Research in Production and Operations Management
University of Isfahan E-ISSN: 2981-0329
Vol. 14, Issue 4, No. 35, Winter 2024, p 61-88
Submit Date: 2024-03-02/ **Accept Date:** 2024-03-31
http://dx.doi.org/10.22108/POM.2024.140822.1544

(Research Paper)

Examining the interconnected factors of maintenance 4.0 and sustainable manufacturing performance: an integrated hybrid Fuzzy DEMATEL - ISM Approach

Saeed Jahanyan *
Department of Management, Faculty of Administrative Sciences & Economics, University of Isfahan, Isfahan, Iran, s.jahanyan@ase.ui.ac.ir
Armina Sadat Daftarian
Department of Management, Faculty of Administrative Sciences & Economics, University of Isfahan, Isfahan, Iran, a.daftarian@ase.ui.ac.ir

Abstract

Purpose: Implementing Industry 4.0 in manufacturing organizations can help them in establishing predictive maintenance, and fostering sustainability. This study aims to explore Maintenance 4.0's impact on sustainable manufacturing performance within a leading Steel Company.

Design/methodology/approach: Initially, 28 valid indicators have been identified through insights from the company's managers. A sequential algorithm integrating Fuzzy DEMATEL and Interpretive Structural Modeling (ISM) has been then utilized to elucidate the intensity and direction of effects among the indicators.

Findings: Findings reveal that the “social” dimension of sustainable manufacturing had the most significant influence on other sustainability dimensions, while the” economic” dimension was found as the most influenced item. “Real-time communication” and “collaboration among humans, machines, and sensors” emerged as the most potent capabilities of Maintenance 4.0 for enhancing product sustainability. The item "Operating costs" was addressed as a key performance indicator.

Practical implications: Based on the proposed approach of this study, organizations can enhance their understanding of Maintenance 4.0, optimize their sustainable

* Corresponding author, Orcid: 0000-0002-6084-6708

manufacturing performance, and contribute to a more environmentally responsible and socially conscious approach to production.

Originality/Value: This study underscores the intertwining nature of digitalization and sustainability, highlighting their potential synergy in driving performance indicators within a company. While previous research has predominantly focused on traditional maintenance performance metrics, overlooking the comprehensive effects of Industry 4.0 and its technologies on maintenance and manufacturing performance, this study fills such a gap by employing a hybrid Fuzzy DEMATEL-ISM approach.

Keywords: Industry 4.0, Maintenance 4.0, Sustainable Manufacturing, Fuzzy DEMATEL, Interpretive Structural Modeling (ISM), Real-time monitoring

1. Introduction

The intensifying competition and evolving consumer demands within the supply chain have driven organizations to adopt technological innovations for transitioning from conventional manufacturing operations to smart operations (Samadhiya et al., 2023). However, this shift has led to the generation of various forms of waste throughout the entire product lifecycle, including preparation, manufacturing, and customer delivery, many of which pose environmental risks. Addressing these challenges is crucial to mitigate the adverse impacts of manufacturing waste on the environment and promote sustainable development (Bag & Pretorius, 2022).

Sustainability has emerged as a critical aspect of modern manufacturing processes (Javaid et al., 2022), with the fourth-generation industry model presenting significant potential for fostering sustainable practices by infusing intelligence into factories and manufacturing processes through digital technologies (Franciosi et al., 2020). These technologies play a vital role in advancing manufacturing sustainability by facilitating the identification and implementation of effective solutions (Khanzode et al., 2021; Jasiulewicz-Kaczmarek et al., 2020; Nara et al., 2021; Ching et al., 2022).

The concept of Maintenance 4.0, which integrates maintenance processes with the capabilities and technologies of the fourth industrial revolution, enables predictive actions through real-time data analysis and harnessing big data (Jasiulewicz-Kaczmarek & Gola, 2019; Nissoul et al., 2020). While previous research has primarily focused on the application of Industry 4.0 technologies in maintenance and sustainable manufacturing performance indicators across different sectors, there is a gap in understanding their interplay with Maintenance 4.0 (Li et al., 2022a; Drakaki et al., 2021; Markowski et al., 2020; Silvestri et al., 2020; Gadekar et al., 2022; Ching et al., 2022; Enyoghasi & Badurdeen, 2021; Khanzode et al., 2021; Legutko, 2022; Hien et al., 2022; Jamwal et al., 2022; Javaid et al., 2022; Lambán et al., 2022; Tortorella et al., 2022; Di Carlo et al., 2021; Sharma et al., 2021).

