

An integrated model for the exploration and evaluation of the obstacles of sustainable logistics in the manufacturing sector

Niousha Zeidyahyae, Sajjad Shokouhyar, Alireza Motameni, Abdolreza Yazdani-Chamzini, Jonas Šaparauskas, Zenonas Turskis

Abstract

Sustainable supply chain management (SSCM) is a tactical concern for managers seeking a long-term result. Different managers are attempting to apply SSCM in order to get a competitive advantage. One of the critical processes is the identification of strategy implementation hurdles, which has been a research focus. As a result, this paper identifies these obstacles and analyzes their interrelationships. A list of obstacles was initially established by a survey of the literature and expert judgment in the form of the fuzzy Delphi approach. Next, an investigation was designed to collect expert opinions on the interrelationships between these obstacles. The fuzzy DEMATEL (FDEMATEL) approach was employed for examining the causal linkages and interdependencies of these obstacles. Subsequently, the interpretative structural modeling (ISM) technique was utilized to create a classified structure and to identify the driving and dependent connections. A fuzzy MICMAC analysis was applied for categorizing the obstacles based on driving and dependent power. The results reveal that barriers, “cost of implementation sustainability (B1)”, “lack of financial resources (B2)”, “institutional complexity (B3)”, “complexity in measuring and monitoring sustainability practices (B4)”, “lack of effective regulations (B5)”, “lack of a proper evaluation system for suppliers (B6)”, “lack of sustainability knowledge (B7)”, and “strategic and structural restraints (B8)”, are the influence-forwarding obstacles. These obstacles influence “inadequate government support (B9)”, “high investments for sustainability and less return-on-investments (B10)”, “old equipment and machinery (B11)”, and “lack of management commitment (B12)”, which are the greatest influences on SSCM practices. Identifying the important obstacles and their interdependences can help policymakers in the manufacturing sector minimize or overcome them, boosting the possibilities of effectively incorporating sustainable principles into these projects.

Keywords: Manufacturing, SSCM, fuzzy Delphi, fuzzy DEMATEL, ISM, fuzzy MICMAC

JEL Classification: O11, O21, I15, F15.

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1. INTRODUCTION

The manufacturing industry plays a crucial role in many developed and developing countries. In Iran, as a developing nation, this industry not only funds the nation but also leads to a high rate of employment. Iran’s manufacturing sector has considerably grown in recent decades. However, the impact of international sanctions on Iran have posed a new challenge for Iranian industries. Based

on data from the Statistical Center of Iran, the manufacturing sector accounted for 18.6% of GDP in 2021. This indicates an increase in the share of the manufacturing sector. This resulted from creating more resilient supply chains and identifying multiple suppliers from different countries in order to ensure that inventories of raw materials are not a key limitation on production.

This sector negatively affects the environment and is known as the world's second most polluting industry after the oil industry by polluting soil, water, and air. The emission of greenhouse gases is a critical issue for both the environment and human life. The manufacturing sector accounts for 54% of the world's energy usage and one-fifth of global carbon emissions. The emission of greenhouse gases comes from burning fossil fuels for energy generation and chemical reactions from producing goods from raw materials. Reducing carbon emissions from the manufacturing sector can lead to a permanent diminution in global climate changes. Manufacturers that effectively manage their carbon emissions can minimize waste, increase efficiency, and stay compliant with strict legislation.

Paying attention to environmental issues has become important. Sustainable supply chain management (SSCM) or Green SCM (GSCM) is essential. The market is also pushed towards the implementation of a sustainable supply chain (SSC) by the influence of organizations and governments. Furthermore, a number of companies advocate for a transition from pollution control to prevention (Lăzăroiu et al., 2020; Shahrabi et al., 2021; Mirzaei & Shokouhyar, 2023; Shakur et al., 2024).

SSCM controls the whole supply chain with the goal of reducing negative environmental, social, and economic consequences while boosting positive benefits (Carter & Liane, 2011). The goal of the SSCM practices is to conduct the supply chain operations in a sustainable way without influencing the society or environment. The supply chain management idea is founded on the concepts that the SSCM implementation has a substantial influence on the society and environment. SSCM implementation encompasses all operations involved in the production and delivery of a service or product, from the extraction of raw materials to the production of the final product (Carter & Rogers, 2008).

Due to the key importance of SSCM, different studies have been conducted to find out the relationship between SSC and its corresponding components (Lu et al., 2024; Echefaj et al., 2024).

Kumar and Rao (2023) created a model to identify the important behavioral elements influencing the effective implementation of GSSM in the Indian leather sector and the interconnections between the components. Abualigah et al. (2023) offered an outline of the SSCM principles and the problems that firms confront in attaining SSCM. Seuring et al. (2022) considered the research requirements for each construct of the SSCM framework. In the context of Jordanian manufacturing enterprises, Alzubi and Akkerman (2022) investigated the impact of sustainable practices on economic performance improvement in emerging nations.

Wang et al. (2023) expanded on the theoretical framework of SSCM and company performance by investigating the impact of possible moderating factors on the link between SSCM and firm performance. Kuwornu et al. (2023) investigated the impact of SSCM methods on food enterprises' long-term performance and food quality assurance. Mugoni et al. (2024) evaluated the impact of sustainable supply chain management practices (SSCMPS) on environmental performance. Amiri et al. (2021) introduced a new model for sustainable supplier selection (SSS) in the supply chain using a triangular fuzzy method. Cui et al. (2023) suggested a hybrid model for evaluating the key

SSS criterion in three MTSC structures that combines a Bayesian network, stepwise weight assessment ratio analysis, and fuzzy set theory. Karmaker et al. (2023) investigated the interplay of modern technology and sustainable practices, as well as their role as a bridge between Industry 4.0 and SSC performance. Asha et al. (2023) constructed a model for customer satisfaction that blends SSCM, product quality, organizational culture, and technological orientation based on value percept theory and natural resources. Aytekin et al. (2024) focused on green energy problems to connect energy with sustainable business strategies.

However, studies have often ignored the cause-and-effect relationship and interrelationships between evaluation components. This paper explores and evaluates the SSCM challenges. These challenges can be explored by an in-depth literature review and consultations with scientific and professional experts under the Delphi method, a structured and iterative approach, to predict the future by integrating independent opinion of experts (Dalkey & Helmer, 1963). Expert opinion is utilized for finding out the relationship among the elements and conducting the statistical analysis. Fuzzy logic theory is an adequate engineering solving tool in an uncertain environment (Yazdani-Chamzini, 2014). Therefore, a fuzzy Delphi method is adopted for identifying the evaluation criteria in a three-round way.

The DEMATEL method is a powerful tool for revealing cause and effect criteria. A fuzzy DEMATEL technique formulates cause and effect relations between the components and analytically exposes the strength of influence or the degree of relation (Seker & Zavadskas, 2017).

Similarly, interpretive structural modelling (ISM) allows for the efficient construction of a directed graph or network representation of a complicated design of a contextual connection between a group of elements (Malone, 1975). ISM has showed distinct benefits in analyzing event causes and comprehending impacting components (Wu et al., 2023). While ISM demonstrates a hierarchical connection among elements, it ignores how individual aspects influence one another. To overcome this limitation, the cross-impact matrix multiplication applied to classification (MICMAC) approach is utilized to compute the dependence and driving strength of the components analyzed by ISM (Mandal & Deshmukh, 1994).

This paper uses a robust approach to, firstly, explore the evaluation criteria by employing a fuzzy Delphi method; secondly, identify the cause-and-effect relationship by using fuzzy DEMATEL; thirdly, to extract the relationship between the criteria by applying interpretive structural modeling (ISM); fourthly, to identify the most important criteria through the MICMAC technique; and finally, to analyze the relationships between causes and effects of components. The main purpose of this study is to understand the barriers of SSCM in the manufacturing sector. An integrated model based on a fuzzy Delphi method, fuzzy DEMATEL, ISM, and fuzzy MICMAC is proposed to identify current challenges faced by the manufacturing industry.

The following is the order in which this document is organized. Section 2 contains a study of the literature as well as the identification of barriers. Section 3 illustrates the research methods, which covers methodologies such fuzzy Delphi, DEMATEL, ISM, and MICMAC. Section 4 comprises a discussion section, which essentially includes the results obtained after executing the study approach. The results and suggestions are presented in Section 5. Furthermore, it presents limits as well as the future scope.

