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Analysing Lean 4.0 adoption factors towards manufacturing sustainability in SMEs: A hybrid ANN-Fuzzy ISM framework

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Manufacturing industries across the globe are undergoing a digital transformation that demands both efficiency and sustainability. Industry 4.0 (I4.0) and Lean 4.0 (L4.0) methodologies have become focal points in these efforts. Despite widespread recognition of the benefits of integrating L4.0 and I4.0, more studies need to address the practical challenges of this integration, especially the key factors that influence its successful implementation. Small and medium-sized enterprises (SMEs) in emerging economies often face significant challenges in integrating L4.0 practices due to resource limitations and complex operational challenges. This study bridges a critical research gap by proposing an integrated framework that combines Artificial Neural Networks (ANN) with fuzzy Interpretive Structural Modeling (FISM) to identify and prioritise the critical success factors (CSFs) for L4.0 adoption. A survey of 216 manufacturing SMEs was used to validate these CSFs through Exploratory Factor Analysis (EFA). The ANN analysis revealed that Process Factors have the highest influence with normalised importance (NI) of 100%, followed by Organizational Factors (NI = 60.46%), Human Factors (NI = 58.93%), Technological Factors (NI = 43.21%), External Factors (NI = 42.13%), and Environmental Factors (NI = 39.63%). Complementary FISM and Cross-Impact Matrix Multiplication Applied to Classification (MICMAC) analyses further structured these relationships, underscoring the key roles of Change Management, Organizational Culture, Waste Reduction, and Regulatory Compliance. These findings offer both a theoretical advancement in understanding complex CSF interactions and practical guidance for SMEs striving to achieve sustainable manufacturing practices.

Keywords Lean 4.0, Industry 4.0, SMEs, Manufacturing sustainability, ANN, Fuzzy ISM, Critical success factors

Business digitization, product personalization, and globalization push the traditional manufacturing sector to adopt new business models and transition to Industry 4.0 (I4.0)[1]. I4.0 facilitates the connection of different manufacturing networks, offering potential societal and environmental benefits[2]. It enables real-time information sharing and improved man–machine interfaces for informed decision-making[3]. I4.0 integrates technologies such as the Internet of Things (IoT), big data, cybersecurity, cloud computing, and digital twins to create a balanced, sustainable manufacturing ecosystem[4,5]. These advancements help the manufacturing sector address challenges related to the United Nations Sustainable Development Goals. I4.0 supports long-term value creation in environmental, economic, and social sustainability[6,7]. Sustainable manufacturing focuses on optimizing systems, products, and processes to produce quality products while ensuring efficient resource utilization and a secure ecosystem[8]. Alongside I4.0 and sustainability, the Lean concept, rooted in the Toyota Production System, has emphasised streamlining operations, reducing waste, and achieving economies of scale[9].

Lean 4.0 (L4.0) is emerging as a key driver for sustainable manufacturing, particularly in industries such as textiles, chemicals, and food processing. Small and medium-sized enterprises (SMEs) in emerging economies continue to face substantial challenges due to limited resources and the inherent complexity of integrating digital and lean practices[10]. This study focuses on multiple industrial sectors to provide a comprehensive analysis of these

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challenges to propose a tailored framework for L4.0 adoption. The integration of lean practices is increasingly essential for any manufacturing sector. Despite its importance, there remains a need for a comprehensive understanding of the factors underlying lean manufacturing (LM), making it challenging to conduct in-depth research on lean theory, especially in emerging technologies such as I4.0 and intelligent manufacturing[11]. LM is fundamentally a production system driven by organizational learning through continuous improvement. An IoT-enabled information infrastructure facilitates the use of real-time data for lean control. However, identifying practical lean indicators necessitates an effective coordination strategy to harmonize decision-making across all units within the manufacturing sector[12].

LM, recognized for its efficiency and simplicity, has been adopted by many industries to enhance financial and operational performance[13]. Over time, it has evolved into a framework that is a crucial source of competitive advantage. The application of LM extends beyond the shop floor and is relevant to virtually every aspect of an organization[14]. It is employed across various industries and even in service sectors[15]. LM principles focus on a value-creation system designed to deliver high-value products and services while systematically eliminating the seven types of cardinal waste. This is achieved through adopting"Lean Thinking"and implementing lean tools and principles[16].

"Lean Thinking"is continuously evolving, with additional process improvement methods emerging in tandem with it. These approaches have been developed to address lean limitations and criticisms, leading to integrated methodologies such as lean sustainability, Six Sigma, automation, and agility[17]. I4.0 encompasses recent technological innovations integrating physical products with their virtual models and services, achieving synchronisation across organisational boundaries to create a smart, connected, and agile value chain. This concept has taken on new significance in the manufacturing environment[18].

Embracing I4.0 enhances value creation and product quality, while Lean improves resource utilization. I4.0 emphasizes technical innovation, whereas Lean focuses on people, organizations, and culture. Integrating Lean and I4.0 modern manufacturing industries. The efficient adoption of these technologies still needs to be determined, suggesting that digital technologies and Lean principles complement each other in enhancing operational execution and decision-making[19]. However, successfully deploying L4.0 depends on technical, socio-technical, and socio-cultural factors. While I4.0 can elevate Lean to new levels of innovation, integrating I4.0 with management practices needs more substantial research and scientific backing. A framework for deploying I4.0 in systems using Lean tools is needed to provide operational visibility and economic benefits[20]. Despite numerous studies on L4.0, few have integrated advanced AI techniques with fuzzy ISM (FISM) to explore the nonlinear interdependencies among critical success factors (CSFs) in SMEs. This study fills this gap by validating key CSFs with robust empirical data and presenting a comprehensive framework that offers new insights into sustainable manufacturing practices. Although L4.0 has been used as a transformative strategy, its implementation in SMEs remains fraught with technical and operational challenges. The sustainability benefits of L4.0 are well documented; however, its practical application is impeded by complex, nonlinear interactions among CSFs, a gap that this study aims to address. Despite rapid advances in digital manufacturing, many SMEs, particularly in emerging economies, continue to struggle with the adoption of L4.0 due to limited resources and complex process integration challenges. Recent studies have identified various challenges; however, few have examined the nonlinear interactions among the CSFs involved. L4.0 implementation among SMEs in India lags behind other countries, particularly in sectors such as electronics, textiles, pharmaceuticals, automobiles, and food. L4.0 adoption in SMEs is still in its early stages, and industries must also prioritise sustainability to meet the UN's 2030 goal[21]. The SME sector faces significant challenges in adopting L4.0 practices, which are crucial for India's goal of becoming an advanced manufacturing hub while ensuring sustainability. This study uses an integrated approach, which incorporates ANN, FISM, and Cross-Impact Matrix Multiplication Applied to Classification (MICMAC) that offers a novel lens through which the complexity of L4.0 adoption can be understood, providing both theoretical insights and practical recommendations. Therefore, this study addresses the pressing need for a comprehensive framework that not only identifies but also hierarchically organises the CSFs for L4.0 adoption by addressing the following research questions (RQ):

RQ1. To identify and validate the critical success factor of L4.0 implementation in manufacturing SMEs.
RQ2. To model the nonlinear relationships among these CSFs using ANN.
RQ3. To develop a framework for manufacturing SMEs using the ANN-FISM technique.
RQ4. To find the most crucial factors by levelling CSFs using the FISM and MICMAC methods.

This study distinguishes itself from existing studies by integrating ANN with FISM to unravel the nonlinear interdependencies within CSFs for L4.0 adoption in SMEs. Unlike existing studies that predominantly used linear models or examined Lean 4.0 in isolation, our integrated approach offers a novel framework that captures both the complexity and hierarchical structure of the factors driving sustainable manufacturing. This unique contribution not only advances theoretical understanding but also provides actionable insights for practitioners operating in resource-constrained environments.

The remaining paper is structured as follows: Section"Literature review"presents the literature review and the research methodology in Section"Research methodology". Section"Data analysis and results"presents the results and discusses the data analysis using methodologies. Section"Discussions"elaborates on the study's discussion. Section"Implications"covers the study's implications. Finally, Section"Conclusions, limitations and future research recommendations"presents the conclusions, limitations, and future research recommendations.

Literature review

This study is grounded in the Practice-Based View, which emphasizes the dynamic interplay between organizational practices and technological innovations. By integrating LM principles with digital transformation theories, our study provides a robust theoretical foundation that explains how L4.0 can drive sustainable manufacturing in SMEs.

The role of lean 4.0 in sustainable manufacturing

LM supports sustainable production by emphasising three core pillars: economic (resource and cost efficiency), social (improved well-being, safety, and stakeholder engagement), and environmental (waste and pollution reduction)[22]. Through Value Stream Mapping (VSM), Lean distinguishes between value-added and non-value-added activities, streamlining operations from raw materials to product delivery[23]. This approach cuts downtime, lowers non-productive tasks, and enables cost-effective, timely, and high-quality outputs. It also fosters eco-friendly processes, faster order responses, and higher customer satisfaction, bolstering sustainability across economic, social, and environmental dimensions[24,25]. Although many organisations have enhanced their competitiveness through Lean, some still struggle to sustain long-term improvements. As industries seek both profitability and social responsibility, Lean is increasingly recognised as a catalyst for socially responsible manufacturing[26]. Figure 1 shows key research contributions at the intersection of Lean and sustainability, highlighting the main factors under consideration. Meanwhile, studies on integrating I4.0 with Lean remain in the early stages. Although both emphasise productivity and quality, I4.0's focus on systems integration often overlooks Lean's strategic elements, making it difficult to predict their combined benefits. Existing research indicates that Lean principles can provide a foundation for I4.0, yet clear frameworks for seamless integration, along with evidence of lasting efficiency gains, are still lacking[27].

Lean 4.0: Related works, literature gaps, and contributions

Several studies have examined the CSFs of implementing L4.0 in manufacturing SMEs. Understanding the impact of advanced L4.0 technologies on manufacturing sustainability is crucial for industries to realise their benefits entirely. L4.0, with its innovative services-driven business model, can reduce environmental impact and enhance societal benefits[28]. Integrating LM with I4.0 is a strategy to improve resource efficiency, sustainable design, and workplace safety[29]. However, limited research on L4.0 and manufacturing sustainability, especially in different regions, highlights the need for more studies. Key success factors for implementing L4.0 include agility, risk management, infrastructure, a clear understanding of benefits, supportive government policies, financial backing, strategic focus, interoperability, organisational culture, research and development, and strong stakeholder relationships. Despite their complementary nature, the adoption of L4.0 in manufacturing is limited by gaps in evidence, knowledge, and understanding of implementing CSFs. This study aims to address these gaps by identifying critical factors for the successful implementation of L4.0.