While existing studies have explored conventional performance indicators such as productivity, accessibility, and reliability, there is a need to emphasize sustainability indicators to address the research gap and drive innovation in this domain (Gutschi et al., 2019; Reis & Campos, 2020). The subsequent sections of this paper are structured as follows: the second part explores the research background on Maintenance 4.0, its associated technologies and capabilities, and the factors influencing Sustainable Manufacturing performance. The third section elucidates the hybrid Fuzzy DEMATEL-ISM approach and MICMAC analysis employed in the research methodology. In the fourth segment, the findings derived from validated indicators and a case study are expounded upon. Finally, the concluding section addresses discussions, and limitations of the study, and offers future recommendations.

2. Literature Review

In the field of manufacturing, advances in science and technology have consistently supported the development of industrialization around the world; however, there is still no global agreement on what constitutes an industrial revolution. Over the centuries, mankind has experienced four stages of the Industrial Revolution. The first industrial revolution emerged in the late 17th century with the invention of the steam engine, which was accompanied by the mechanization of production equipment. In the late 18th century, the second industrial revolution took shape with the use of electricity in industrial and mass production. The Third Industrial Revolution began in the early 1970s and led to the transition to the information age and the Internet (Xu et al., 2021; Sindhwani et al., 2022; Maddikunta et al., 2022; Lukač, 2015; Luthra & Mangla, 2018; Soldatos et al., 2016).

With the advancement of the Third Industrial Revolution, the term Industry 4.0 was first introduced at the Hannover Trade Fair in 2011 with the idea of integrating industry as an important part of the high-tech strategy (Xu et al., 2021; Sindhwani et al., 2022; Maddikunta et al., 2022; Hermann et al., 2016). This revolution seeks to improve the internal communication and digitalization of traditional industries (Lu, 2017). The implementation of Industry 4.0 aims to activate autonomous systems through self-organization, detection, real-time monitoring (RTM), and optimization to reduce the environmental impacts of manufacturing processes (Furstenau et al., 2020). The fourth industrial revolution is empowered by emerging technologies such as Internet of Things (IoT) and Cyber-Physical Systems (CPS), Autonomous/Collaborative Robots (A/CR), Augmented Reality (AR), Virtual Reality (VR), Additive manufacturing (AM), Big Data & Analytics (BDA), Artificial Intelligence (AI), Blockchain, Digital Twin (DT), Cloud Computing (CC), Horizontal/Vertical Integration (HVI), Cyber-Security (CS) and Simulations (Baboli, 2020; Legutko, 2022; Jamwal et al., 2022; Hien et al., 2022; Enyoghasi & Badurdeen, 2021).

This revolution seeks to create intelligent factories and facilitate human-to-machine and machine-to-machine (M2M) communication through above mentioned technologies. Industry 4.0 also represents a phenomenon that can have a significant impact on organizational performance, including efficiency, effectiveness and quality by implementing automated and high-speed systems with completely simpler processes (Kamble et al., 2018; Silvestri et al., 2020). The aim of Industry 4.0 is to activate autonomous systems through self-organization, detection, real-time monitoring (RTM), and optimization to reduce the environmental impacts of manufacturing processes (Furstenau et al., 2020). The main idea of Industry 4.0 is to use emerging technologies in a way that manufacturing processes are deeply integrated in a flexible, efficient and sustainable manner with high quality and low cost (Machado et al., 2020).

Due to a network of digital devices and the installation of more external sensors in manufacturing systems, a set of big data is provided to optimize production and maintenance. Therefore, data analysis and interpretation to optimize production, maintenance and repair processes is one of the challenges in industry-4.0 applications. Reliable data analysis is one of the basic components of the 4.0 industry, especially predictive maintenance in the production environment. On the other hand, the increasing use of highly automated manufacturing systems and complex networks requires organizations to reconsider their maintenance strategies (Uhlmann et al., 2017; Hien et al., 2022; Sahli et al., 2021). Effective data analysis enables manufacturers and machine users to gain a deeper understanding of the requirements regarding equipment, processes, services, staff, suppliers, and regulations (Jasiulewicz-Kaczmarek et al., 2020). Digitalization can enhance maintenance services by using collected data and advanced technologies to monitor equipment health, detect faults, predict and troubleshoot failures before they occur, and even optimize performance (Legutko, 2022).