2. SUSTAINABLE SUPPLY CHAIN MANAGEMENT

Eco-friendly production activities are more common, with the goal of minimizing environmental damage. Furthermore, several researchers have shown that reusing and recycling used things might lead to sustainability. Without a doubt, sustainability motivates decision makers to prioritize eco-friendly conservation and green economic growth by environmental regulations. Green approaches have been widely debated and used throughout the supply chain for an eco-friendly impact and to increase sustainability. As a consequence of the benefits of these measures to strengthen brands, boost competitive competence, and grow company output, SSCM is incorporated into enterprises' corporate strategy. However, some publications make contradictory claims about SSCM practices.

Some researchers, in particular, focused on identifying diversity barriers, causes, or variables that influence SSCM practices in diverse industries. In reality, SCM is a set of complicated duties that require all shareholders to collaborate in order to minimize negative consequences on the environment and society. As a result, the susceptibility of SSCM processes have a major impact on organizational performance. Several problems for SSCM practices have been outlined and must be solved in order to integrate green concepts into the supply chain. Particularly, there are little uniformity and little research on recognizing obstacles to executing sustainability in SCM. Scholars have identified numerous critical factors that influence SSCM practices, depending on the study environment.

3. RESEARCH METHODOLOGY

3.1 Fuzzy Delphi approach

Dalkey and Helmer (1963) developed the conventional Delphi technique, a survey approach based on experts' opinions by a regulated feed-back and iterative process until an agreement on a choice resulted (Hsu et al., 2010). In practice, however, expert judgements in the Delphi approach cannot be correctly transformed and understood in numerical numbers. Furthermore, representing real-life circumstances with precise algebraic standards is unsatisfactory because of the inherent uncertainty in human assessments. Therefore, fuzzy set theory (Zadeh, 1965) was combined with the Delphi technique to create the fuzzy Delphi approach for improving the decision performance (Ishikawa et al., 1993).

Several researchers have utilized fuzzy Delphi method (FDM) to solve supply chain difficulties. The FDM was used in a research project to identify impediments to sustainable waste managing methods (Bui et al., 2020). One such study used a mix of FDM and DEMATEL to predict the hazards in various sectors of the Halal supply chain (Khan et al., 2021). A similar study utilized FDM to identify crucial criteria in supplier selection when taking into account a green SSC (Mabrouk, 2021). The following are the stages involved in the FDM:

1. Identification of the potential barriers. In this paper, the potential barriers are identified through a literature review and the validation of experts in the form of the fuzzy Delphi technique.
2. Gathering the expert perspectives. After identifying the obstacles, the expert team is asked to assess the significance of each barrier based on its influence on the execution of SSCM. A questionnaire is designed to collect expert replies by using linguistic values. The linguistic characteristics are then translated into fuzzy values according to the scale presented in Table 1.

Tab. 1 – Linguistic and fuzzy values

Linguistic value	fuzzy value
Very High	(0.9, 1.0, 1.0)
High	(0.7, 0.9, 1.0)
Medium High	(0.5, 0.7, 0.9)
Medium	(0.3, 0.5, 0.7)
Medium Low	(0.1, 0.3, 0.5)
Low	(0.0, 0.1, 0.3)
Very Low	(0.0, 0.0, 0.1)

3. Weights for group decisions are calculated. In this study, the methodology proposed by Hsu and Yang (2000) was applied to translate individual replies into group decisions as follows:

If $D_{lm} = (a_{lm}, b_{lm}, c_{lm})$ indicates the implication of an element ‘m’ determined by expert ‘l’ of ‘n’ experts;

where $(l = 1, 2, 3, \dots, n)$ and $(m = 1, 2, 3, \dots, k)$;

The fuzzy number related to group decision of element ‘m’ is $D_m = (a_m, b_m, c_m)$

where $(m = 1, 2, 3, \dots, k)$; and

$$\begin{aligned}
 a_m &= \min_l \{a_{lm}\} \\
 b_m &= \frac{1}{n} \sum_{l=1}^n b_{lm} \\
 c_m &= \max_l \{c_{lm}\}
 \end{aligned}
 \tag{1}$$

4. Defuzzification

After this phase, the fuzzy triangular numbers were defuzzified in order to compare the scores obtained for all components (Chang et al., 2011). Defuzzification is used in fuzzy logic to construct quantifiable and comparable numbers (Azadeh et al., 2008). The defuzzification procedure was carried out by using the following equation. This defuzzification approach has been utilized in several studies and is one of the most reliable equations for this purpose (Soltanzadeh et al., 2022):

$$a_i = \frac{1}{4}(a_{i1} + 2a_{i2} + a_{i3})
 \tag{2}$$

5. Identification of critical features

The most relevant factors were evaluated and ranked based on their defuzzified scores, so that any variable with a higher defuzzified value is more critical according to its influence on SSCM. The threshold is used to screen variables, and variables with a lower value than the threshold are excluded as junior factors. In many studies, the threshold value is examined based on the relevance of the issue and other factors. However, the threshold might be chosen by using the research objectives and the researcher’s perspective. In the current investigation, the original number of factors influencing SSCM was 27 factors. However, the limited number of input factors can be employed for assessing the cause-and-effect relations, the threshold value of 0.6 was selected, and

the 12 factors with a value equal to or greater than 0.6 were selected as the most important factors influencing SSCM implement.

3.2 The Fuzzy DEMATEL (FDEMATEL)

The decision-making trial and evaluation laboratory (DEMATEL) (Fontela & Gabus, 1976) is an MCDM with the goal of estimating the direct and indirect effect of variables based on an estimation of the direct influences. Tseng (2009) defines DEMATEL as a tool for analyzing the structure of causal interactions among many variables. Human judgement preferences are frequently ambiguous and difficult to predict by using precise values; therefore, it is necessary to augment the DEMATEL approach with a fuzzy approach for making a reasonable choice (Malviya et al., 2024).

The FDEMATEL can be defined in four steps as follows:

Step 1: Detailed information on variables is collected from the previous phase (fuzzy Delphi Method).

Step 2: A pairwise comparison matrix of assessment criteria is now created to demonstrate the degree of effect. The linguistic term of the degree of effect and corresponding triangular fuzzy number (TFN) for each element of a pairwise matrix is given in Table 2.

Tab. 2 – Fuzzy value scale

Linguistic Expression	Influence value	Equivalent fuzzy value
No influence	0	(0, 0.1, 0.3)
Very low influence	1	(0.1, 0.3, 0.5)
Low influence	2	(0.3, 0.5, 0.7)
High Influence	3	(0.5, 0.7, 0.9)
Very High Influence	4	(0.7, 0.9, 1.0)

Step 3: F is the fuzzy initial direct relation matrix. However, the comparison matrix must be aggregated for achieving the fuzzy combined matrix. Defuzzification is a method for converting fuzziness into crisp numbers, often known as the best non-fuzzy performance value (BNP).

Step 4: The normalized direct-relation matrix $D = [d_{ij}]$ is determined, where all the principal diagonals are zero and $0 \leq m_{ij} \leq 1$,

$$D = F \times \frac{1}{\max_{1 \leq i \leq n} \sum_{j=1}^n m_{ij}} \tag{3}$$

Step 5: The total relational matrix T is calculated. The element t_{ij} represents the indirect effects that factor i has on factor j , so the matrix T can indicate the overall connection between each pair of elements.

$$T = D(I - D)^{-1} \tag{4}$$

Step 6: The degree of influential impact is determined. The sum of row i , which is denoted as r_i , represents all direct and indirect influences given by factor i to all other factors, while c_j represents the sum of column j .

$$r_i = \sum_{j=1}^n t_{ij}, c_i = \sum_{i=1}^n t_{ij} \tag{5}$$

The r_i shows the total effects, both direct and indirect, exerted by the i^{th} factor on the other factors. The c_i shows the total effects, both direct and indirect, received by factor j^{th} from the other factors.

Step 7: Calculate priority weight for each influential factor.

$$W = \frac{\sum_{j=1}^n (r_i + c_i)}{\sum_{i=1}^n \sum_{j=1}^n (r_i + c_i)} \tag{6}$$

Step 8: Draw a cause-and-effect (causal) diagram. By mapping the dataset of $(r_i + c_i, r_i - c_i)$, the causal diagram can be obtained. The sum $r_i + c_i$ produces an index (the position) that represents the overall impacts that the i^{th} factor has both given and received. The difference $r_i - c_i$ represents the net influence that the i^{th} element has on the system. The i^{th} factor is a net receiver when $r_i - c_i$ is negative; it is a net causer when $r_i - c_i$ is positive.