Although there have been studies on L4.0, the specific CSFs for its implementation in SMEs still need to be explored, especially considering the unique constraints SMEs face compared to larger organizations. Most studies focus on general factors without tailoring them to the SME context, which may lead to the omission of critical challenges specific to SMEs, such as limited resources, workforce skills, and resistance to technological

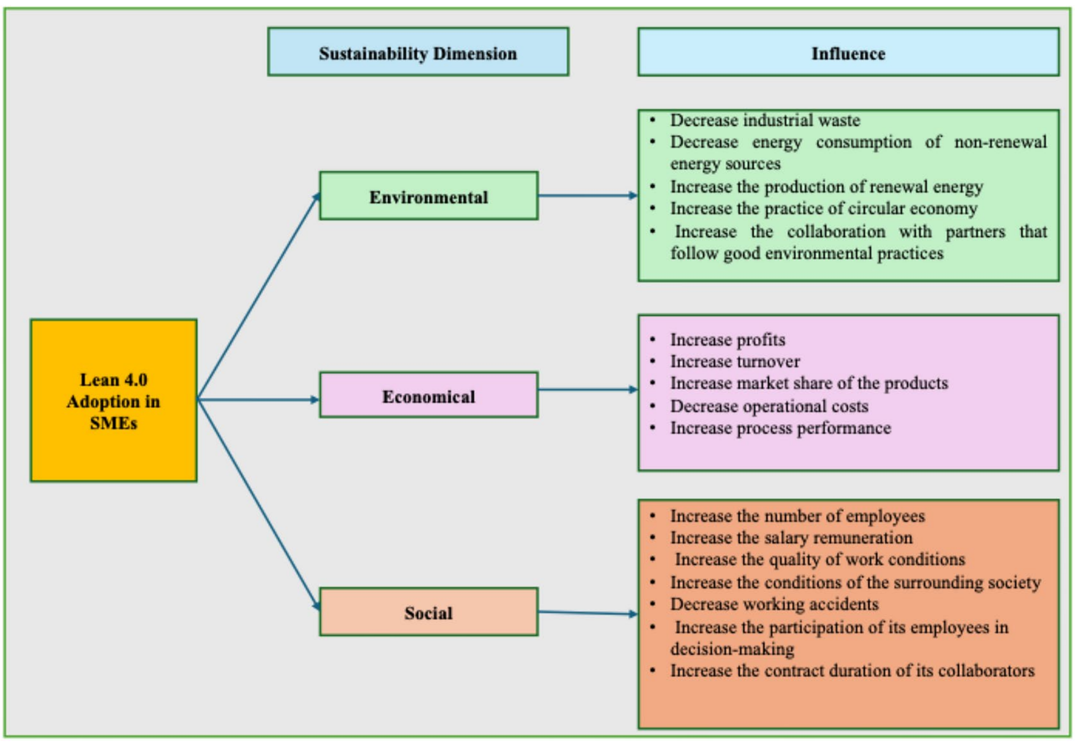

Fig. 1. Influence of LM on manufacturing sustainability.

Main group CSFs	Sub-group CSFs	Description	Reference
Technological factors (TF)	Advanced manufacturing technologies (TF1)	Using AMT like IoT, robotics, and automation to enhance production efficiency	[4,30]
	Digitalization of processes(TF2)	Integration of digital tools and platforms to streamline workflows and improve data accuracy	[31,32]
	Cybersecurity measures (TF3)	Implementing robust cybersecurity protocols to protect digital assets and ensure operational continuity	[33,34]
	Data analytics (TF4)	Leveraging big data and analytics to optimize decision-making and operational performance	[35,36]
Organizational factors (OF)	Upper management support (OF1)	Commitment and active involvement of upper management in driving L4.0 initiatives	[8,24]
	Change management (OF2)	Effective strategies to manage organizational change, ensuring smooth adoption of L4.0 practices	[17,28]
	Resource allocation (OF3)	Adequate allocation of financial, human, and technological resources to support L4.0 adoption	[20,26]
	Organizational culture (OF4)	Fostering a culture that embraces innovation, continuous improvement, and Lean principles	[26], p. 4]
Human factors (HF)	Employee training and development (HF1)	Continuous training programs to enhance employee skills in L4.0 tools and techniques	[20,23]
	Employee involvement (HF2)	Engaging employees at all levels in the L4.0 implementation process, fostering ownership and commitment	[4,37]
	Leadership competency (HF3)	Developing leaders who can effectively guide teams through the L4.0 transformation	[7,24]
Process factors (PF)	Process standardization (PF1)	Establishing standardized processes to ensure consistency and efficiency across operations	[26,38]
	Continuous improvement (PF2)	Commitment to ongoing process improvements through Lean methodologies such as Kaizen	[34,39]
	Waste reduction (PF3)	Identifying and eliminating non-value-added activities to enhance process efficiency	[17,40]
Environmental factors (EnF)	Sustainable practices (EnF1)	Integrating environmentally friendly practices into L4.0 initiatives to minimize waste and energy consumption	[20,41]
	Regulatory compliance (EnF2)	Ensuring adherence to industry regulations and standards throughout L4.0 implementation	[5,42]
	Risk management (EnF3)	Identifying, assessing, and mitigating risks associated with L4.0 adoption	[11,43]
External factors (EF)	Customer collaboration (EF1)	Working closely with customers to align L4.0 practices with their needs and expectations	[27,44]
	Supplier integration (EF2)	Collaborating with suppliers to ensure seamless integration of L4.0 practices across the supply chain	[28,45]
	Market responsiveness (EF3)	Adapting quickly to market changes and demands through agile L4.0 practices	[31,46]
	Industry benchmarking (EF4)	Comparing L4.0 practices with industry standards to identify areas for improvement	[19,47]

Table 1. CSFs for implementing L4.0 in manufacturing SMEs.

Study	Focus	Identified gap	Contribution of current study
[37]	L4.0 Implementation	Limited analysis of nonlinear interactions among CSFs	Uses ANN to capture nonlinear dependencies
[48]	Sustainable manufacturing	Lack of SME-specific frameworks for L4.0	Develops a tailored ANN-FISM framework for SMEs
[17]	Expert-based decision-making	Inadequate justification of expert selection criteria	Provides rigorous expert selection criteria and validation

Table 2. Summary of literature gaps and contributions.

change. While previous studies have identified various CSFs, there need to be studies that explore the nonlinear and interdependent relationships among these factors. Most studies assume a linear relationship, neglecting the complex dynamics that can significantly impact the successful implementation of L4.0 in SMEs. This gap calls for more sophisticated analytical methods to uncover these nonlinear interactions. Table 1 represents the CSFs for successfully implementing L4.0 within manufacturing SMEs.

Identification and categorization of CSFs
Table 1 represents the CSFs for successfully implementing L4.0 within manufacturing SMEs.

The application of advanced techniques like ANN combined with FISM is rare. There needs to be more research that utilizes these methodologies to develop a robust and adaptable framework specifically for SMEs, which can provide more accurate and actionable insights for practitioners. Despite the use of various prioritization techniques in the literature, the integration of FISM and MICMAC methods to identify and level the most crucial CSFs has yet to be extensively explored, particularly in the context of L4.0 in SMEs. The gap lies in the need for research that combines these methods to offer a more comprehensive understanding of CSFs' hierarchy and influence on successful L4.0 adoption. Table 2 represents the summary of literature gaps and contributions.

Research methodology
The identified CSFs from the literature review are validated through a survey conducted among Indian SMEs to confirm that these CSFs significantly impact manufacturing sustainability in emerging economies. A case study is conducted on a leading Indian SME to analyse the proposed framework in a real-world context. The study employs a hybrid approach, with the methodological flow presented in Fig. 2.

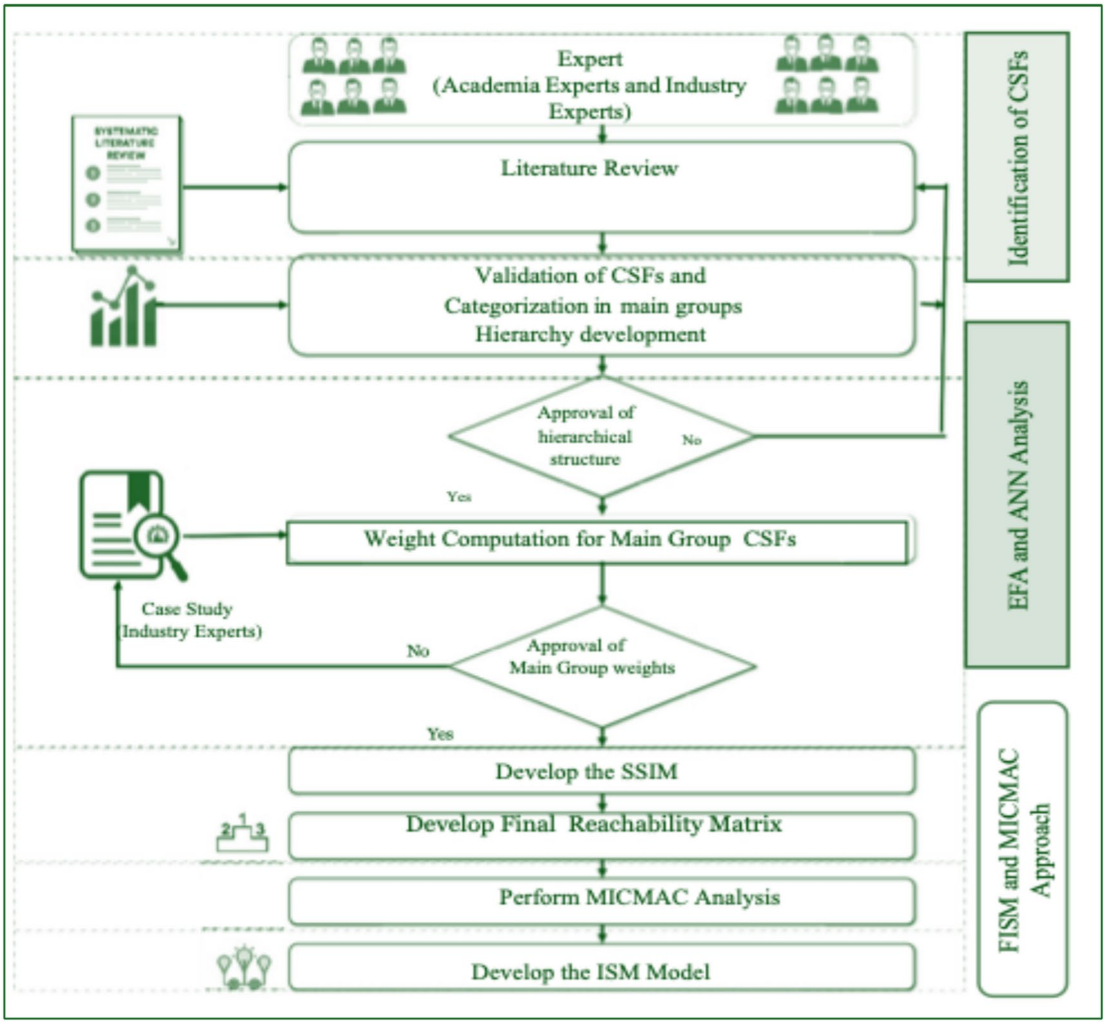

Fig. 2. Research methodology.