Maintenance 4.0, also known as Predictive Maintenance 4.0 (PdM 4.0), is a cutting-edge strategy that leverages digital data and advanced analytics to continuously monitor the condition of machine components or processes, enabling proactive maintenance interventions based on real-time insights (Li et al., 2022a; Hien et al., 2022; Sahli et al., 2022a; Enyoghasi & Badurdeen, 2021; Sahba et al., 2021). This approach not only anticipates potential breakdowns of equipment and machinery through the analysis of real-time and big data but also prescribes the most effective predictive actions. The primary objective of Maintenance 4.0 is to harness the transformative technologies of Industry 4.0 for the strategic planning, execution, monitoring, and analysis of maintenance processes in manufacturing settings. By utilizing real-time data analysis, Maintenance 4.0 revolutionizes maintenance practices, distinguishing itself from traditional reactive approaches (Jasiulewicz-Kaczmarek & Gola, 2019; Assad et al., 2021). Through the adoption of PdM 4.0, organizations can achieve superior maintenance operations, reduce maintenance costs, and extend the operational lifespan of equipment effectively (Li et al., 2022b). Real-time data analysis empowers maintenance and sets it apart from traditional and reactive approaches (Jasiulewicz-Kaczmarek & Gola, 2019). PdM 4.0 can realize high-quality maintenance operations, minimize maintenance costs, and maximize the useful life of the device (Li et al., 2022a; Legutko, 2022; Nissoul et al. 2020).

A formal definition of sustainable manufacturing is the creation of manufactured goods through the use of a series of processes that minimize negative environmental impacts, and save energy and natural resources, for employees, communities and consumption which are safe and economically sound (Franciosi et al., 2020). Due to today's complex world, organizations have a strong need for global competition, and the condition of survival is to be close to customers and provide value-added services or products in the shortest possible time (Mirhosseini et al., 2019), so organizations must turn to sustainable manufacturing. The benefits of sustainable manufacturing include reducing costs through improving compliance, increasing business brand reputation, access to new markets, lowering labour turnover by creating attractive work environments and adopting a long-term business approach by creating opportunities for access to financial resources (Machado et al., 2020; Ching et al., 2022). Advanced data-based technologies of Industry 4.0 support manufacturing innovations and sustainability in manufacturing organizations (Jamwal et al., 2022) and form the concept of sustainability 4.0. The concept of sustainable manufacturing is described as the development of environmentally friendly products and processes (Harikannan et al., 2021). A more formal definition of sustainable manufacturing is the creation of manufactured goods through the use of a series of processes that minimize negative environmental impacts, and save energy and natural resources, for employees, communities and consumption which are safe and economically sound (Franciosi et al., 2020). Sustainability 4.0 necessitates the complete integration of digital technologies across all facets of an organization, establishing digitalization as a fundamental organizational principle (Javaid et al., 2022). Moreover, emphasizing data sharing, transparency, seamless integration of physical and virtual systems, and advocating for decentralization and cloud-based organizational structures throughout the manufacturing process enhances operational efficiency and capacity, driving integrated value creation processes within and across companies (Gadekar et al., 2022).

Each dimension of sustainability represents a distinct evolving system centred around the creation of digital value; thus, any implemented solution can have direct and indirect impacts on system stability (Machado et al., 2020). Sustainable maintenance plays a crucial role in reducing life cycle costs, mitigating the environmental and social footprints of systems, enhancing equipment longevity, and promoting socioeconomic well-being (Jasiulewicz-Kaczmarek & Gola, 2019; Im et al., 2021). Historically, manufacturing sustainability has lagged in meeting sustainability benchmarks, underscoring the critical need for Maintenance 4.0 to drive the development of more sustainable products.

3. Research methodology and data analysis

In the realm of Industry 4.0, digital transformation, Maintenance, and sustainable manufacturing, prior studies have utilized DEMATEL, Fuzzy DEMATEL, and ISM methods either independently or in conjunction with other MADM methods (e.g., Ching et al., 2022; Mishra et al., 2021; Singh & Sarkar, 2020; Sonar et al., 2020). Furthermore, hybrid DEMATEL-ISM approaches have been employed in studies such as Vishwakarma et al. (2022), Trivedi et al. (2021), and Rajput & Singh (2018); however, these hybrid approaches did not incorporate Fuzzy DEMATEL calculations.

In contrast, the present study adopts a five-phase methodology to address the aforementioned research inquiries. Initially, the study identifies the capabilities of Maintenance 4.0, its outcomes, and the performance indicators within the Triple Bottom Line (TBL) of sustainable manufacturing through a comprehensive literature review. Subsequently, the identified capabilities and indicators are validated through consultations with managers and specialists from a leading Steel Company. Next, the study employs a hybrid Fuzzy DEMATEL-ISM approach to ascertain the intensity and direction of the influence of the technological capabilities of Maintenance 4.0 on the performance indicators in the TBL of sustainable manufacturing. Following this, the study calculates the degree of penetration and interdependence of capabilities and indicators, culminating in the creation of a Matriced Impacts on Conflict and Dependency (MICMAC) diagram. In the final phase, the models derived from the Fuzzy DEMATEL, ISM, and MICMAC methods are compared, and conclusions are drawn based on the findings. The sequential steps of the research methodology are depicted in Fig. 1 for clarity and reference.