3.3 The ISM Technique

The interpretive structural model (ISM) was employed to assess the interrelationships among obstacles in order to find the most potent factors. Warfield (1974) developed the ISM approach to create an interconnection matrix, based on experts’ opinions, for converting several aspects into a cohesive and comprehensible model. However, due to its unique features, the application area of the ISM technique has been rapidly expanding, notably in qualitative investigations (Huang et al., 2022). The key advantage is that it does not require a large number of data, and that it is able to swiftly gather the experts’ thoughts (Pandey et al., 2021; Menon & Ravi, 2021; Qureshi et al., 2022); thus, Agrawal’s research (2019) required just two professionals.

Furthermore, participants in this approach must have comprehensive information (Huang et al., 2022). Several scholars have suggested that the ISM approach is the most successful and accessible in investigating findings, demonstrating a rational link between factors (Menon & Ravi, 2021; Abbas et al., 2022). Notably, this approach also uses the driving power values to suggest the leading factors (Amini & Alimohammadlou, 2021). As a result, our study aligns with earlier studies in applying the ISM method for investigating the interrelations between the SSCM factors (Chen et al., 2022). The ISM approach is implemented in the following fundamental steps:

Step 1: Create a Structural Self-Interaction Matrix (SSIM)

Some critical factors are recognized by using the insights of the related literature mixed with the discussion of the decision team, and the findings come from the fuzzy Delphi method for making the SSCM components in the theoretical study. As a result, an appropriate link is formed as “Vi leads

to V_j ” in the SSIM. The SSIM matrix includes four verbal signals in total: V, A, X, and O, which represent the following connections (Vishwakarma et al., 2022):

V = barrier ‘i’ will impact variable ‘j’.

A = barrier ‘j’ will impact variable ‘i’.

X = barrier ‘i’ and ‘j’ will impact each other.

O = barrier ‘i’ and ‘j’ are unrelated.

Step 2: Create Reachability Matrix

The SSIM matrix is transformed into the binary matrix based on the values of “1” and “0”. This indicates that if the entry (i,j) is “1,” and the adjacent cell (j,i) is “0” (Ullah et al., 2021). In this stage, we can also assess two important variables, “driving power” and “dependence power”, by multiplying the total number involved in rows and columns, respectively.

Step 3: Divide Factors into Phases

In this step, after constructing the reachability matrix, level partitioning is used to emphasize that the intersection is comprised of the “reachability set” and “antecedent set” (Ullah et al., 2021).

Step 4: Create a Directed Graph

As a result, the ISM model shows the relationships in the form of a bottom to top graph. This graph depicts the strong factors at the bottom. Likewise, for any conceptual inconsistencies, verification is required, and any necessary changes are made (Chen et al., 2022).

3.4 The Fuzzy MICMAC Analysis

The ISM approach uses 0 and 1 to represent the relationship between the two barriers. However, by utilizing the fuzzy MICMAC approach, it is possible to delve further into this relationship. Fuzzy theory is utilized to address ambiguity in the decision process (Zadeh, 1965). Professional judgement is used to turn language assessments into fuzzy numbers. Table 3 shows the scaling of barriers. The expert views’ values are then superimposed on the binary direct reachability matrix (BDRM) to produce the fuzzy direct reachability matrix (FDRM).

Fuzzy matrix multiplication occurs in a fuzzy MICMAC analysis; this multiplication procedure differs significantly from conventional matrix multiplication (Patidar et al., 2017; Vishwakarma et al., 2022; Gadekar et al., 2024). The product of two fuzzy matrices is similar to a fuzzy matrix, according to the fuzzy multiplication rule (Khan & Haleem, 2012). This multiplication procedure is stated in a fuzzy multiplication equation as matrix A and B.

$$AB = \max \{ \min(a_{ij}, b_{ij}) \} \quad (7)$$

where,

$$A = (a_{ij})$$

$$B = (b_{ij})$$

To begin the process, the FDRM is used as the preliminary matrix. The matrix is repeatedly multiplied and iterated. This procedure will continue until the driving and dependency power values stabilize.

After the fuzzy MICMAC analysis, we obtain the driving power and dependency of each individual element. All elements are divided into four divisions based on the levels of dependency and driving power. These quadrants are I, II, III, and IV. These quadrants are named for their values: autonomous, dependent, linkage, and independent.

Autonomous elements

These are the initial quadrant components with the least driving power and the least dependence power. These are placed in the first quadrant.

Dependent elements

These are the items in the second quadrant with the highest dependence and the lowest driving power. Because of their limited driving force, dependent barriers are the least important factors.

Linkage elements

These are the third quadrant components with strong dependability and driving force. The linking parts have significant influence and rely heavily on one another. They are in the intermediate of the structure.

Independent elements

These are the fourth quadrant elements, and they are independent or have low dependence power. However, they have a lot of driving power. As a result, they can impact the other elements. These obstacles are located at the bottom of the structure.

4. THE PROPOSED METHOD

To identify and evaluate the barriers of SSCM practices, an integrated fuzzy Delphi-DEMATEL-ISM-MICMAC model is suggested. The methodological framework is graphically depicted in Fig. 1. A team of sixteen experts with high experience and knowledge has been formed. The team was asked to provide their opinions on a questionnaire to prepare the decision matrix and make the final assessment. The proposed approach is typically divided into four main phases. The first phase is to identify the barriers influencing the SSCM implementation in the form of a fuzzy Delphi method. Then, the FDEMATEL approach, which uses criteria to obtain cause-and-effect linkages, is used in the second phase. In the third phase, the ISM approach is employed to extract causes of events and influencing factors. Finally, the fuzzy MICMAC method is applied for computing the dependency and driving power of the factors extracted from the previous phase. This process screens the barriers to accomplish the most essential ones in SSCM implementation. The findings of this study are descriptive and provide a better understanding of the decisions that enable managers adopt effective SSCM implementation strategies.