Methodological rationale

Traditional linear models often fail to capture the inherent complexity and nonlinear interactions among the critical success factors. To overcome this limitation, we integrated ANN with FISM. ANN is adept at uncovering nonlinear relationships, while FISM provides a structured, hierarchical depiction of factor interdependencies under conditions of uncertainty. Although incorporating additional CSFs and an expert panel could offer further granularity, our selection criteria, focusing on experts with extensive experience in both L4.0 and digital transformation, ensured that the most relevant and impactful factors were examined. The ISM approach has been employed and validated in several studies, demonstrating its superior capability in providing nuanced insights with simple procedural steps as compared to Total Interpretive Structural Modeling (TISM) or Total Interpretive Structural Modeling with Polarity (p-TISM).

Empirical analysis

An empirical analysis using quantitative and qualitative approaches provides a robust theoretical foundation for the study. Exploratory Factor Analysis (EFA), in the"Statistical Package for the Social Sciences"(SPSS 23.0), is used to structure the CSFs and analyze the data collected from participants through the questionnaire survey.

Development of the questionnaire survey and data collection

In the initial phase, an empirical investigation was conducted to ensure statistical validity and establish a theoretical foundation for the CSFs identified through the comprehensive literature review. Following this, a questionnaire survey was designed using a five-point Likert scale (ranging from 1-No influence to 5- very high influence), drawing from previously published studies in this area[38]. Three professors, one from the management department, two from the industrial engineering department, and five experts from the leading manufacturing sector actively involved in L4.0 and digitalisation projects, pre-tested the questionnaire (refer to Table 3). Experts were selected based on a stringent set of criteria, including extensive experience in L4.0 and digital transformation, senior managerial roles, and active involvement in research. This rigorous selection process

Expert	Area	Experience
Expert 1	Academia	33
Expert 2	Assistant manager	12
Expert 3	Manager	15
Expert 4	General manager	10
Expert 5	Academia	18
Expert 6	Section head	18
Expert 7	Academia	20
Expert 8	Manufacturing head	16

Table 3. Expert summary for the questionnaire pretesting.

ensured that the insights gathered were not only credible but also directly applicable to the practical challenges faced by SMEs.Their feedback led to a few revisions that were incorporated following formal discussions. The sampling process and criteria for selecting organizations for this study are detailed below.

Sampling process and eligibility criteria
To select the manufacturing sector included in this study, we adopted a systematic sampling approach, which was executed in the following steps:

a) Sampling Frame: In the initial phase, we compiled a comprehensive list of manufacturing industries using relevant industry databases and government records. This list served as the sampling frame, forming the foundation for selecting potential participants.
b) Inclusion Criteria: Organizations must meet specific criteria to be eligible for the study. These criteria focused on the organization's size, an operational website to verify current operations and the adoption of any I4.0 technologies for LM. The study targeted small to medium-sized manufacturing industries that had either implemented or were in the process of implementing L4.0 practices related to manufacturing sustainability or key enabling technologies of I4.0. This ensured that the selected organizations were aligned with the research objectives.
c) Exclusion Criteria: Organizations that did not meet the inclusion criteria or were unwilling to participate were excluded from the study. Industries with incomplete or unreliable data were also excluded to maintain the quality and integrity of the data. All study participants were provided with informed consent, and the study design was conducted according to ethical principles for Parul University. It was approved by the Research Ethics Committee: Mechanical Engineering Research of Parul University (Approval Code: PIT/PU/01/2022, Ethics Committee Date: 16.01.2022).

A list of 1,054 manufacturing firms spread across various geographical regions of India was compiled from industry directories. Industries were contacted via email and offline through a site visit, which included the purpose of the survey and a general description of the factors being studied. A total of 216 responses were finalized after excluding 3 biased submissions. Compared to other empirical studies, the overall response rate of 20.493% is considered acceptable and robust within the Indian context, as supported by previous studies. Responses were kept anonymous to minimise potential biases and ensure the authenticity of the primary data collected from industries. The initial email also briefly described the CSFs to enhance respondents' understanding and clarity regarding the survey. The demographic summary of the respondents is presented in Table 4.

Methodological justification
This study integrates ANN with FISM, which stems from the limitations of traditional linear methods in capturing complex, nonlinear relationships among CSFs. ANN effectively models these nonlinearities, while FISM organizes the factors into a clear hierarchical structure, even under uncertainty. This combined approach has been validated in recent studies[48] and offers superior predictive accuracy and interpretability compared to conventional regression models. FISM was selected for its proven capability to structure complex relationships under uncertainty. FISM, combined with expert judgment and fuzzy logic, provides enhanced clarity and flexibility in modeling the intricate interdependencies among CSFs, as supported by recent research[49].

Data analysis and results
The data collected in this study is evaluated using various statistical tools, with further details provided below.

Reliability and validity check
The accuracy of the data gathered from SMEs is thoroughly assessed using SPSS 23.0 software, which conducts reliability and validity tests to ensure the"goodness of a measure."The reliability of the data is confirmed through "Cronbach's alpha", with a value of 0.793 deemed acceptable. Convergent validity is verified if each variable's factor loading exceeds 0.5[50]. In this research, all factors demonstrate factor loadings above 0.5, affirming the convergent validity of the data. After determining the factor structure of L4.0 CSFs through EFA, Cronbach's alpha value for each dimension (main group) is calculated. The resulting range of 0.604–0.874 validates the convergent validity of the instruments.

Indicator	Response	Frequency	Percentage (%)
Industry	Textile	64	30
	Rubber and tire	53	25
	Chemical	47	21
	Food processing	52	24
	Total	216	
Gender	Male	197	91
	Female	19	9
Qualification	Graduation	110	51
	Masters	67	31
	Doctorate	39	18
Work experience	Less than 5 years	32	15
	5 to 10 years	103	48
	More than 10 years	81	37
Respondent background	Manager	53	24
	General manager	38	18
	Assistant manager	94	44
	Supervisor	31	14

Table 4. Demographic profile of respondents.

Exploratory factor analysis

The EFA methodology is widely used in operations management for its effectiveness in identifying factor structures, offering several advantages over other methods. One of its key strengths is condensing many variables into a more manageable structure without significant information loss. We conducted "Bartlett's test of sphericity and the Kaiser–Meyer–Olkin (KMO)" measure to assess the data's suitability for EFA. According to[51], Bartlett's test should yield a p value of less than 0.01, and the KMO value should be at least 0.60. In this study, the KMO value was 0.722, indicating that the data were well-suited for EFA[52].

With the data deemed appropriate, we applied varimax factor rotation to determine the factor structure of the variables. As outlined in Table 1, the CSFs associated with L4.0 adoption in manufacturing SMEs were grouped into six main categories: Process Factors, Organizational Human Factors, Technological Factors, External Factors, and Environmental Factors. These categories accounted for a total variance of 71.52%. The factor loadings for each CSF ranged from 0.679 to 0.873, exceeding the acceptable limits as suggested in the literature. The final EFA analysis results for the L4.0 adoption CSFs are presented in Table 5.

Framework development

The EFA analysis results show that all the CSFs related to L4.0 adoption are highly significant to this study. The results were then shared with a team of experts tasked with categorising these CSFs into different groups for framework development. Figure 3 illustrates the comprehensive framework developed for manufacturing SMEs based on the EFA findings.

Summary of the case industry

To test the framework, we selected a ball-bearing manufacturing industry as the focus of our case study. This sector supports L4.0 practices. The chosen organization, XY, was established in 1946 as a manufacturing plant in northern India. This industry has embraced green business practices. XY serves a range of clients, including several large international corporations.

The organization is deeply committed to manufacturing sustainability initiatives, regularly offering employee training and awareness programs. After discussions with the top management, they agreed to participate in our study. An expert team of six members was assembled for the case study, consisting of two managers, an R&D manager, an assistant manager, a manufacturing head, and an operations manager (refer to Table 6). Each team member has over 10 years of experience in the manufacturing industry, and three are actively involved in LM projects. These experts identified key CSFs critical to adopting L4.0, which were then analysed further using ANN, F-ISM, and MICMAC techniques. The expert panel included professionals from industry, academia, and those working at the intersection of both domains.

To develop pair-wise associations among the factors, the experts were asked to provide their insights using four options: achieved by, leads to, bidirectional, or no relation across the rows and columns of a table listing these factors.

Artificial neural networks

In this step of ANN-FISM modelling, ANN was chosen for its flexibility in handling input data without requiring a specialised equation form. It adapts easily to different datasets and excels at managing issues related to incomplete or partial data[53]. ANN's predictive accuracy is notably higher than that of traditional linear models.

FISM is a widely used method, particularly effective for analysing predictors with statistically significant impacts on dependent variables. However, a key limitation of traditional linear statistical methods, including

Main group CSFs	Sub-group CSFs	Mean	Loading	Cronbach alpha(α)
TF	TF1	3.20	0.780	0.862
	TF2	3.59	0.834	
	TF3	3.25	0.854	
	TF4	3.70	0.681	
OF	OF1	3.65	0.824	0.604
	OF2	3.55	0.873	
	OF3	4.01	0.763	
	OF4	3.07	0.751	
HF	HF1	3.80	0.832	0.733
	HF2	3.94	0.722	
	HF3	3.86	0.693	
PF	PF1	3.38	0.892	0.782
	PF2	4.05	0.851	
	PF3	3.42	0.679	
EnF	EnF1	3.39	0.803	0.874
	EnF2	3.43	0.811	
	EnF3	3.77	0.783	
EF	EF1	3.30	0.842	0.657
	EF2	3.48	0.712	
	EF3	3.12	0.776	
	EF4	4.15	0.730	

Table 5. EFA results for L4.0 CSFs.