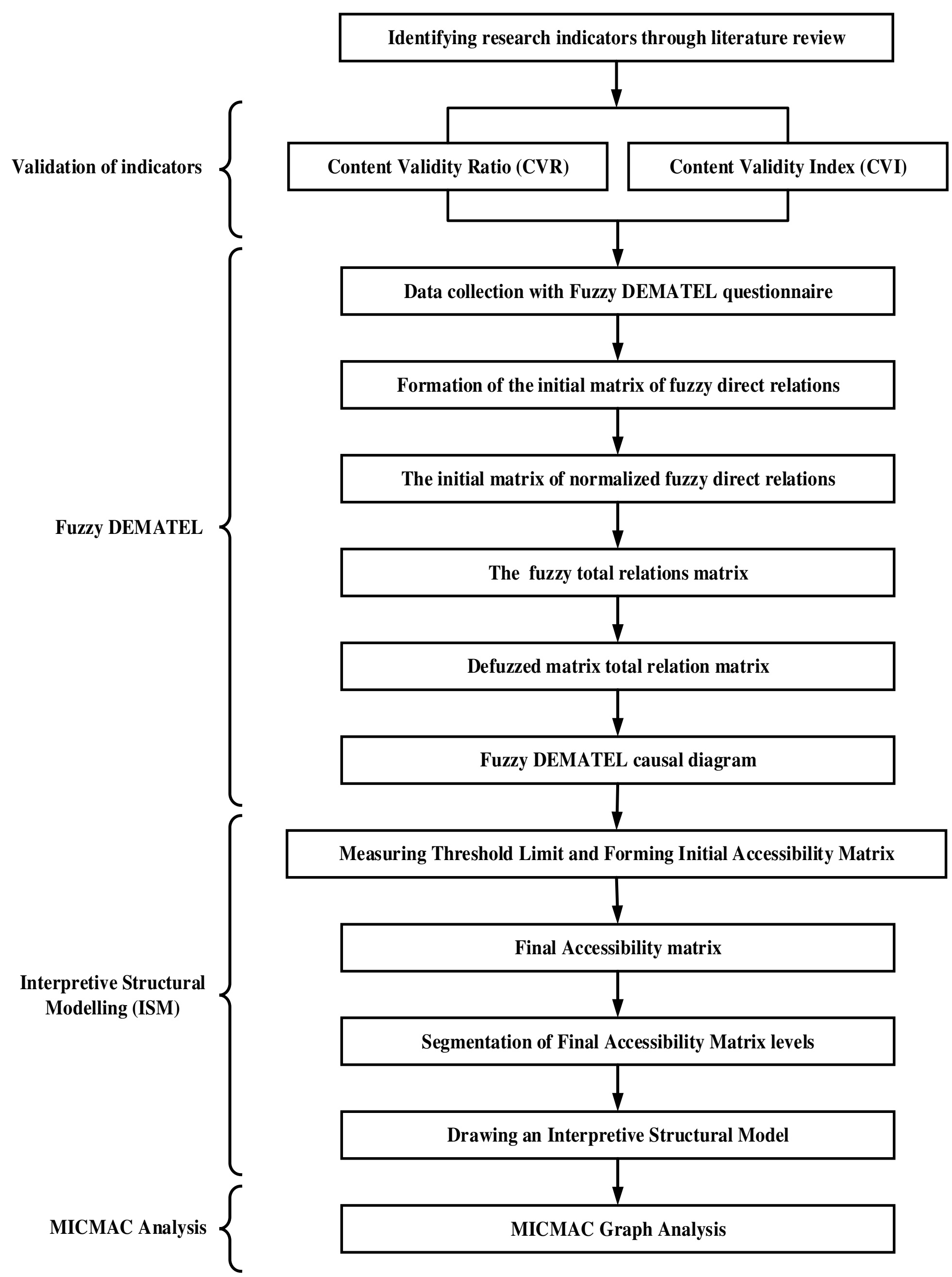


Fig. 1. The steps of the research methodology

3.1 Validation of indicators

Content validity evaluation is done quantitatively, based on the opinions of specialists and experts, by calculating two indicators «Content Validity Ratio» and «Content Validity Index» (Newman et al., 2013).

3.1.1 Content Validity Ratio (CVR)

To quantitatively determine this ratio, experts and experts in the field are asked to classify each of the indicators of the tool used based on the three-part Likert spectrum:

i) necessary, ii) useful but not necessary, and iii) not necessary. After collecting the opinion of the experts, the validity ratio of the content is calculated as follows through Eq. (1). The value of the calculated content validity ratio is lower than the desired value according to the number of evaluators should be excluded from the analysis.

$$CVR = \frac{n_e - \frac{n}{2}}{\frac{n}{2}} \tag{1}$$

In this equation, n is the total number of experts and n_e is the number of experts who have chosen the necessary option.