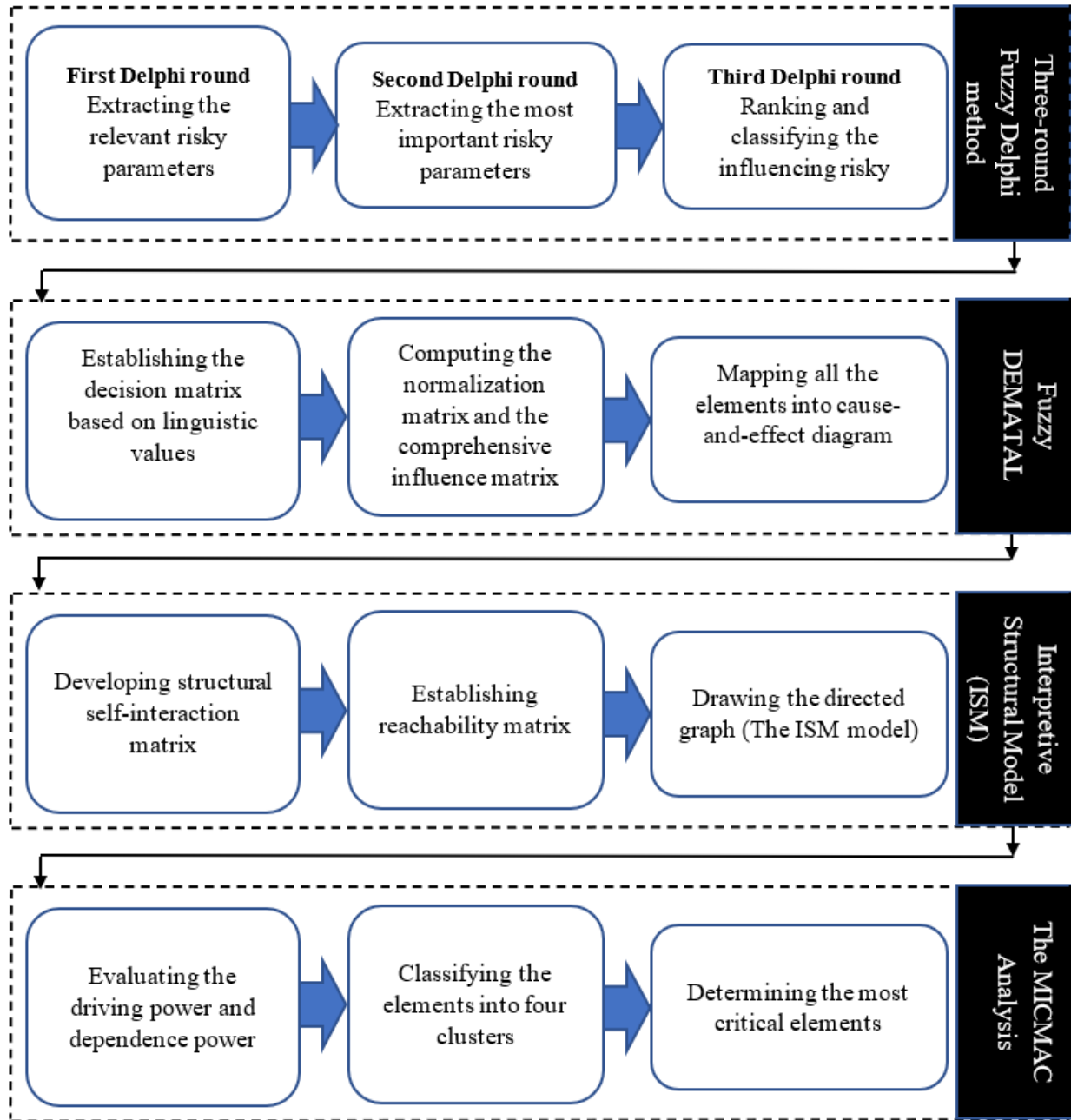


Fig. 1 – The proposed model

5. RESULTS

5.1 Most important variables identified

After the extraction of 27 obstacles via literature review and qualitative investigations, the barriers were re-evaluated in three phases of the fuzzy Delphi survey by 16 professional experts with extensive expertise and knowledge in SSCM implementation.

The first questionnaire was produced in the first stage of the fuzzy Delphi survey by collecting 27 obstacles from the literature search. Respondents contributed to the study by proposing four new obstacles as well as ideas for including certain barriers in the first and second rounds. After three rounds of fuzzy Delphi, experts chose the final obstacles. The Kendal correlation coefficient (W) is used to calculate the answer consensus, whereas the benefit benchmark indicates the degree of coordination of the participants with mean and standard deviation (Schmidt, 1997). Kendall’s concordance coefficient W indicates the degree of agreement. It is a number ranging from 0 to 1:

$W > 0.7$ indicates a high level of agreement.

$W = 0.5$ denotes a moderate level of agreement.

$W < 0.3$ denotes a lack of agreement.

The third-round findings reveal that consensus has been reached, and the fuzzy Delphi procedure may thus be terminated. As a result, in the first round, the experts assessed 27 common impediments to SSCM implementation based on a literature analysis and recommended additional potential barriers. The obstacles were validated in the second round of the Delphi research, and prioritized in the third round. Table 3 summarizes the findings of three rounds in the fuzzy Delphi survey. Table 4 lists the final impediments to SSCM practices in the manufacturing industry.

Tab. 3 – Literature review

Barrier	Description	Category	Some supporting literature
Cost of implementation sustainability (B1)	The issue of higher costs of product makes the company less competitive, as the extra costs of the products get transferred to customers.	Financial	Narayanan et al., 2019; Sajjad et al., 2020
Lack of financial resources (B2)	Lack of financial infrastructure to support suppliers’ needs in meeting their sustainability pressures.	Financial	Govindan et al., 2014; Narayanan et al., 2019
Institutional complexity (B3)	This issue is a result of having multiple, and conflicting, institutional logic.	Policy	Sayed et al., 2017; Narimissa et al., 2020
The complexity in measuring and monitoring sustainability practices (B4)	The complexity based on the individual perspectives of the buyer and the supplier.	Technology	Narimissa et al., 2020; Pachar et al., 2022
Lack of effective regulations (B5)	Government regulations play a central role in compelling companies to streamline their social and environmental impacts in SSCM operations.	Policy	Sayed et al., 2017; Sajjad et al., 2020
Lack of a proper evaluation system for suppliers (B6)	Sustainability standards are difficult to quantify and measure.	Technology	Pachar et al., 2022
Lack of sustainability knowledge (B7)	Buyers sometimes focus excessively on buying products at the lowest feasible price, without understanding the costly sustainable process that the item may have undergone.	Human resources	Delmonico et al., 2018; Sarkis, 2021
Inadequate government support (B8)	Government attitudes, legislation and regulations can stymie the successful implementation of sustainable practices.	Policy	Sajjad et al., 2020; Kazancoglu et al., 2021
Strategic and structural restraints (B9)	Strategic and structural issues may limit corporate proactivity towards implementation of SSCM.	Policy	Narayanan et al., 2019; Oyedijo et al., 2024

High investments for sustainability and less return-on-investments (B10)	Initial investment costs towards sustainability initiatives are a barrier hindering the implementation of SSCM practices.	Financial	Delmonico et al., 2018; Sajjad et al., 2020
Old equipment and machinery (B11)	Lack of access to sustainable technology and infrastructure hinders the ability to prepare for and manage disruptions.	Technology	Narimissa et al., 2020; Gupta et al., 2020
Lack of management commitment (B12)	Commitment of managers to sustainability is a critical ingredient for the success of SSCM.	Policy	Chen & Chen, 2019; Kitsis & Chen, 2021

Tab. 4 – The results of fuzzy Delphi

Row	Variable	Defuzzified score of Delphi study
1	B1	0.856
2	B2	0.820
3	B3	0.804
4	B4	0.789
5	B5	0.760
6	B6	0.757
7	B7	0.732
8	B8	0.727
9	B9	0.711
10	B10	0.695
11	B11	0.651
12	B12	0.617

The obstacles that prevent businesses from using SSCM are addressed in this section. According to the data, firms have found a variety of impediments to SSCM adoption. Table 4 includes the most effective obstacles based on expert judgement from the previous phase.

5.2 Cause and effect relations between the recognized factors

The expert team expresses the effect of each assessment criteria on the others using the fuzzy linguistic scale shown in Table 2 based on the results of the previous phase. Next, each expert’s assessment data is collected. Likewise, the data from evaluators were gathered, and crisp values were derived by aggregation and defuzzification of the data, which were then analyzed using the methodologies given. The crisp value derived from fuzzy assessment after aggregating the assessment data was composed of the original directional matrix. Next, the normalized matrix was obtained as depicted in Table 5. The total relation matrix was then calculated as shown in Table 6.

Finally, as shown in Table 7, the scores for each assessment criterion and the related important weight were computed. The information in this table will be useful in making decisions.

The D (Fig. 2) and R (Fig. 3) values are respectively calculated for assigning the effect and influence impact index. In Fig. 2, lack of financial resources has the maximum impact on other factors, whereas, old equipment and machinery has the minimum effect. In Fig. 3, cost of implementation sustainability is the most effective factor of the manufacturing industry. However, high investments for sustainability and less return-on-investments is the least effective factor of the industry.

The D + R value (Fig. 4) determines the interaction rates among factors. From the figure, cost of implementation sustainability has the maximum interaction rate. Similarly, institutional complexity has the minimum interaction rate among factors.

The D-R value (Fig. 5) depicts the type of interaction (cause or effect) of each factor. For the D-R values greater than “0”, the factor is known as a cause one, and for the D-R values lower than “0”, the factor is known as an effect one. From the figure, lack of financial resources with the maximum D-R values is the strongest root factor influencing the manufacturing sector.

The findings of cause-and-effect relationships (Fig. 6) resulting from the FDEMATEL technique demonstrate that lack of financial resources, inadequate government support, and strategic and structural restraints are located in Zone 1 as the strongest root factors. Zone 2 consisted of high investments for sustainability and less return-on-investments, lack of effective regulations, and lack of a proper evaluation system for suppliers as less important than factors located in Zone 1. Zone 3 includes the complexity in measuring and monitoring sustainability practices, lack of sustainability knowledge, old equipment and machinery, and institutional complexity. This zone includes the factors influenced by the factors placed in Zones 1 and 2 but influencing the factors located in Zone 4. The last zone is comprised of cost of implementation sustainability and lack of management commitment. Since the factors located in Zone 4 are prioritized as the last ones, the amendatory measures must be accomplished after the factors involved in other zones. Consequently, improving the factors involved in Zone 4 together with factors involved in Zones 1, 2, and 3 can reduce the chance of successfulness.