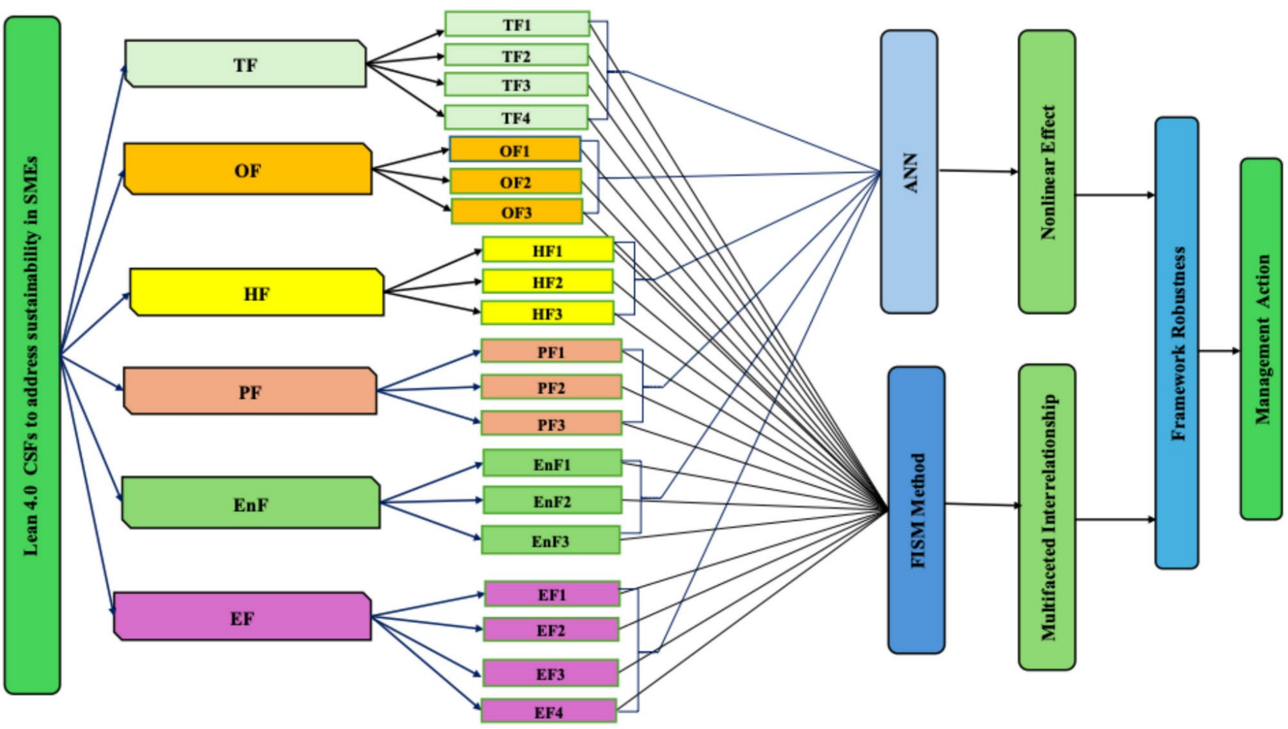

Fig. 3. Framework for SMEs to achieve manufacturing sustainability through L4.0 CSFs.

sequential FISM, is their ability to detect only linear relationships, which can oversimplify the complex nature of human decision-making[42]. To address this limitation, we integrate ANN, one of the most prominent AI models, into our approach.

ANN, especially in its multi-layer perceptron form, is designed to model nonlinear relationships and can be learned through input and output mapping[54]. Its architecture is inspired by the human brain, allowing it to detect nonlinear and non-compensatory relationships, a distinct advantage over linear models. ANN offers

Experts	Area	Experience
Expert 1	Manager	12
Expert 2	Manager	14
Expert 3	Manufacturing head	18
Expert 4	R&D manager	12
Expert 5	Operation manager	15
Expert 6	Assistant manager	18

Table 6. Expert's summary involved in case study.

superior predictive accuracy, adaptability, and robustness. However, since ANN is unsuited for examining causal relationships, we developed a two-step method combining ANN with FISM for a more comprehensive analysis.

ANN training phase
The ANN training phase aims to fine-tune the network's internal weights to accurately model the underlying relationships between inputs and outputs. This process involves using a set of input and output pairs, each representing a specific input and its corresponding output. Through training, the ANN learns to map these inputs to the correct outputs, effectively capturing the implicit patterns and relationships in the data.

$$\mathrm{P} = (\mathrm{C1},\ \mathrm{R1}), (\mathrm{C2},\ \mathrm{R2}), \ldots, (\mathrm{Cni},\ \mathrm{Rni}) \tag{1}$$

Here, Ri represents the ith sample of the input parameter vector, and Ci is the corresponding vector of output responses. These samples contain the implicit nonlinear relationship between the input parameters and output responses. The aim is to develop an ANN model capable of learning and capturing this hidden relationship. The general form of the ANN output can be expressed as follows:

$$\mathrm{X} = \mathrm{X}(\mathrm{R},\ \mathrm{W}) \tag{2}$$

In this formulation, W represents the vector of unknown weights within the ANN, R denotes the input parameters, and X is the vector of output responses generated by the ANN. The objective is to determine the optimal vector of weights by solving an optimization problem. This problem minimises the difference between the ANN's predicted and desired outputs by adjusting the network's weights. The optimization is expressed through the following mathematical formulation:

$$\mathrm{W}^* = \min \mathrm{X}\ \mathrm{Et} = \min \mathrm{X} \sum_{\mathrm{i}} \parallel \mathrm{C_i} - \mathrm{Y}(\mathrm{X_i} - \mathrm{W}) \parallel \tag{3}$$

In this context, Et represents the norm of the error across all samples. Various methods can be employed to solve the optimization problem, with one of the most common being the back-propagation method[55]. This method involves calculating the gradient of the error function with respect to the weights. The weights are then updated based on this gradient to enhance the accuracy of the network's response.

$$\mathrm{W_{next}} = \mathrm{W_{present}} - \mathrm{Q}\frac{\mu\mathrm{E}\tau}{\mu_{\mathrm{w}}} \tag{4}$$

In this process, Q represents the learning rate of the ANN. Initially, the weights are randomly assigned. The process continues iteratively until a solution to Eq. (3) is achieved.

To accurately train the function, the optimization and calibration Wi and Vi must be repeated continuously. The optimal values of Wi and Vi will minimize the mean square error. This process continues until the desired level of accuracy is reached. The calibration method for adjusting the weights and biases approach is outlined as:

$$\mathrm{P_i} = \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{W_{ij}X_i} + \mathrm{V_i} \tag{5}$$

where the bias Vi is a nonzero value added to the sum of the input and its corresponding weight. This sum, Pi is then transformed using a transfer function, also known as an activation function. The activation value for the unit, Ki can be calculated as follows:

$$\mathrm{K_i} = \mathrm{f}(\mathrm{P_i}) \tag{6}$$

ANN performance measure
The performance of ANNs is typically evaluated using metrics such as RMSE, absolute mean deviation, and the coefficient of determination R^2 which are calculated as follows:

$$\mathrm{RMSE}^2=\left[\frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{Oi}-\mathrm{Oic})^2\right] \tag{7}$$

$$\mathrm{R}^2=1-\frac{\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{Oi}-\mathrm{Oic})^2}{\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{Oic}-\mathrm{Om})^2} \tag{8}$$

$$\mathrm{AMD}=\left[\frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}}\frac{(\mathrm{Oi}-\mathrm{Oic})}{\mathrm{Oic}}\right]*100 \tag{9}$$

Here Oic represents the actual value, Oi is the predicted value, Om is the mean of the actual values, and m is the total number of data points.

Results obtained by ANN

In the second step of this hybrid approach, we develop our ANN model using only the main groups of CSFs. FISM is a widely used method for identifying interrelationships among factors significantly impacting dependent variables. However, traditional linear methods like FISM have limitations, particularly their inability to detect nonlinear relationships, which can oversimplify the complexity of human decision-making. We use ANN, an advanced AI method, to model the decision-making process to address this limitation.

In this research, 70% of the data is used to train the network model, while the remaining 30% is used for testing. To ensure validity, tenfold cross-validation is employed. The ANN model takes six variables (Only the main group) as inputs: Perceived economic benefits, perceived degree of resource utilization, perceived level of trust, perceived effort expectancy, perceived external stimuli, risk analysis and feasibility planning, organizational competency and capability, and perceived business concerns. The dependent variable, L4.0 adoption, serves as the output in the ANN model.

The evaluation results, as shown in Table 7, highlight the strong performance of our ANN model. The mean RMSE value for the testing model is 0.04, while it is 0.27 for the training model, indicating that the ANN model effectively captures the nonlinear relationships between the independent and dependent variables in L4.0 adoption for manufacturing SMEs (refer to Fig. 4). A comparative overview of root mean squared error (RMSE) values is shown in Fig. 5.

A sensitivity analysis of the ANN model was conducted to determine the relative importance of the independent variables (Factors) in predicting L4.0 adoption. The summary of these variables' normalized importance (NI) is represented in Table 7. This normalized importance measures how much the output values predicted by the network change in response to changes in the independent variables.

The ANN results indicate that Process Factors, with a normalized importance (NI) of 100%, are the most critical factor affecting L4.0 adoption in manufacturing SMEs. This is followed by Organizational Factors (NI = 60.46%), Human Factors (NI = 58.93%), Technological Factors (NI = 43.21%), External Factors (NI = 42.13%), and Environmental Factors (NI = 39.63%). A detailed overview of these importance rankings is outlined in Table 8.

Fuzzy-Interpretive Structural Modelling (FISM)

In this research, we employed the ISM technique, enhanced with fuzzy logic. ISM is an interactive approach that relies on the insights of independent experts to decipher the complex interrelationships between factors. The integration of ISM with fuzzy logic, known as FISM, has been widely recognized and utilized by researchers[56]. This extension of traditional ISM has proven more effective than other interpretive methods like, the Analytic Network Process (ANP) and Analytic Hierarchy Process (AHP).

SS (Training)	SSE (Training)	RMSE (Training)	SS (Testing)	SSE (Testing)	RMSE (Testing)
153	7.63	0.33	63	5.29	0.50
151	5.34	0.28	65	3.14	0.35
152	9.3	0.39	64	7.39	0.49
149	5.84	0.32	67	8.33	0.48
150	4.24	0.25	66	5.88	0.53
155	3.18	0.22	61	6.81	0.51
156	4.64	0.26	60	8.252	0.59
148	2.86	0.22	68	5.39	0.40
157	2.12	0.20	59	4.92	0.37
154	2.04	0.18	62	3.82	0.35
Mean	4.72	0.27	Mean	5.92	0.04
SD	2.38	0.07	SD	1.67	0.08

Table 7. RMSE values and performance evaluation. SS = Sample Size, SSE = Sum of square error.