3.1.2 Content Validity Index (CVI)

To calculate this index, evaluators should comment on each indicator of the tool used, regarding the three criteria of "relevant or specific, simple or fluent, clear or transparent". Then, using the Eq. (2), the validity index of the content is calculated:

$$CVI = \frac{n_e}{n} \tag{2}$$

The minimum acceptable value for the content validity index is equal to 0.79, and if the value of the content validity index of an indicator is lower than 0.79, that indicator should be removed (Newman et al., 2013).

3.2 Fuzzy DEMATEL technique

Fuzzy DEMATEL is a well-known and comprehensive method for obtaining a structural model and provides causal relationships between indicators in complex real-world problems. (Khan et al., 2019). To perform the fuzzy DEMATEL technique for identifying the causal relationships between indicators in a system, the following process must be performed:

3.2.1 Data collection with Fuzzy DEMATEL questionnaire

To identify the causal relationships between the indicators and classify the affecting and influenced indicators, a pairwise comparison questionnaire is designed with valid indicators. In this questionnaire, the indicators formed the rows and columns of the matrix and the numbers of the main diameters of the matrix ($\widetilde{Z_{ij}}$) were considered zero then, asked from experts to assert the intensity of the impact and the relationships between the indicators with the help of Table 1 by inserting a definite number between zero and four in the questionnaire matrix. The general form of the pairwise comparison matrix is shown in Eq. (3).

$$\begin{array}{cc} & \begin{array}{cccc} p_i & p_j & \cdots & p_n \end{array} \\ D = & \begin{bmatrix} 0 & \widetilde{d_{12}} & \cdots & \widetilde{d_{1n}} \\ \widetilde{d_{21}} & 0 & \cdots & \widetilde{d_{2n}} \\ \vdots & \vdots & \cdots & \vdots \\ \widetilde{d_{n1}} & \widetilde{d_{n2}} & \cdots & 0 \end{bmatrix} \end{array} \tag{3}$$

In the above Eq. (3): p_i represents (*i*)th element in the pairwise comparison matrix; $\widetilde{d_{ij}} = (l_{ij}, m_{ij}, u_{ij})$ indicates the effect of (*i*)th element on (*j*)th element; l_{ij}, m_{ij} and u_{ij} are lower, middle and upper limits of the triangular fuzzy number, respectively; and *D* is paired comparison matrix.

Table 1. Scales in pairwise comparison matrix

Verbal Phrases	Symbol Phrases	Crisp Value	Triangular Fuzzy Value
No Effect	NO	0	(0 , 0 , 0.25)
Very low effect	VL	1	(0 , 0.25 , 0.5)
Low effect	L	2	(0.25 , 0.5 , 0.75)
High effect	H	3	(0.5 , 0.75 , 1)
Very High effect	VH	4	(0.75 , 1 , 1)

3.2.2 Formation of the initial matrix of fuzzy direct relations ($\widetilde{Z_{ij}}$)

After collecting the questionnaires completed by the experts, first, all the crisp numbers in the matrix of the questionnaires are replaced with their corresponding triangular fuzzy numbers, according to Table 1, and the expert opinion matrix is aggregated using the arithmetic mean method (according to Eq. (4)) and the initial matrix of fuzzy direct relations is obtained.

$$\widetilde{z_{ij}} = \frac{\sum \tilde{d}_{ij}}{k} \tag{4}$$

where *K* represents the number of experts and $\widetilde{z_{ij}}$ is (*ij*)th element in the initial matrix of fuzzy direct relations.

3.2.3 The initial matrix of normalized fuzzy direct relations ($\widetilde{X_{ij}}$)

After the formation of the initial matrix of direct fuzzy relations, it must be normalized. For this purpose, first, the sum of the upper boundaries of each indicator is calculated and then the maximum value of the sum of the upper boundaries of the rows (*r*) is determined according to Eq. (5). In the last step, based on Eq. (6), all the elements of the initial matrix of direct relations are divided by the value of r, and the normalized initial matrix is obtained.

$$r = max_{1 \le i \le n}\left(\sum_{j=1}^{n} u_{ij}\right) \tag{5}$$

$$\widetilde{x_{ij}} = \frac{\widetilde{Z_{ij}}}{r} = \left(\frac{l_{ij}}{r}, \frac{m_{ij}}{r}, \frac{u_{ij}}{r}\right) = \frac{\widetilde{Z_{ij}}}{r} \tag{6}$$

Where r is the maximum value of the sum of the boundaries above the rows of the initial matrix; and $\widetilde{x_{ij}}$ is normalized (*ij*)th element in the initial matrix of direct fuzzy relations.