Tab. 5 – Initial direct influence matrix

	B1	B2	B3	...	B11	B12
B1	(0.00,0.00,0.00)	(0.00,0.02,0.04)	(0.00,0.01,0.04)	...	(0.09,0.11,0.13)	(0.09,0.11,0.13)
B2	(0.09,0.11,0.13)	(0.00,0.00,0.00)	(0.00,0.01,0.04)	...	(0.09,0.11,0.13)	(0.09,0.11,0.13)
B3	(0.02,0.04,0.06)	(0.00,0.01,0.04)	(0.00,0.00,0.00)	...	(0.00,0.01,0.04)	(0.02,0.04,0.07)
B4	(0.04,0.06,0.09)	(0.01,0.03,0.06)	(0.00,0.02,0.04)	...	(0.00,0.02,0.04)	(0.00,0.02,0.04)
B5	(0.04,0.06,0.09)	(0.01,0.04,0.06)	(0.08,0.11,0.12)	...	(0.02,0.04,0.07)	(0.01,0.02,0.05)
B6	(0.04,0.06,0.09)	(0.04,0.06,0.09)	(0.02,0.04,0.07)	...	(0.00,0.01,0.04)	(0.02,0.03,0.06)
B7	(0.09,0.11,0.13)	(0.01,0.04,0.06)	(0.01,0.04,0.06)	...	(0.01,0.02,0.05)	(0.04,0.06,0.09)
B8	(0.09,0.11,0.13)	(0.04,0.06,0.09)	(0.04,0.06,0.09)	...	(0.02,0.04,0.07)	(0.02,0.04,0.07)
B9	(0.06,0.09,0.11)	(0.04,0.06,0.09)	(0.04,0.06,0.09)	...	(0.04,0.06,0.09)	(0.04,0.06,0.09)
B10	(0.08,0.10,0.12)	(0.06,0.09,0.11)	(0.02,0.05,0.07)	...	(0.09,0.11,0.13)	(0.04,0.06,0.09)
B11	(0.06,0.08,0.11)	(0.00,0.02,0.04)	(0.01,0.02,0.05)	...	(0.00,0.00,0.00)	(0.00,0.01,0.04)
B12	(0.01,0.03,0.05)	(0.06,0.08,0.11)	(0.06,0.09,0.11)	...	(0.01,0.02,0.05)	(0.00,0.00,0.00)

Tab. 6 – Total influence matrix

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12
B1	0.118	0.101	0.097	0.115	0.089	0.099	0.144	0.116	0.105	0.077	0.190	0.194
B2	0.286	0.123	0.135	0.146	0.124	0.121	0.186	0.218	0.189	0.199	0.245	0.245
B3	0.133	0.083	0.067	0.126	0.092	0.126	0.114	0.091	0.076	0.067	0.086	0.114
B4	0.172	0.106	0.092	0.079	0.077	0.153	0.145	0.112	0.104	0.074	0.101	0.106
B5	0.207	0.134	0.197	0.135	0.083	0.174	0.153	0.178	0.130	0.118	0.149	0.138
B6	0.194	0.148	0.126	0.153	0.098	0.084	0.181	0.151	0.117	0.087	0.113	0.139
B7	0.224	0.118	0.116	0.123	0.086	0.111	0.090	0.125	0.110	0.089	0.119	0.158
B8	0.264	0.167	0.166	0.173	0.149	0.162	0.179	0.109	0.142	0.126	0.163	0.168
B9	0.242	0.168	0.166	0.173	0.127	0.136	0.177	0.167	0.097	0.145	0.182	0.186
B10	0.245	0.180	0.141	0.150	0.128	0.110	0.135	0.121	0.151	0.081	0.222	0.179
B11	0.169	0.080	0.085	0.126	0.087	0.080	0.088	0.078	0.072	0.067	0.070	0.088
B12	0.152	0.161	0.167	0.169	0.153	0.100	0.111	0.104	0.097	0.088	0.117	0.095

Tab. 7 – Results of the cause-and-effect model

	D	R	D+R	D-R	Cause/Effect
B1	1.444	2.404	3.8486	-0.960	Effect
B2	2.218	1.570	3.787	0.648	Cause
B3	1.174	1.555	2.729	-0.380	Effect
B4	1.321	1.668	2.989	-0.347	Effect
B5	1.798	1.292	3.090	0.506	Cause
B6	1.590	1.456	3.046	0.134	Cause
B7	1.468	1.702	3.171	-0.234	Effect
B8	1.967	1.570	3.536	0.397	Cause
B9	1.965	1.390	3.355	0.575	Cause
B10	1.845	1.220	3.065	0.625	Cause
B11	1.089	1.757	2.847	-0.668	Effect
B12	1.513	1.809	3.322	-0.296	Effect