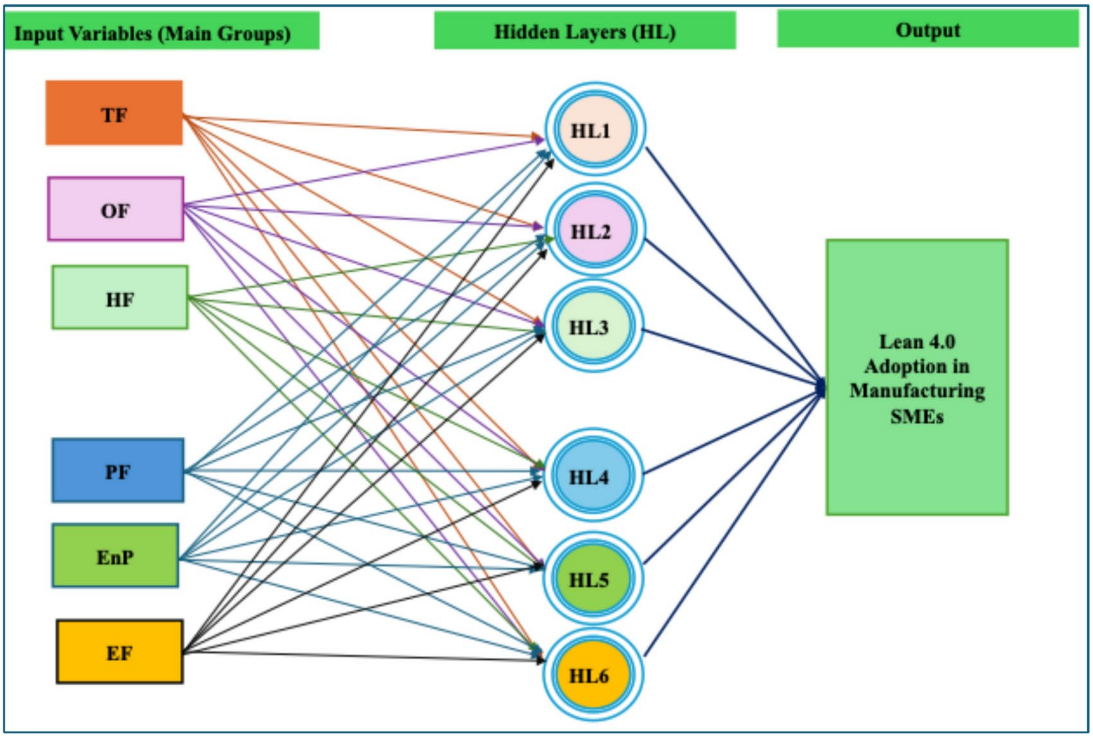

Fig. 4. Proposed ANN model.

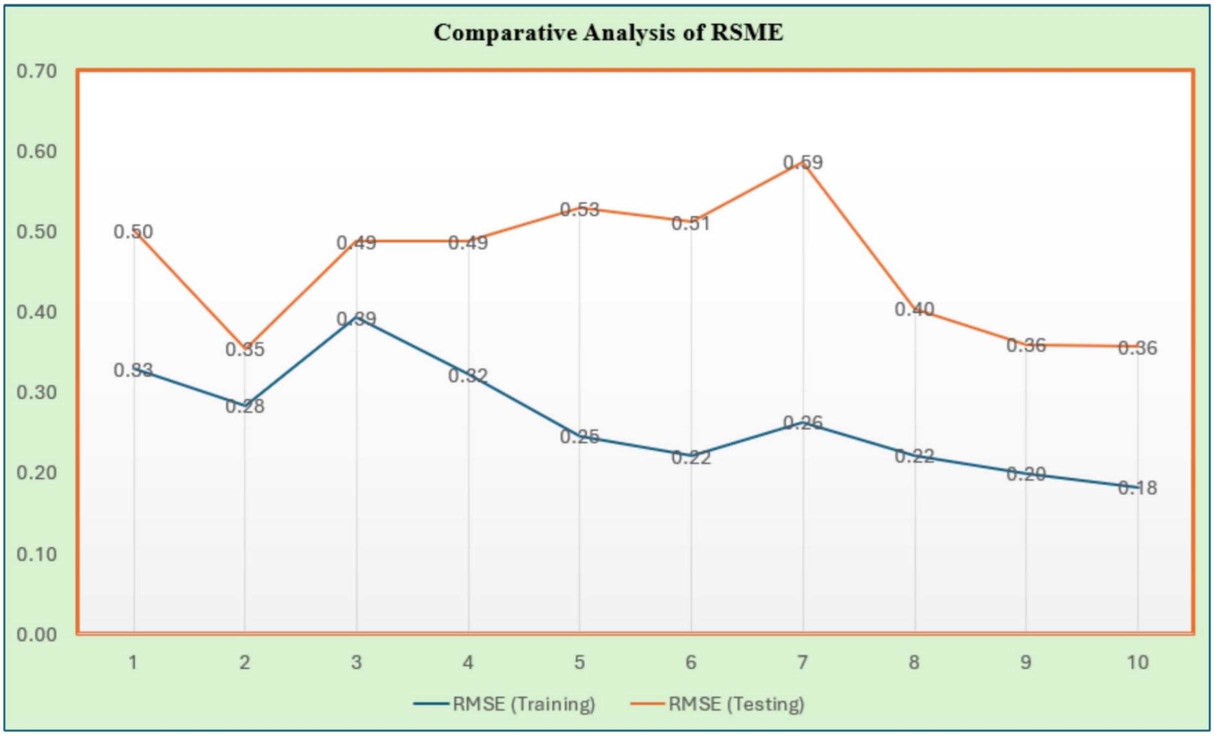

Fig. 5. RMSE analysis training and testing.

Main group CSFs	TF	OF	HF	PF	EnF	EF
NI(in %)	12.26	41.62	35.19	100.00	12.19	27.90
NI(in %)	19.00	72.97	96.75	100.00	23.80	42.10
NI(in %)	62.17	45.23	60.09	79.80	67.12	16.22
NI(in %)	56.29	57.25	72.20	100.00	56.45	38.77
NI(in %)	43.34	77.18	61.19	100.00	48.12	32.29
NI(in %)	67.12	15.39	42.90	100.00	29.10	61.10
NI(in %)	26.10	48.22	52.81	100.00	18.67	82.23
NI(in %)	65.82	91.46	55.11	100.00	82.43	54.12
NI(in %)	39.11	47.72	64.34	100.00	35.21	22.30
NI(in %)	32.19	95.33	36.86	100.00	15.25	35.80
Average Score	42.34	59.24	57.74	97.98	38.83	41.28
Normalize Score (%)	43.21	60.46	58.93	100.00	39.63	42.13
Rank	4	2	3	1	6	5

Table 8. Sensitivity analysis (Normalized importance).

Linguistic description	Corresponding TFN	Influence scope
No influence(NI)	(0, 0.1, 0.3)	1
Very low influence(VI)	(0.1, 0.3, 0.5)	2
Low influence(LI)	(0.3, 0.5, 0.7)	3
High influence(hi)	(0.5, 0.7, 0.9)	4
Very high influence(vi)	(0.7, 0.9, 1)	5

Table 9. Fuzzy linguistic scale.

CSFs	TF1	TF2	TF3	TF4	OF1	OF2	OF3	OF4	HF1	HF2	HF3	PF1	PF2	PF3	EnF1	EnF2	EnF3	EF1	EF2	EF3	EF4
Driving power	10	11	9	10	9	10	6	10	9	13	12	8	10	11	8	13	10	11	8	15	6
Dependence power	13	8	12	9	10	14	10	11	12	4	10	9	8	12	5	10	12	9	11	9	11

Table 10. Driving power and dependence power.

Particularly in uncertain environments, ISM combined with fuzzy logic unveils intricate connections among CSFs by examining their driving and dependence. By leveraging an ISM-based hierarchical model, the importance of CSFs can be clearly understood[57].

In this study, FISM was chosen to explore the broader interrelationships among CSFs crucial for the effective implementation of L4.0 in manufacturing SMEs, especially under uncertain conditions. The ISM-MICMAC technique was also employed to investigate the binary relationships among the identified CSFs. Recognizing that these relationships are not uniformly strong or weak, we extended our analysis beyond traditional ISM-MICMAC by incorporating fuzzy theory.

We identified 21 key CSFs through a comprehensive literature review and expert consultations, which were then analysed using ANN and FISM. This methodology employs triangular fuzzy numbers to represent the relationships between elements. Specifically:

- O indicates that elements i and j are unrelated, with no contextual relationship.
- X signifies that elements i and j are mutually influential, with i leading to j and vice versa.
- A denotes that element j leads to i.
- V means that element i leads to j.

The fuzzy linguistic scale used in this study is represented in Table 9. Based on expert inputs, an aggregated Self-Structural Interaction Matrix (SSIM) is constructed, as shown in Table 12 (refer to Appendix A). The next step involves generating an initial fuzzy reachability matrix using the aggregated SSIM. Initial Reachability Matrix (IRM) using fuzzy numbers is presented in Table 13 (refer to Appendix A). The linguistic variables in the initial fuzzy reachability matrix are then converted into fuzzy numbers; the final reachability matrix is presented in Table 14 (refer to Appendix A).

The next step is calculating the crisp values for the elements i and j. The driving and dependence powers obtained from the final reachability matrix are represented in Table 10. Following the procedure described in Eqs. (10–14). The process of computing these crisp values is adapted from the method described[38]. When alternatives are evaluated based on the ith criterion, denoted as fij where j ranges from 1 to j, and represented as triangular fuzzy numbers" fij = (lij, mij, rij)", the crisp value is calculated using the following steps:

1. Normalization

$$\begin{aligned} X\alpha^{k}_{1ij} &= (\alpha^{k}_{1ij} - \alpha^{k}_{1ij})/\Delta^{max}_{min} \\ X\alpha^{k}_{2ij} &= (\alpha^{k}_{2ij} - \min \alpha^{k}_{2ij})/\Delta^{max}_{min} \\ X\alpha^{k}_{3ij} &= (\alpha^{k}_{3ij} - \min \alpha^{k}_{3ij})/\Delta^{max}_{min} \end{aligned} \tag{10}$$

2. Compute of left (l_s) and right (r_s) normalisation value

$$Xls^{k}_{ij} = x\alpha^{k}_{2ij}/(1 + x\alpha^{k}_{2ij} - x\alpha^{k}_{1ij}) \tag{11}$$

$$xrs^{k}_{ij} = x\alpha^{k}_{3ij}/(1 + x\alpha^{k}_{3ij} - x\alpha^{k}_{2ij})$$

3. Calculation of crisp value using the following equation.

$$x^{k}_{ij} = [xls]^{k}_{ij}\left(1 - xls^{k}_{ij}\right) - \left(xrs^{k}_{ij}\right) \wedge^{2}]/\left(1 - xls^{k}_{ij} + xrs^{k}_{ij}\right) \tag{12}$$

4. Calculation of total normalized crisp value the following equation.

$$w^{k}_{ij} = \min \alpha^{n}_{ij} + x^{n}_{ij}\Delta^{max}_{min} \tag{13}$$

5. Calculate the average value from the different opinions of k decision-maker.

$$w^{k}_{ij} = \frac{1}{K}\left(w^{1}_{ij} + w^{2}_{ij} + \ldots + w^{k}_{ij}\right) \tag{14}$$

The driving and dependence power obtained from the final reachability matrix is then utilized to classify the CSFs into four categories: Autonomous, dependent, linkage, and independent variables. The results of the MICMAC analysis are depicted in Fig. 6.