3.2.4 The total fuzzy relations matrix ($\widetilde{T_{ij}}$)

To form a fuzzy total relational matrix that indicates the intensity of the relative direct and indirect effects in the system, Eq. (8) is performed for the lower, middle and upper bounds of the indicators.

$$\widetilde{t_{ij}} = (l''_{ij} , m''_{ij} , u''_{ij}) \quad (7)$$

$$[l''_{ij}] = \widetilde{X_l} \times (I - \widetilde{X_l})^{-1} \quad (8)$$

$$[m''_{ij}] = \widetilde{X_m} \times (I - \widetilde{X_m})^{-1}$$

$$[u''_{ij}] = \widetilde{X_u} \times (I - \widetilde{X_u})^{-1}$$

In the above equations., I is the unit matrix; $\tilde{T}$ is the total fuzzy relations matrix; $\widetilde{t_{ij}}$ is (ij)th element in the total fuzzy relations matrix and $\widetilde{X_l}$, $\widetilde{X_m}$ and $\widetilde{X_u}$ are $N \times N$ matrixes whose entries respectively form lower number, middle number and upper number of triangular fuzzy numbers of $\widetilde{x_{ij}}$ matrix.

3.2.5 Defuzzified matrix total relation matrix (T_{ij})

At this point, all the fuzzy numbers of the total fuzzy relational matrix are returned to the crisp numbers in the form of a defuzzified matrix using Eq. (9). Where T_{ij} is the defuzzified total relations matrix.

$$\mathrm{T}_{ij} = \frac{l_{ij} + 4m_{ij} + u_{ij}}{6} \quad (9)$$

3.2.6 Fuzzy DEMATEL causal diagram

To construct a causal diagram, the initial step involves computing the sum of the elements in each row (R) and the sum of the elements in each column (D) from the generalized fuzzy relations matrix (as per Eqs. (10) and (11)). Here, the value of R signifies the degree of influence, while the value of D represents the degree of impact. Subsequently, utilizing the calculated values of R and D, the quantities (R+D) and (R-D) are determined. Finally, based on the value of (R-D), a ranking is assigned to the elements in the matrix.

$$\tilde{R} = \left[\sum_{j=1}^{n} \widetilde{t_{ij}}\right]_{1\times n}^{\alpha=0} = \left[\sum_{j=1}^{n} l_{ij} ; \sum_{j=1}^{n} m_{ij} ; \sum_{j=1}^{n} u_{ij}\right] \quad (10)$$

$$\widetilde{D} = \left[\sum_{i=1}^{n} \widetilde{t_{ij}}\right]_{1\times n}^{\alpha=0} = \left[\sum_{i=1}^{n} l_{ij} ; \sum_{i=1}^{n} m_{ij} ; \sum_{i=1}^{n} u_{ij}\right] \quad (11)$$

Then, using the calculated values (R+D) and (R-D) for all indicators, a Cartesian coordinate system is formed, the longitudinal axis of which is in terms of values (R+D) and its transverse axis in terms of values (R-D).

3.3 Interpretive Structural Modelling (ISM)

To implement the ISM technique, the following process must be performed to obtain the relationships between the indicators and their levelling in a system:

3.3.1. Forming Structural Self-Interaction Matrix (SSIM)

In the integration of the Fuzzy DEMATEL technique with the ISM technique, the result obtained from the Fuzzy DEMATEL technique (de-fuzzy total relations matrix) can be directly utilized as the input for the ISM technique (formation of the structural self-interaction matrix). Consequently, in this study, given the application of these two techniques within a sequential algorithm, the initial step of the ISM technique (formation of the structural self-interaction matrix) is omitted from the procedure.

3.3.2 Measuring Threshold Limit and Forming Initial Accessibility Matrix (A_{ij})

To form the initial accessibility matrix of ISM, first, the mean value of the de-fuzzy total relations matrix (threshold limit) is extracted. Then, to fill the initial accessibility matrix, each element of the total de-fuzzy relation matrix is compared with the mean value obtained (according to Eq. 12). In this equation, A_{ij} is the Initial Accessibility Matrix.

If $(A_{ij} \geq Average\ _{T\ Matrix}\ ; 1\ ; 0)\ , Average\ _{T\ Matrix}$ (12)

3.3.3 Final Accessibility Matrix (M_{ij})

Once the initial accessibility matrix has been obtained, the next step is to establish internal consistency between all indicators. For elements of the final access matrix that did not meet the above consistency condition, a consistency relation is established according to Eq. (13), and this process continues until all the components of the final access matrix can be the same as the resulting matrix from the previous stage.