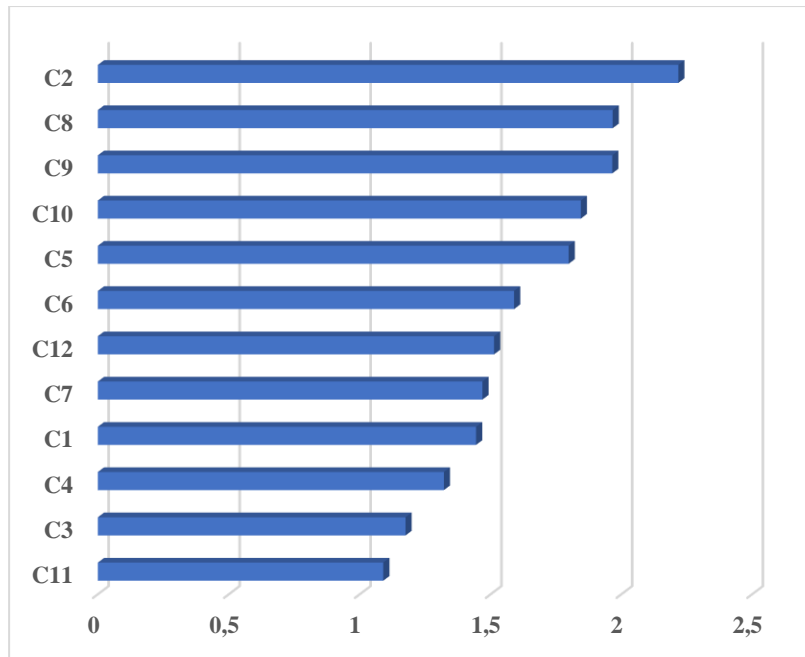


Fig. 2 – The impact of each factor on other factors

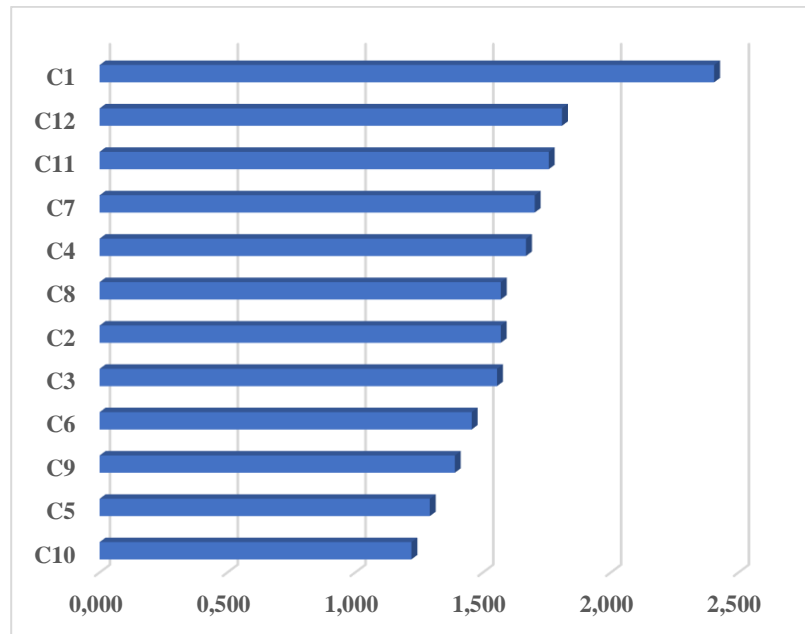


Fig. 3 – The influence impact index for each factor

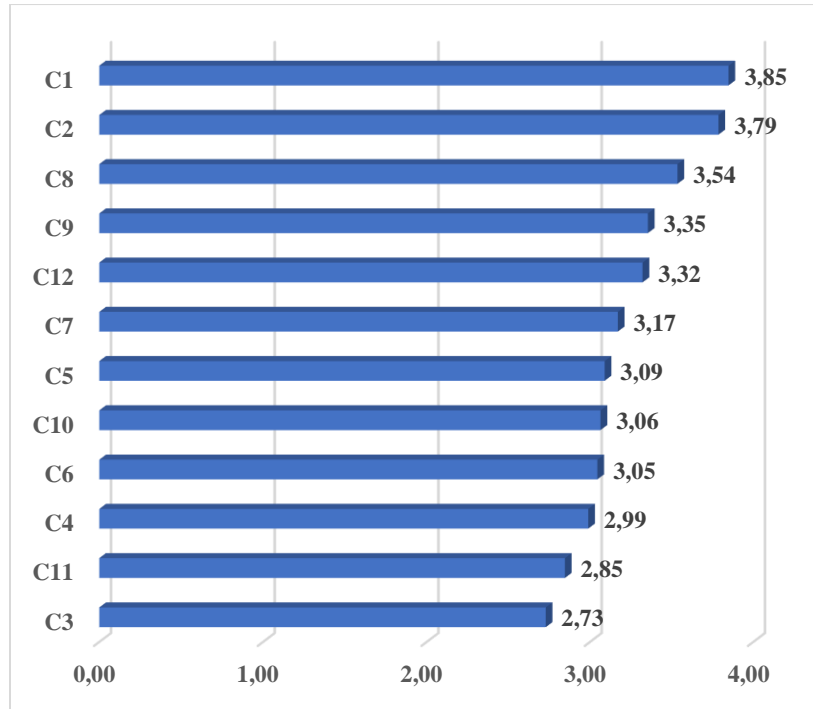


Fig. 4 – Interaction rate among factors

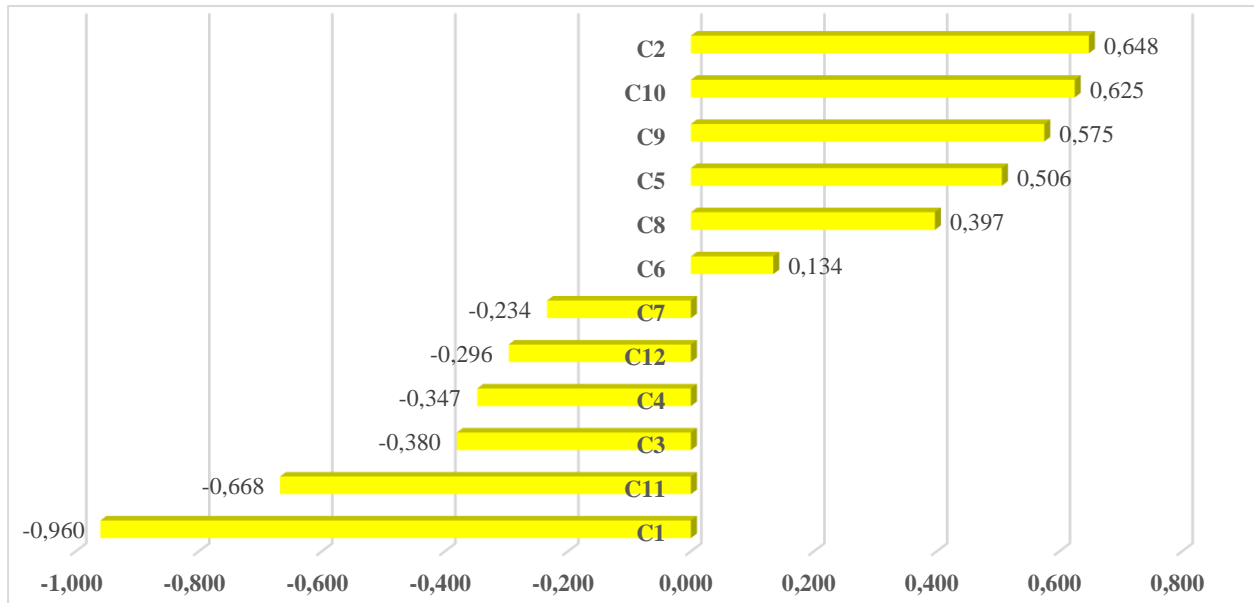


Fig. 5 – D-R values

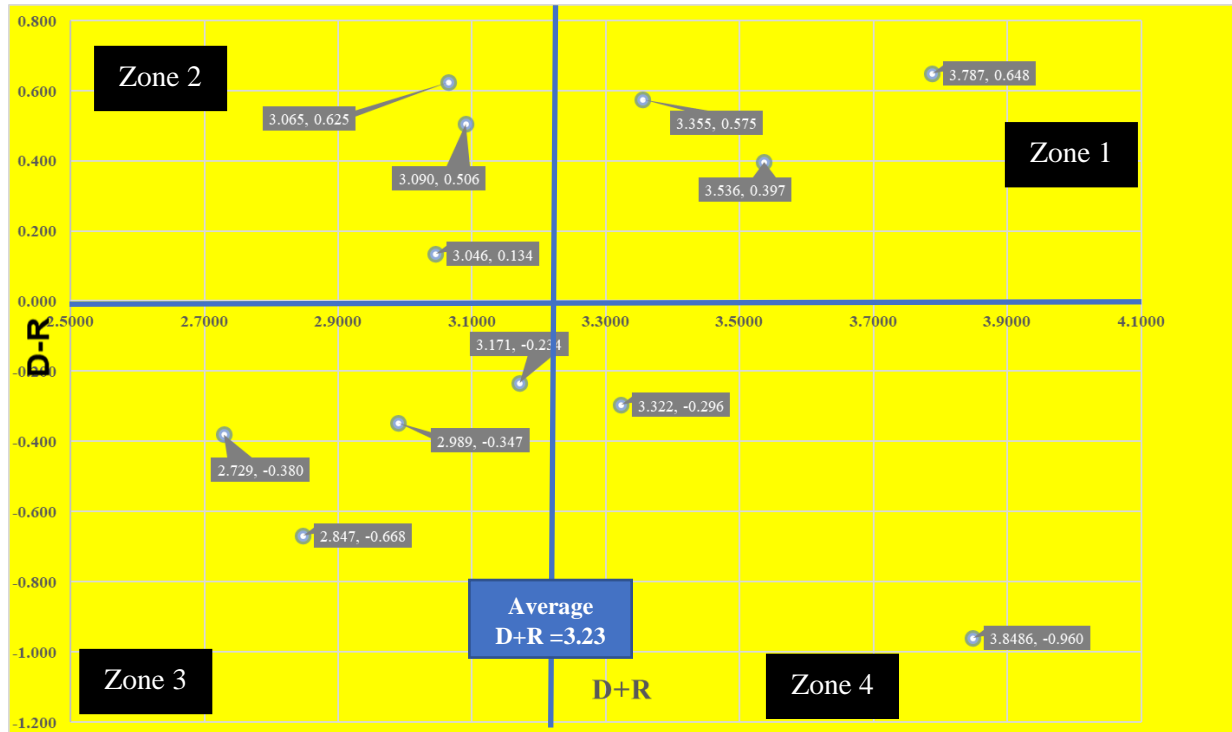


Fig. 6 – Cause and effect diagram

From these tables and figures, several findings can be revealed. The values along the vertical axis vary from (0.96) to +0.648. “Lack of financial resources (B2)”, “lack of effective regulations (B5)”, “lack of a proper evaluation system for suppliers (B6)”, “strategic and structural restraints (B8)” inadequate government support (B9)”, and “high investments for sustainability and less return-on-investments (B10)” were listed as the influencing obstacles. These obstacles have an effect on “cost of implementation sustainability (B1)”, “institutional complexity (B3)”, “the complexity in measuring and monitoring sustainability practices (B4)”, “lack of sustainability knowledge (B7)”, “old equipment and machinery (B11)”, and “lack of management commitment (B12)”.

Likewise, the values along the horizontal axis vary from +2.729 to +3.849. Moreover, the importance of the obstacles is prioritized from maximum to minimum as follows: (B1), (B2), (B8), (B9), (B12), (B7), (B5), (B10), (B6), (B4), (B11), and (B3).

5.3 ISM Results

The holistic impact matrix H (see Table 8) is calculated. In Step 8, the relative equations are used to compute the reachable matrix S (Table 9) by using the full impact matrix. Based on the opinions of the experts, $\lambda = 0.15$ was chosen for this investigation. The level of the obstacles was established in Step 9. For each barrier, the reachability matrix determines the intersection set $Q(a_i) = P(a_i) \cap T(a_i)$, the input set T(ai), and the output set P(ai). For $Q(a_i) = P(a_i)$, this obstacle is located at

the top level; obstacles are then deleted from the sets, and the approach is repeated until all obstacles are separated hierarchically (depicted in Table 10).