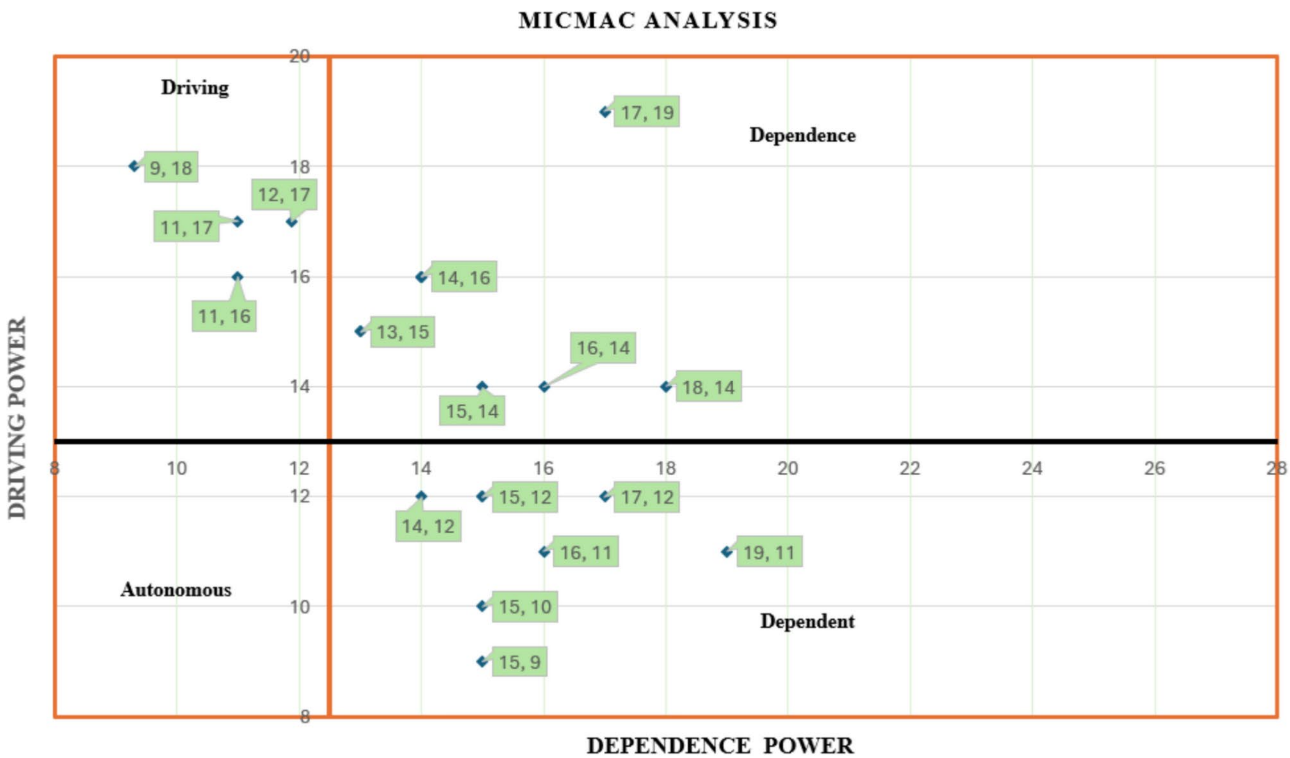

Fig. 6. Cluster of CSFs by MICMAC analysis.

a) Cluster 1: This group includes CSFs with low driving and dependence power. These variables are somewhat isolated from the system, making them autonomous variables.
b) Cluster 2: In this cluster, we find CSFs with limited driving power but strong dependence on other variables. These are classified as dependent variables.
c) Cluster 3: This category comprises CSFs exhibiting strong driving and dependence power. These variables are unstable and require careful analysis, as any changes can impact other variables and themselves. They are referred to as linkage variables.
d) Cluster 4: This group contains CSFs with strong driving power but low dependence on others. Known as independent variables, these factors can influence other variables, except for the autonomous ones.

The next step involves level partitioning for all identified CSFs. The reachability and antecedent set are determined from the final reachability matrix. The intersection set is formed by identifying the common elements between these two sets. Levels are identified when the reachability set and intersection set are identical. After a level is determined, those factors are removed from the entire set, and the process is repeated until every factor is assigned a level. The final factors and their corresponding levels are outlined in Table 11, while the ISM hierarchical model is illustrated in Fig. 7.

Discussions

This research identified 21 key CSFs (refer to Table 1) through a comprehensive literature review for implementing L4.0 in manufacturing SMEs. The EFA approach was initially employed to classify these CSFs into six distinct groups: Process Factors, Organizational Factors, Human Factors, Technological Factors, External Factors, and Environmental Factors. A hybrid method was applied to analyse the data, combining ANN and FISM techniques. FISM alone is limited to detecting linear associations, making it less suitable for complex decision-making, such as adopting L4.0 CSFs for achieving sustainability in manufacturing SMEs. To address this, ANN was integrated with FISM to capture linear and nonlinear relationships among the CSFs involved in L4.0 adoption.

The linear relationships explored how one determinant might refine another, while ANN helped identify the non-compensatory characteristics of L4.0 adoption through nonlinear relationships. Although FISM is widely used to determine associations, its limitation lies in its ability to detect only linear relationships, which oversimplifies the complexity of human decision-making. To overcome this, ANN, specifically the multi-layer perceptron type, was employed for its ability to model nonlinear relationships through input–output mapping. The ANN model in this study was developed using SPSS 23.0, with a sigmoid function in the hidden layer. The model's accuracy was measured using RMSE, with the number of hidden nodes varying from 1 to 10 for cross-validation, as no fixed algorithm exists for determining the required number of hidden nodes.

A sensitivity analysis was conducted to rank the independent variables influencing L4.0 adoption. The ANN results indicate that Process Factors, with a normalized importance (NI) of 100%, are the most critical factor affecting L4.0 adoption in manufacturing SMEs. This is followed by Organizational Factors (NI =60.46%), Human Factors (NI =58.93%), Technological Factors (NI =43.21%), External Factors (NI =42.13%), and Environmental Factors (NI =39.63%).

CSFs	Level
Advanced manufacturing technologies (TF1)	IV
Digitalization of processes(TF2)	IV
Cybersecurity measures (TF3)	I
Data analytics (TF4)	III
Upper management support (OF1)	VII
Change management (OF2)	I
Resource allocation (OF3)	V
Organizational culture (OF4)	VII
Employee training and development (HF1)	I
Employee involvement (HF2)	IV
Leadership competency (HF3)	VII
Process standardization (PF1)	III
Continuous improvement (PF2)	V
Waste reduction (pf3)	II
Sustainable practices (enf1)	VI
Regulatory compliance (EnF2)	V
Risk management (EnF3)	I
Customer collaboration (EF1)	VI
Supplier integration (EF2)	II
Market responsiveness (EF3)	V
Industry benchmarking (EF4)	VI

Table 11. CSFs and level partitioning.

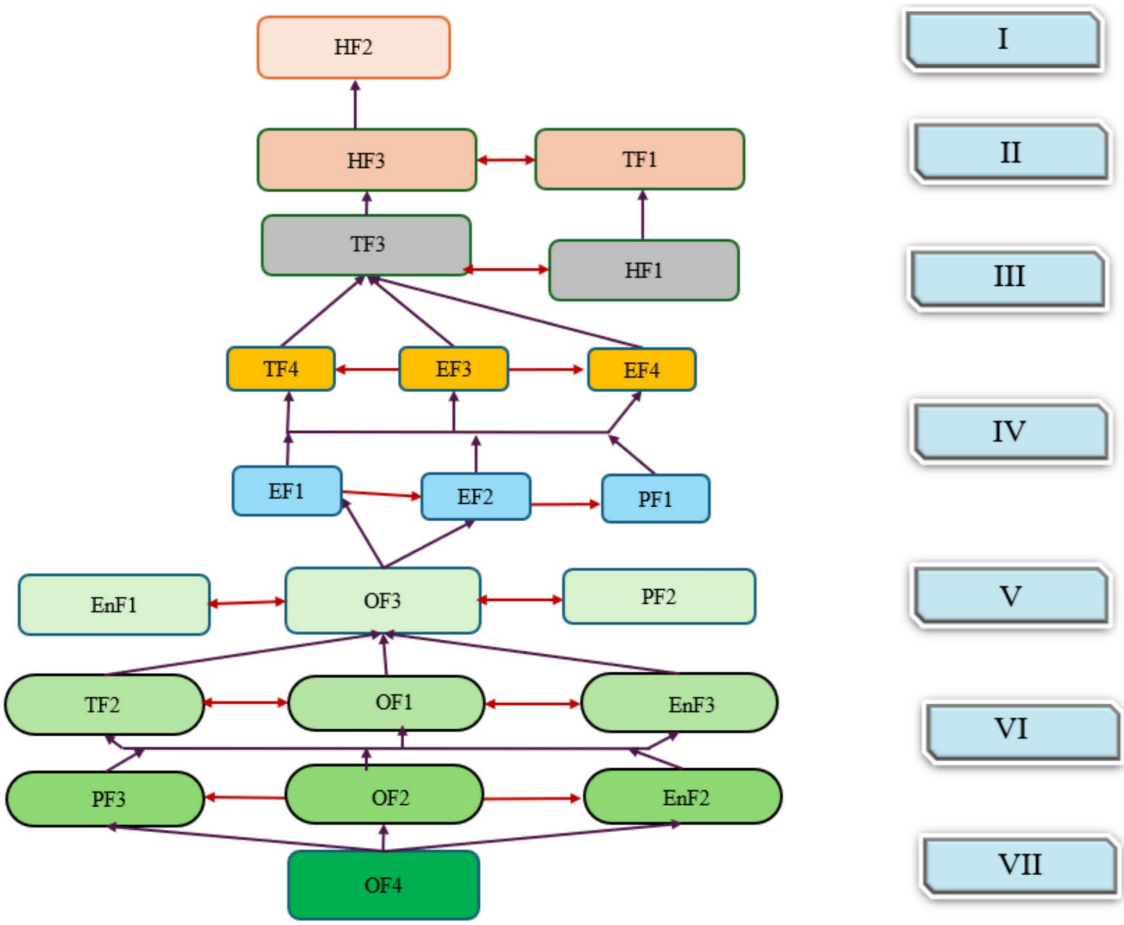

Fig. 7. ISM hierarchical model.

Through MICMAC and ISM analysis, it was found that Change Management (OF2), Organizational Culture (OF4), Waste Reduction (PF3), and Regulatory Compliance (EnF2) are key CSFs with high influence on the successful implementation of L4.0. These factors hold the most weight in guiding implementation efforts.

The hierarchical model, validated through MICMAC analysis, reveals that Data Analytics (TF4), Change Management (OF2), Employee Training and Development (HF1), and Customer Collaboration (EF1) act as independent factors, forming the foundation for the entire system.

Factors like Cybersecurity Measures (TF3), Change Management (OF2), Continuous Improvement (PF2), Waste Reduction (PF3), Supplier Integration (EF2), and Industry Benchmarking (EF4) belong to linkage group factors that play a crucial role between independent group factor and dependent group factors. The remaining factors fall into dependent groups factors, requiring support from others for effective implementation. No CSFs were classified as autonomous, emphasizing that each CSF is crucial in the L4.0 implementation process.