$M_{ij} = (\ A_{ij} + I\ )^{k+1}\ , k \geq 1$ (13)

Where I am the unit matrix; M_{ij} is the Consistent final access matrix; and k represents the number of iterations of matrix $A_{ij} + I$. In each iteration for the $A_{ij} + I$ matrix, the operations must adhere to Boolean's rule, necessitating that all elements in the matrix be replaced with either zero or one based on Eq. (14). Subsequently, in the resulting final accessibility matrix, elements that transitioned from zero to one (originally zero in the initial accessibility matrix) are denoted with a star (*).

If $((\ A_{ij} + I\ )^{k+1} \geq 1; 1\ ; 0)$ (14)

3.3.4 Segmentation of Final Accessibility Matrix Levels

After determining the inputs and outputs and their commonalities, the indicators that had the same outputs and communalities were placed at the highest level of the Interpretive Structural Model hierarchy (level 1). Then, to find the components of the next level of the system, the identified components are removed and the next level is identified through a repeating process. The process continues until all indicators are classified into levels.

3.3.5 Drawing an Interpretive Structural Model

The model is drawn based on the specified levels. Relationships between indicators are also determined according to the initial accessibility matrix.

3.4 MICMAC Analysis

MICMAC analysis is a system of matrices used in indirect relationship analysis that aims to analyze the degree of influence (power) and dependence of indicators and place the indicators on the coordinates in a two-dimensional rectangular plane with the degree of dependence on the x-axis. And plots the degree of influence (power) on the y-axis (Singh et al., 2021; Vinodh, 2021; Ching et al., 2022; Shafiee et al., 2022). After calculating the influence and dependence values of all indicators, a Cartesian coordinate system is formed and Eq. (15) is used to determine the horizontal and vertical boundaries between the indicators, in which n represents the number of indicators.

$$\text{Determining boundaries} = \left(\frac{n}{2}\right) + 1 \quad (15)$$

3.4.1 MICMAC Graph Analysis

MICMAC analysis is a method involving matrices used to analyze indirect relationships, focusing on assessing the degree of influence (power) and dependence of indicators. It positions the indicators on a two-dimensional rectangular plane, with the degree of dependence on the x-axis and the degree of influence on the y-axis (Singh et al., 2021; Vinodh, 2021; Ching et al., 2022; Shafiee et al., 2022).

Following the computation of influence and dependence values for all indicators, a Cartesian coordinate system is established, and Eq. (15) is employed to determine the horizontal and vertical boundaries among the indicators, where 'n' denotes the number of indicators. In MICMAC analysis, indicators are categorized into four groups based on their degree of penetration and dependence:

a) Autonomous indicators (Area 1): These indicators exhibit low penetration and dependence, operating independently from the system and other communication indicators.

b) Dependent indicators (Area 2): These indicators possess low influence but high dependence levels.

c) Linked indicators (Area 3): These indicators demonstrate high penetration and dependence, playing a critical role.

d) Independent indicators (Area 4): Referred to as "key indicators," these indicators exhibit high penetration and low dependence, significantly impacting the system process (Mishra et al., 2021; Singh et al., 2021; Vinodh, 2021; Sonar et al., 2020; Shafiee et al., 2022; Rajput & Singh, 2018).

4. Case study and findings

In the case study, the manufacturing company in focus is a renowned Iranian firm specializing in steel sheet production. With a mission to contribute significantly to the industrial, economic, and social progress of the nation while elevating the technological standards of the steel industry, this leading organization manufactures more than half of the country's steel consumption. Their product range serves diverse sectors such as automotive and parts industries, light metal industries, heavy and fluid transfer pipes, packaging industries, home appliances, electrical components, pipes, and profiles. The company operates two primary plants encompassing hot and cold rolling zones.

4.1 Validation of indicators

To finalize the selection of indicators, all Maintenance 4.0 capabilities, outcomes, and sustainable manufacturing performance indicators underwent validation with the assistance of managers and experts from the designated plant within the company. Tables 2 to 6 display the approved indicators for Maintenance 4.0 capabilities and outcomes across different facets of manufacturing sustainability, complete with their respective codes, technologies, and pertinent references.

Table 2. Valid technological capabilities of Maintenance 4.0.