Tab. 8 – Holistic influence matrix

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12
B1	1.118	0.101	0.097	0.115	0.089	0.099	0.144	0.116	0.105	0.077	0.19	0.194
B2	0.286	1.123	0.135	0.146	0.124	0.121	0.186	0.218	0.189	0.199	0.245	0.245
B3	0.133	0.083	1.067	0.126	0.092	0.126	0.114	0.091	0.076	0.067	0.086	0.114
B4	0.172	0.106	0.092	1.079	0.077	0.153	0.145	0.112	0.104	0.074	0.101	0.106
B5	0.207	0.134	0.197	0.135	1.083	0.174	0.153	0.178	0.13	0.118	0.149	0.138
B6	0.194	0.148	0.126	0.153	0.098	1.084	0.181	0.151	0.117	0.087	0.113	0.139
B7	0.224	0.118	0.116	0.123	0.086	0.111	1.09	0.125	0.11	0.089	0.119	0.158
B8	0.264	0.167	0.166	0.173	0.149	0.162	0.179	1.109	0.142	0.126	0.163	0.168
B9	0.242	0.168	0.166	0.173	0.127	0.136	0.177	0.167	1.097	0.145	0.182	0.186
B10	0.245	0.18	0.141	0.15	0.128	0.11	0.135	0.121	0.151	1.081	0.222	0.179
B11	0.169	0.08	0.085	0.126	0.087	0.08	0.088	0.078	0.072	0.067	1.07	0.088
B12	0.152	0.161	0.167	0.169	0.153	0.1	0.111	0.104	0.097	0.088	0.117	1.095

Tab. 9 – The reachability matrix

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	DR
B1	1	0	0	0	0	0	0	0	0	0	1	1	3
B2	1	1	0	0	0	0	1	1	1	1	1	1	8
B3	0	0	1	0	0	0	0	0	0	0	0	0	1
B4	1	0	0	1	0	1	0	0	0	0	0	0	3
B5	1	0	1	0	1	1	1	1	0	0	0	0	6
B6	1	0	0	1	0	1	1	1	0	0	0	0	5
B7	1	0	0	0	0	0	1	0	0	0	0	1	3
B8	1	1	1	1	0	1	1	1	0	0	1	1	9
B9	1	1	1	1	0	0	1	1	1	0	1	1	9
B10	1	0	0	0	0	0	0	0	1	1	1	1	5
B11	1	0	0	0	0	0	0	0	0	0	1	0	2
B12	1	1	1	1	1	0	0	0	0	0	0	1	6
DE	11	4	5	5	2	5	5	5	3	2	6	7	

Tab. 10 – Level partition of the ISM model

	P(ai)	T(ai)	Q(ai)	Level
B1	1,11,12	1, 2, 4, 5, 6, 7, 8, 9, 10, 11, 12	1,11,12	7
B2	1,2, 7, 8, 9, 11, 12	2, 8, 9, 12	2, 8, 9, 12	1
B3	3	3, 5, 8, 9, 12	3	6
B4	1, 4, 6	4, 6, 8, 9, 12	4, 6	6
B5	1, 3, 5, 6, 7, 8	5, 12	5	4
B6	1, 4, 6, 7, 8	4, 5, 6, 7, 8	4, 6, 7, 8	4
B7	1, 7, 12	2, 5, 6, 7, 8, 9	7	6
B8	1, 2, 3, 4, 6,7, 8, 11, 12	2, 5, 6, 8, 9	2, 6, 8	4
B9	1, 2, 3, 4, 7, 8, 9, 11, 12	2, 9, 10	2, 9	3
B10	1, 9, 10, 11, 12	2, 10	10	2
B11	1, 11	1, 2, 8, 9, 10, 11	1,11	7
B12	1, 2, 3, 4, 5, 12	1, 2, 7, 8, 9, 10, 12	1, 2, 12	5

The classified structure is formed, as depicted in Table 10 and Fig. 7. “Lack of financial resources (B2)” occupies the first level. “High investments for sustainability and less return-on- investments (B10)” occupies the second level. “Inadequate government support (B9)” occupies the third level. The barriers, namely “lack of effective regulations (B5)”, “lack of a proper evaluation system for suppliers (B6)”, and “strategic and structural restraints (B8)” occupy the fourth level. “Lack of management commitment (B12)” occupies the fifth level. “Institutional complexity (B3)”, “the complexity in measuring and monitoring sustainability practices (B4)”, and “lack of sustainability knowledge (B7)” occupy the sixth level. “Cost of implementation sustainability (B1)” and “old equipment and machinery (B11)” occupy the seventh level.

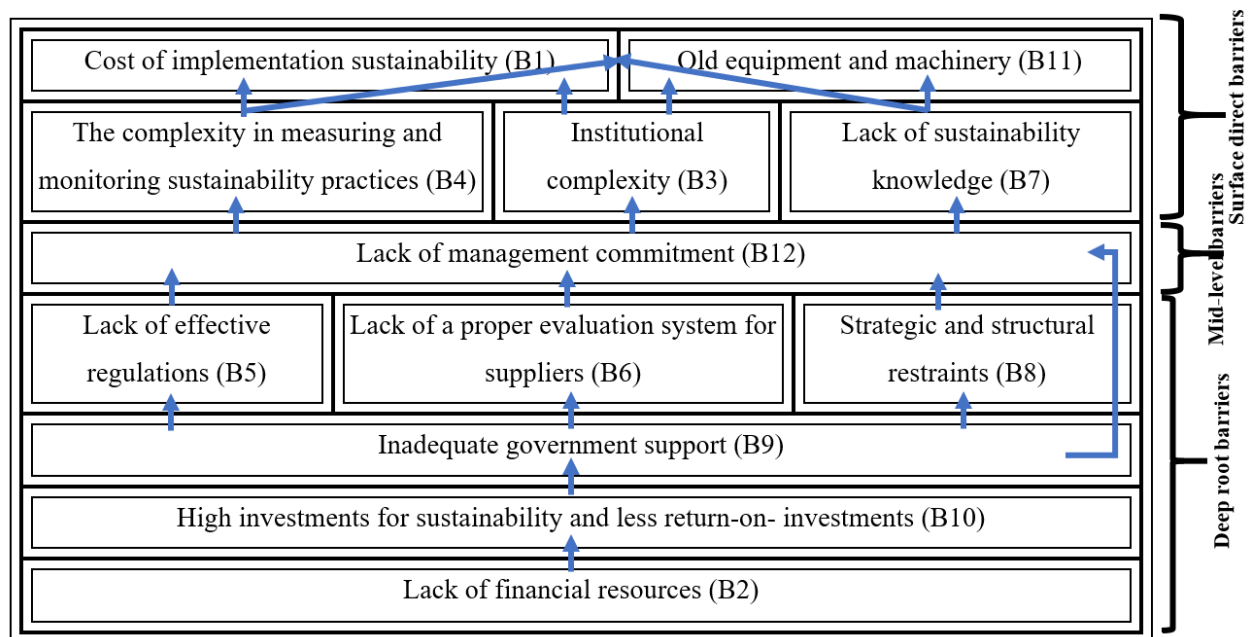


Fig. 7 – The five-level hierarchical structure model of the barriers

5.4 Fuzzy MICMAC Analysis Results

The reachability matrix was analyzed using fuzzy MICMAC to classify obstacles based on their driving and dependent power. Table 9 shows the output of driving and dependency power. The obstacles are divided into four groups (as shown in Fig. 8):

- **Autonomous:** These are the barriers that have low driving and dependence power. These obstacles are less connected with the others and have less impact. This cluster has three barriers (B3), (B4) and (B7).
- **Dependent:** the obstacles with a low driving power and a high dependence power are located in this zone. Since these obstacles represent the outputs, they are extremely responsive to changes in the driver and linkage obstacles. This cluster includes (B1) and (B11).
- **Linkage:** These are the obstacles with a lot of driving and relying power. They have a mutual relationship with other obstacles. Any adjustments to the obstacles have a significant impact on others. (B12) is the only obstacle in this cluster.
- **Independent:** the barriers with a high driving force and a low dependency power are located in this cluster. They are frequently unhindered by other obstacles and wield immense power. The efficacy of these obstacles will have a substantial impact on the overall system. This cluster includes (B2), (B5), (B6), (B8), (B9), and (B10).