The combined FISM and MICMAC approach highlights the most crucial CSFs, particularly those at the base of the hierarchy, like Change Management (OF2), Organizational Culture (OF4), Waste Reduction (PF3), and Regulatory Compliance (EnF2). These findings are significant for managers and practitioners. A clear understanding of these CSFs aids in improving L4.0 systems, guiding short- and long-term decisions, and aligning with regulatory requirements. The study encourages businesses, including startups, to adopt techniques like L4.0. Management support is vital, and fostering a motivated workforce is key to successful adoption. The findings of this study resonate with existing studies that emphasise the importance of process optimisation in sustainable manufacturing. However, our results extend these insights by revealing the nonlinear dynamics among CSFs, a nuance often overlooked in existing studies. This comparative analysis validates the theoretical understanding of L4.0 and provides a deeper understanding of its practical implications for SMEs. These insights suggest that while traditional models have focused on linear correlations, a hybrid approach is necessary to fully understand and implement L4.0 for manufacturing sustainably. The findings align with the past study of sustainable manufacturing practices[54].

Implications

The implications of our findings extend well beyond local contexts. Globally, SMEs face similar challenges in adopting advanced manufacturing practices amid resource constraints. The integrated ANN-FISM framework provides a robust decision-support tool for local practitioners and offers a scalable model that can be adapted across different regions and industries. By highlighting the critical influence of process factors and the interdependencies among CSFs, our study contributes to the broader discourse on sustainable manufacturing, offering valuable guidance for policymakers and industry leaders across the globe.

Theoretical implications

This study enriches the theoretical understanding of L4.0 adoption in manufacturing SMEs by integrating the practice-based view, highlighting the synergy between Lean principles and I4.0 technologies for achieving manufacturing sustainability. The research reveals the intricate interplay between technology and organizational practices, emphasizing that successful L4.0 implementation requires strong leadership, a culture of continuous improvement, and employee engagement. The novel methodological approach combining, ANN and FISM offers a comprehensive tool for analysing the complex relationships among CSFs, providing a robust foundation for future research on L4.0 adoption and its impact on organizational performance.

Practical implications

This study identifies key CSFs crucial for L4.0 implementation in SMEs. The study provides actionable insights on prioritising these factors based on their driving and dependence power, aiding managers in allocating resources and efforts effectively. This study offers practical guidance on integrating I4.0 technologies into Lean practices, emphasizing the need for alignment with organizational strategy and operational practices to enhance competitiveness and achieve long-term manufacturing sustainability goals.

Sustainability implications

Adopting L4.0 in manufacturing SMEs has significant sustainability implications, promoting resource efficiency, waste reduction, and alignment with global sustainability goals (UN's SDGs). By minimizing waste and optimizing production processes, L4.0 contributes to more sustainable manufacturing practices and offers long-term environmental and economic benefits, such as reduced operational costs and increased profitability. The study also underscores L4.0's role in fostering innovation, enabling SMEs to develop sustainable products and processes that meet market demands while supporting environmental conservation.

Conclusions, limitations and future research recommendations

This research identified 21 key CSFs (refer to Table 1) through a comprehensive literature review for implementing L4.0 in manufacturing SMEs. The EFA approach was initially employed to classify CSFs into six main groups. A hybrid method was applied to analyse the data, combining ANN and FISM techniques. An ANN was used to assess the nonlinear effects of the CSFs. The ANN results indicate that Process Factors, with a normalised importance (NI) of 100%, are the most critical factor affecting L4.0 adoption in manufacturing SMEs. This is followed by Organizational Factors (NI =60.46%), Human Factors (NI =58.93%), Technological Factors (NI =43.21%), External Factors (NI =42.13%), and Environmental Factors (NI =39.63%). The CSFs were then prioritised using F-ISM and categorised into four quadrants with the MICMAC approach. The combined FISM and MICMAC approach highlights the most crucial CSFs, particularly those at the base of the hierarchy, like Change Management (OF2), Organizational Culture (OF4), Waste Reduction (PF3), and Regulatory Compliance (EnF2). These factors hold the most weight in guiding implementation efforts. The findings are significant for managers and practitioners. A clear understanding of these CSFs aids in improving L4.0 systems, guiding short- and long-term decisions, and aligning with regulatory requirements. This study confirms that Process Factors are paramount in driving L4.0 adoption in SMEs while revealing the complex, nonlinear interactions among various CSFs. These insights deepen our theoretical understanding of sustainable manufacturing practices and offer practical strategies for industry practitioners. By bridging the gap between digital transformation and traditional lean principles, our integrated framework provides a valuable roadmap for SMEs across the globe. Future research should build on these findings to explore additional factors and refine the framework further, ensuring it remains responsive to evolving industrial challenges.

Limitations and future research recommendations

While this study provides valuable insights into implementing L4.0 in manufacturing SMEs, it has certain limitations. Firstly, the research is primarily based on expert opinions and literature, which may introduce biases and limit the generalizability of the findings. Secondly, the study focuses on a specific set of CSFs, potentially overlooking other relevant factors influencing L4.0 adoption in different industries. While innovative, the integration of ANN and FISM may be complex for practitioners without advanced knowledge of these methodologies, potentially limiting their practical application. The study primarily considers SMEs, so the findings may not fully apply to larger organizations with different resource capacities and operational complexities. While this study provides a comprehensive framework for L4.0 adoption, several limitations remain for future exploration. Future research could expand the set of CSFs to include emerging factors influenced by rapid technological advances, explore longitudinal changes in the interplay of these factors, and validate the framework in different industrial and geographic contexts. Comparative studies employing alternative analytical methods such as TISM or p-TISM could further elucidate the robustness and generalizability of our findings.

Data availability
Data are available in the manuscript.

Appendix A
See Tables 12,13,14

Questionnaire
This research is about evaluating the *Critical success factors (CSFs)* in adopting *Lean 4.0* practices for *sustainable manufacturing in SMEs*. We identified the *CSFs* through literature and experts' inputs. Please respond to confirm the *CSFs* using a five-point Likert scale (5 = Strongly Agree to 1 = Strongly Disagree).
Please tick (√) in the appropriate box.

Enablers name	Strongly agree 5	Agree 4	Natural 3	Disagree 2	Strongly disagree 1
1. Advanced manufacturing technologies					
2. Digitalization of processes					
3. Cybersecurity measures					
4. Data analytics					
5. Upper management support					
6. Change management					
7. Resource allocation					
8. Organizational culture					
9. Employee training and development					
10. Employee involvement					
11. Leadership competency					
12. Process standardization					
13. Continuous improvement					
14. Waste reduction					
15. Sustainable practices					
16. Regulatory compliance					
17. Risk management					
18. Customer collaboration					
19. Supplier integration					
20. Market responsiveness					
21. Industry benchmarking					

CSFs	EF4	EF3	EF2	EF1	EnF3	EnF2	EnF1	PF3	PF2	PF1	HF3	HF2	HF1	OF4	OF3	OF2	OF1	TF4	TF3	TF2	TF1
TF1	V(AI)	V(LI)	X(HI, AI)	A(AI)	X(AI)	V(AI)	A(MI)	V(AI)	X(MI)	X(LI, HI)	X(MI)	V(MI)	X(MI)	V(MI)	A(MI)	V(AI)	X(MI)	X(LI, HI)	V(AI)	X(HI, AI)	1
TF2	X(AI)	V(LI)	X(AI)	X(LI)	X(AI, MI)	X(MI)	X(LI, HI)	X(HI)	A(MI)	X(HI)	A(MI)	X(MI, LI)	X(LI, HI)	O(NI)	X(AI, MI)	X(LI, HI)	A(MI)	A(MI)	X(HI)	1	
TF3	O(NI)	A(AI)	A(LI)	X(HI)	V(LI)	X(MI, LI)	A(MI)	V(HI)	X(MI, LI)	X(HI, MI)	V(HI)	O(NI)	A(MI)	X(LI, HI)	X(HI)	X(HI, MI)	X(MI, LI)	X(LI, AI)	1		
TF4	A(MI)	V(AI)	X(HI)	X(MI, LI)	X(HI, MI)	O(NI)	X(HI, LI)	X(MI, HI)	V(MI)	X(LI, HI)	V(MI)	X(LI, HI)	V(MI)	X(AI, MI)	X(MI)	A(MI)	V(MI)	1			
OF1	X(MI)	A(LI)	X(HI, LI)	X(MI)	V(MI)	X(HI, MI)	X(MI, LI)	A(MI)	X(MI)	X(HI, LI)	A(MI)	X(MI, LI)	X(HI, LI)	A(MI)	V(AI)	V(MI)	1				
OF2	V(MI)	A(MI)	X(MI, LI)	X(HI, LI)	X(MI, HI)	A(MI)	V(MI)	V(AI)	X(MI, LI)	X(HI, AI)	X(HI)	X(HI, MI)	X(HI, AI)	X(LI, AI)	X(LI)	1					
OF3	X(HI)	X(MI, HI)	V(HI)	X(HI, MI)	V(MI)	X(HI, LI)	A(MI)	X(LI)	X(LI, AI)	X(MI)	X(LI)	V(MI)	X(HI, LI)	X(MI)	1						
OF4	A(MI)	A(MI)	V(AI)	V(MI)	A(MI)	O(NI)	X(HI, AI)	X(HI, MI)	O(NI)	A(MI)	X(LI, HI)	X(LI, AI)	X(AI, MI)	1							
HF1	X(MI, HI)	V(MI)	V(MI)	X(MI, LI)	X(MI)	X(MI)	X(LI)	X(HI, LI)	X(LI, HI)	X(HI, LI)	X(MI, HI)	X(HI, LI)	1								
HF2	X(MI)	A(MI)	X(MI, LI)	X(HI, LI)	X(MI, HI)	X(LI, HI)	V(MI)	X(MI, HI)	X(HI, LI)	V(AI)	V(AI)	1									
HF3	V(MI)	X(HI, MI)	A(MI)	X(LI)	A(LI)	V(AI)	V(AI)	V(AI)	X(MI, LI)	V(AI)	1										
PF1	V(HI)	V(HI)	A(LI)	X(HI, MI)	X(HI)	A(MI)	V(HI)	X(HI)	X(MI, HI)	1											
PF2	V(AI)	X(LI)	V(AI)	V(AI)	O(NI)	X(LI)	X(LI, AI)	V(MI)	1												
PF3	A(MI)	V(MI)	X(MI, LI)	X(MI)	V(AI)	X(MI, HI)	O(NI)	1													
EnF1	X(MI)	X(AI, MI)	X(LI, MI)	X(MI, HI)	X(MI)	O(NI)	1														
EnF2	V(MI)	V(AI)	X(HI)	A(MI)	X(HI, LI)	1															
EnF3	A(MI)	V(AI)	O(NI)	V(MI)	1																
EF1	V(HI)	X(HI, MI)	X(MI)	1																	
EF2	A(LI)	X(MI)	1																		
EF3	X(LI)	1																			
EF4	1																				

Table 12. Aggregated structural self-interaction matrix (SSIM).

