFIS model (Fig 12). The results of the fuzzy model of flexibility in manufacturing are shown in Fig 10. EM and SM can optimize flexibility and for that, they need to operate at a level better than medium. However, PS can enhance flexibility even at low to medium levels. The obtained results are in concordance with the ANFIS model (Fig 13). The effects of third-group enablers on flexibility in Operations & decision making is shown in Fig 11. It shows that out of PA, EEP, RTA, and CDA, PA has better chances to optimize the flexibility however, it works better when other enablers are also at levels more than medium. Similar results are obtained through the respective ANFIS model (Fig 14). The overall suggested priority of enablers is PS, TT, RTA, EEP, LDM, PMS, EC, CDA, SMO, PA, SM, EM, IM, WO, SO, and MM.