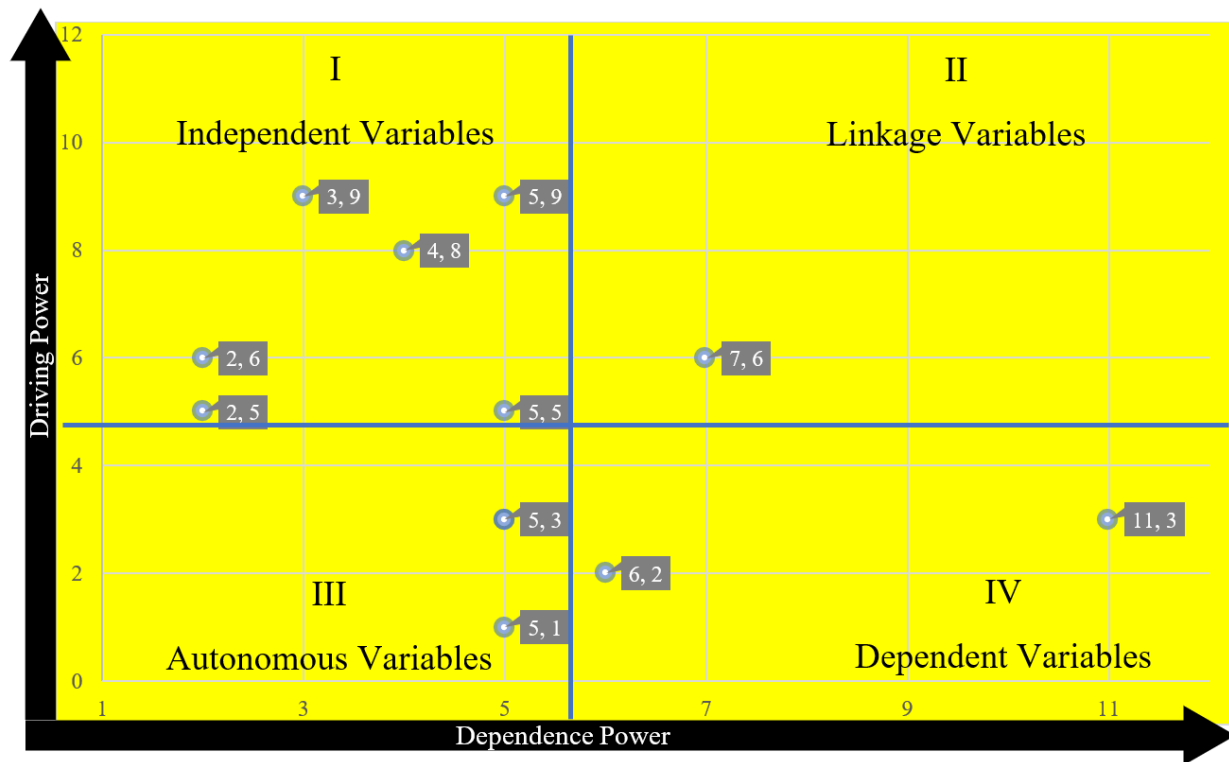


Fig. 8 – Clustering of barriers

6. DISCUSSION

The findings from the proposed model demonstrate the key role of certain obstacles in preventing the SSCM practices. Notably, the identified barriers include “lack of financial resources (B2)”, “high investments for sustainability and less return-on-investments (B10)”, “inadequate government support (B9)”, “lack of effective regulations (B5)”, “strategic and structural restraints (B8)”, and “lack of a proper evaluation system for suppliers (B6)”. These obstacles appear as the most powerful, having a major influence on all other barriers. As indicated in Figure 6, these obstacles are considered causative barriers and are located in the first quadrant of Fig. 8, occupying the lowest levels of the classified graph (Fig. 7), indicating their crucial situation in the proposed graph.

These obstacles have an impact on “the complexity in measuring and monitoring sustainability practices (B4)”, “institutional complexity (B3)”, “old equipment and machinery (B11)”, “lack of sustainability knowledge (B7)”, “cost of implementation sustainability (B1)”, and “lack of management commitment (B12)”.

Based on the classified graph (Fig. 7), “lack of financial resources (B2)” is associated with “high investments for sustainability and less return-on-investments (B10)” and “inadequate government support (B9)”. These interrelationships make a ripple effect, influencing other obstacles among the graph. This confirms the findings of the previous studies, which found that these factors are major challenges in SSCM implementation. The remaining three obstacles at the fourth level of the classified graph are “lack of effective regulations (B5)”, “strategic and structural restraints (B8)”, and “lack of a proper evaluation system for suppliers (B6)”.

The barriers at the fifth level of the classified graph are listed as the linkage among the crucial barriers located at the lowest level and the direct obstacles at the highest level. Often these obstacles are related to management. The barrier “lack of management commitment (B12)” is related to the managerial components.

Obstacles “institutional complexity (B3)”, “the complexity in measuring and monitoring sustainability practices (B4)”, and “lack of sustainability knowledge (B7)” emerge as autonomous variables when associated with other obstacles, as shown by their little driving and reliance power, placing them in the MICMAC analysis’s third quadrant. The complexity of the SSCM implement poses substantial hurdles to the continuous and successful adoption of sustainable practices.

Two barriers, “cost of implementation sustainability (B1)” and “old equipment and machinery (B11)” are located at the highest level with the maximum links. These barriers are depicted as the most effective obstacles in Fig. 6.

7. CONCLUSIONS AND RESEARCH IMPLICATIONS

In this paper, four categories with twelve critical difficulties for the implementation of sustainable concepts for the SCM of Iran’s industrial industry are effectively identified. The fuzzy MICMAC analysis is used based on two fundamental values, “driving power” and “dependence power”, at the end of the ISM method to define the function of each issue. All twelve tasks were assigned to one of four distinct quadrants, which served as the foundation for making a comparison analysis

with other scholars and offering various scientific suggestions in both practical and theoretical domains. To assist firms, sustainability has been presented and proven in the framework of SSM.

This study attempted to meet research aims by providing practical evidence for the SSCM literature, using Iran's manufacturing industry as a specific sample. As a result, the fuzzy Delphi technique is utilized to include expert opinions from several sources. It was discovered that the four most significant challenge clusters are organized by twelve separate factors. Similarly, the fuzzy DEMATEL approach was used to determine the cause-and-effect linkages between the components. We effectively modeled the interrelationships between these difficulties using the ISM model and the fuzzy MICMAC analysis to determine the critical parameters. Based on "driving" and "dependence" power, this paper indicates that "inadequate government support (B9)" along with "strategic and structural restraints (B8)" have the highest ranks, followed by the "lack of financial resources (B2)" obstacle.

The results showed that manufactures can improve sustainability standards by strengthening governmental support. Manufactures can foster sustainability outputs by eliminating or diminishing strategic and structural restraints. In addition, sustainability outputs can be improved by increasing the financial resources.

This paper provides a practical study in Iran as well as various contributions to the SSCM and environmental issues. However, it still has significant restrictions that can become intriguing concepts for other academics to investigate. To begin with, because the ISM approach only requires a limited quantity of responders for the investigation, the proposed approach must be mathematically verified using a huge dataset to ensure that it is generalizable to other developing nations; consequently, structural equation modeling is proposed for future analysis. Second, the environmental issue is taken into account in Iran's manufacturing supply chain. As a result, using and evaluating this model in various circumstances, as well as comparing study findings, will expand the SSCM literature.

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Contact information

Niousha Zeidyahyae, Ph.D.

Shahid Beheshti University
Faculty of Management and Accounting
Department of Industrial and Information Management
Iran

E-mail: niushayahyae@yahoo.com

ORCID: 0000-0002-8396-2218

Prof. Sajjad Shokouhyar, Ph.D.

Shahid Beheshti University
Faculty of Management and Accounting
Department of Industrial and Information Management
Iran

E-mail: s_shokouhyar@sbu.ac.ir

ORCID: 0000-0001-8875-0006

Prof. Alireza Motameni, Ph.D.

Shahid Beheshti University
Faculty of Management and Accounting
Department of Industrial and Information Management
Iran
E-mail: a-motameni@sbu.ac.ir
ORCID: 0000-0002-8680-6683

Abdolreza Yazdani-Chamzini, Ph.D. (Corresponding Author)

Islamic Azad University
South Tehran Branch
Young Researchers and Elite Club
Iran
E-mail: abdalrezaych@gmail.com
ORCID: 0000-0001-5594-7726

Assoc. Prof. Jonas Šaparauskas, Ph.D.

Vilnius Gediminas Technical University
Faculty of Civil Engineering
Department of Construction Management and Real Estate
Lithuania
Email: jonas.saparauskas@vilniustech.lt
ORCID: 0000-0003-3685-7754

Prof. Zenonas Turskis, Ph.D.

Vilnius Gediminas Technical University
Faculty of Civil Engineering
Institute of Sustainable Construction
Lithuania
E-mail: zenonas.turskis@vilniustech.lt
ORCID: 0000-0002-5835-9388