CSFs	TF1	TF2	TF3	TF4	OF1	OF2	OF3	OF4	HF1	HF2	HF3	PF1	PF2	PF3	EnF1	EnF2	EnF3	EF1	EF2	EF3	EF4
TF1	111	0.70.91	0.70.91	0.70.91	0.50.70.9	0.70.91	0.70.91	0.50.70.9	0.70.91	0.70.91	0.50.70.9	0.70.91	0.70.91	0.70.91	0.70.91	0.50.70.9	0.50.70.9	0.70.91	0.70.91	0.50.70.9	0.70.91
TF2	0.10.30.5	111	0.10.30.5	0.10.30.5	0.30.50.7	0.10.30.5	0.10.30.5	0.30.50.7	00.10.3	0.30.50.3	00.10.3	00.10.3	0.10.30.5	0.30.50.7	00.10.3	0.10.30.5	0.10.30.5	00.10.3	0.10.30.5	00.10.3	0.10.30.5
TF3	00.10.3	0.10.30.5	111	0.10.30.5	0.10.30.5	0.30.50.7	0.30.50.7	0.30.50.7	0.70.91	0.30.51	00.10.3	0.30.50.7	0.30.50.7	0.30.50.7	0.10.30.5	0.10.30.5	0.10.30.5	0.10.30.5	0.10.30.5	0.10.30.5	0.10.30.5
TF4	0.30.50.7	0.10.30.5	0.50.70.9	111	0.30.50.7	0.10.30.5	0.50.70.9	0.50.70.9	0.30.50.7	0.10.30.7	00.10.3	0.50.70.9	0.10.30.5	00.10.3	0.30.50.7	0.10.30.5	00.10.3	0.10.30.5	0.10.30.5	0.30.50.7	0.30.50.7
OF1	0.10.30.5	0.10.30.5	00.10.3	0.10.30.5	111	00.10.3	0.30.50.7	0.10.30.5	0.50.70.9	0.10.30.9	0.30.50.7	0.10.30.5	0.50.70.9	0.50.70.9	0.30.50.7	0.30.50.7	0.10.30.5	0.70.91	0.10.30.5	0.50.70.9	0.10.30.5
OF2	0.10.30.5	0.10.30.5	0.10.30.5	00.10.3	0.50.70.9	111	0.50.70.9	00.10.3	0.10.30.5	0.30.50.5	00.10.3	00.10.3	0.10.30.5	0.30.50.7	0.10.30.5	0.10.30.5	0.10.30.5	0.30.50.7	0.10.30.5	0.50.70.9	0.50.70.9
OF3	0.10.30.5	00.10.3	0.10.30.5	0.50.70.9	0.50.70.9	0.50.70.9	111	0.10.30.5	0.10.30.5	0.10.30.5	0.10.30.5	0.30.50.7	0.10.30.5	00.10.3	00.10.3	0.70.91	0.50.70.9	0.10.30.5	00.10.3	00.10.3	0.10.30.5
OF4	00.10.3	00.10.3	00.10.3	0.30.50.7	00.10.3	0.10.30.5	00.10.3	111	0.10.30.5	0.10.30.5	0.10.30.5	0.50.70.9	00.10.3	00.10.3	0.70.91	00.10.3	00.10.3	0.70.91	0.10.30.5	0.10.30.5	0.10.30.5
HF1	0.50.70.9	00.10.3	0.10.30.5	0.30.50.7	0.50.70.9	00.10.3	0.50.70.9	0.10.30.5	111	0.10.30.3	0.10.30.5	00.10.3	00.10.3	00.10.3	00.10.3	0.70.91	00.10.3	00.10.3	0.10.30.5	0.70.91	0.10.30.5
HF2	0.10.30.5	0.50.70.9	0.30.50.7	0.50.70.9	0.10.30.5	0.10.30.5	0.10.30.5	0.30.50.7	0.10.30.5	111	0.30.50.7	0.10.30.5	00.10.3	0.50.70.9	0.10.30.5	0.10.30.5	0.10.30.5	00.10.3	0.30.50.7	00.10.3	0.10.30.5
HF3	0.50.70.9	00.10.3	00.10.3	00.10.3	00.10.3	00.10.3	0.30.50.7	0.50.70.9	00.10.3	0.50.70.3	111	0.30.50.7	00.10.3	0.10.30.5	0.50.70.9	00.10.3	0.10.30.5	0.10.30.5	0.50.70.9	0.30.50.7	0.30.50.7
PF1	0.10.30.5	0.10.30.5	0.30.50.7	0.10.30.5	0.30.50.7	0.30.50.7	0.10.30.5	0.10.30.5	0.30.50.7	0.50.70.7	0.10.30.5	111	0.10.30.5	0.10.30.5	0.70.91	00.10.3	0.10.30.5	0.30.50.7	0.30.50.7	0.50.70.9	0.10.30.5
PF2	0.10.30.5	0.30.50.7	0.10.30.5	0.10.30.5	0.50.70.9	0.10.30.5	0.70.91	0.50.70.9	0.10.30.5	0.50.70.5	0.50.70.9	0.30.50.7	111	0.50.70.9	0.10.30.5	0.50.70.9	0.70.91	0.70.91	00.10.3	0.50.70.9	0.70.91
PF3	0.30.50.7	0.10.30.5	0.70.91	00.10.3	00.10.3	0.10.30.5	0.30.50.7	0.10.30.5	0.70.91	0.11	0.30.50.7	0.30.50.7	0.50.70.9	111	0.10.30.5	0.10.30.5	0.70.91	0.30.50.7	0.50.70.9	0.30.50.7	00.10.3
EnF1	0.30.50.7	0.30.50.7	0.30.50.7	0.30.50.7	0.50.70.9	00.10.3	00.10.3	0.50.70.9	0.50.70.9	0.30.50.9	0.70.91	00.10.3	00.10.3	0.70.91	111	0.30.50.7	00.10.3	0.10.30.5	0.30.50.7	0.30.50.7	0.10.30.5
EnF2	0.10.30.5	0.30.50.7	0.50.70.9	00.10.3	0.30.50.7	00.10.3	00.10.3	0.50.70.9	0.10.30.5	0.10.30.5	0.10.30.5	0.10.30.5	0.50.70.9	0.10.30.5	0.30.50.7	111	00.10.3	00.10.3	0.50.70.9	0.50.70.9	0.10.30.5
EnF3	0.70.91	0.50.70.9	0.70.91	0.50.70.9	0.70.91	0.70.91	0.30.50.7	0.30.50.7	0.50.70.9	0.70.90.9	0.70.91	0.50.70.9	0.70.91	0.70.91	0.70.91	0.70.91	111	0.70.91	0.70.91	0.50.70.9	0.70.91
EF1	0.30.50.7	0.50.70.9	0.70.91	0.50.70.9	0.10.30.5	0.30.50.7	0.30.50.7	0.30.50.7	0.70.91	0.50.71	0.50.70.9	0.70.91	0.50.70.9	00.10.3	00.10.3	0.10.30.5	00.10.3	111	0.30.50.7	00.10.3	0.50.70.9
EF2	0.10.30.5	0.50.70.9	00.10.3	0.10.30.5	0.10.30.5	0.10.30.5	0.10.30.5	0.10.30.5	00.10.3	0.10.30.3	00.10.3	00.10.3	0.10.30.5	0.10.30.5	0.10.30.5	0.10.30.5	0.10.30.5	0.10.30.5	111	0.10.30.5	0.50.70.9
EF3	0.10.30.5	0.10.30.5	0.10.30.5	0.10.30.5	0.30.50.7	0.10.30.5	0.10.30.5	0.30.50.7	0.10.30.5	0.10.30.5	0.30.50.7	0.30.50.7	0.10.30.5	0.10.30.5	0.30.50.7	0.10.30.5	0.10.30.5	0.10.30.5	0.10.30.5	111	0.10.30.5
EF4	0.70.91	0.50.70.9	0.70.91	0.50.70.9	0.70.91	0.70.91	0.50.70.9	0.70.91	0.70.91	0.70.91	0.70.91	0.70.91	0.70.91	0.70.91	0.50.70.9	0.70.91	0.70.91	0.70.91	0.70.91	0.50.70.9	111

Table 13. Initial reachability matrix (RM) using fuzzy number.

Factor	TF1	TF2	TF3	TF4	OF1	OF2	OF3	OF4	HF1	HF2	HF3	PF1	PF2	PF3	EnF1	EnF2	EnF3	EF1	EF2	EF3	EF4	Dependence
TF1	1	0	1	1	1	1	1	0	1	1	0	0	1	0	0	1	1	0	1	1	0	17
TF2	0	1	0	0	0	0	1	0	0	0	1	1	0	1	1	1	0	0	0	1	0	15
TF3	0	1	0	0	1	0	0	0	1	1	1	1	1	1	1	1	0	1	0	1	0	13
TF4	0	1	0	0	0	1	0	0	0	1	1	0	1	0	1	0	1	1	0	1	0	12
OF1	1	1	1	0	0	1	0	0	1	0	1	0	1	0	1	0	0	1	1	0	0	18
OF2	1	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	0	1	1	1	1	11
OF3	0	0	1	1	0	1	0	1	0	1	1	1	1	0	0	1	0	1	0	0	0	14
OF4	1	1	1	1	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0	1	1	15
HF1	0	0	1	0	0	0	0	1	1	1	1	0	1	1	1	1	0	0	1	1	1	9
HF2	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	19
HF3	1	1	0	0	0	1	0	0	0	0	1	0	1	1	0	1	1	1	0	0	1	15
PF1	0	0	0	0	0	1	0	1	0	0	0	1	1	1	0	1	1	1	0	1	0	14
PF2	1	1	0	1	0	0	0	1	1	0	0	1	0	0	0	0	0	0	1	1	0	17
PF3	0	0	0	1	1	1	1	1	1	1	0	1	0	0	1	1	1	1	0	0	0	15
EnF1	0	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	13
EnF2	0	0	1	1	1	0	1	1	0	1	1	0	0	1	0	0	0	0	0	1	1	14
EnF3	1	0	0	1	0	0	0	0	1	1	0	1	1	1	1	1	1	0	1	1	0	16
EF1	0	0	0	0	0	0	1	1	0	1	1	0	0	1	0	0	1	1	0	1	1	11
EF2	1	0	0	1	1	0	0	0	0	1	1	0	1	1	0	1	1	1	0	1	0	14
EF3	0	1	1	0	0	1	0	1	0	1	0	0	0	0	0	1	1	0	1	1	0	15
EF4	1	1	1	1	1	1	0	0	1	1	0	1	0	0	1	0	0	0	0	1	0	16
Driving	12	10	15	17	14	17	12	9	18	11	12	16	19	14	15	16	11	16	16	12	14	

Table 14. Final reachability matrix.

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Declarations

Competing interests

The authors declare no competing interests.

Additional information

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