No.	Code	Capability	Techno logy	References
1	MC_ 01	Ability to diagnose and predict	IoT, BDA, CC	Abidi et al. (2022); Hien et al. (2022); Lambán et al. (2022); Legutko (2022); Li et al. (2022 b); Di Carlo et al. (2021); Drakaki et al. (2021); Çınar et al. (2020); Markowski et al. (2020); Reis & Campos (2020); Gutschi et al. (2019); Eschen et al. (2018)
2	MC_ 04	Facilitate transparency and traceability throughout the maintenance management cycle	IoT, Blockch ain	Lambán et al.(2022); Li et al. (2022 a); Li et al. (2022 b); Tortorella et al. (2022); Paudel & Neupane (2021); Liu et al. (2020); Xenakis et al. (2019)
3	MC_ 06	Identify malfunctions and root causes	IoT, BDA, CC	Samadhiya et al. (2023); Abidi et al. (2022); Jamwal et al. (2022); Legutko (2022); Machado et al. (2020); Markowski et al. (2020); Nissoul et al. (2020)
4	MC_ 11	Possibility of remote access	IoT, BDA	Jamwal et al. (2022); Li et al. (2022 b); Tortorella et al. (2022); Paudel & Neupane (2021); Franciosi et al. (2020); Jasiulewicz-Kaczmarek & Gola (2019); Eschen et al. (2018)
5	MC_ 12	Ability to store and make available big data	IoT, BDA, CC	Ching et al. (2022); Gadekar et al. (2022); Hien et al. (2022); Jamwal et al. (2022); Javaid et al. (2022); Lambán et al.(2022); Legutko (2022); Li et al. (2022 b); Paudel & Neupane (2021); Franciosi et al. (2020); Silvestri et al. (2020)
6	MC_ 13	Automatic control, health assessment and life expectancy of equipment	IoT, BDA, CC	Samadhiya et al. (2024); Abidi et al. (2022); Lambán et al.(2022); Legutko (2022); Li et al. (2022 a); Paudel & Neupane (2021); Sharma et al. (2021); Çınar et al. (2020); Jasiulewicz-Kaczmarek & Gola (2019); Xenakis et al. (2019); Eschen et al. (2018)
7	MC_ 25	Real-time monitoring of physical processes, equipment and machinery	IoT, CC, AR - VR	Jamwal et al. (2022); Legutko (2022); Tortorella et al. (2022); Bhanji et al. (2021); Drakaki et al. (2021); Enyoghasi & Badurdeen (2021); Sharma et al. (2021); Franciosi et al. (2020); Markowski et al. (2020); Gutschi et al. (2019); Xenakis et al. (2019)
8	MC_ 32	Provide high volume and variety of real-time data and their analysis	IoT, BDA, CC	Abidi et al. (2022); Ching et al. (2022); Gadekar et al. (2022); Hien et al. (2022); Javaid et al. (2022); Lambán et al. (2022); Legutko (2022); Li et al. (2022 a); Di Carlo et al. (2021); Sharma et al. (2021); Çınar et al. (2020); Nissoul et al. (2020); Reis & Campos (2020)
9	MC_ 48	Real-time communication and cooperation of humans, machines and sensors	IoT	Samadhiya et al. (2024); Ching et al. (2022); Gadekar et al. (2022); Legutko (2022); Bhanji et al. (2021); Di Carlo et al. (2021); Franciosi et al. (2020); Silvestri et al. (2020); Jasiulewicz-Kaczmarek & Gola (2019)

Table 3. Valid results of Maintenance 4.0.

No.	Code	Result	References
1	ME_02	Availability of spare parts and manufacturing equipment	Hien et al. (2022); Lambán et al.(2022); Legutko (2022); Bhanji et al. (2021); Enyoghasi & Badurdeen (2021); Franciosi et al. (2020); Jasiulewicz-Kaczmarek et al (2020); Nissoul et al. (2020); Gutschi et al. (2019); Franciosi et al. (2018)
2	ME_03	Unexpected outages and disruptions in manufacturing	Lambán et al.(2022); Legutko (2022); Drakaki et al. (2021); Çınar et al. (2020); Franciosi et al. (2020); Jasiulewicz-Kaczmarek et al.(2020); Jasiulewicz-Kaczmarek & Gola (2019); Xenakis et al. (2019)
3	ME_04	Spare parts inventory level	Hien et al. (2022); Javaid et al. (2022); Legutko (2022); Sharma et al. (2021); Çınar et al. (2020); Franciosi et al. (2020); Jasiulewicz-Kaczmarek et al. (2020); Nissoul et al. (2020)
4	ME_05	Maintenance time	Abidi et al. (2022); Javaid et al. (2022); Lambán et al.(2022); Tortorella et al. (2022); Bhanji et al. (2021); Enyoghasi & Badurdeen (2021); Çınar et al. (2020); Nissoul et al. (2020); Reis & Campos (2020); Gutschi et al. (2019)
5	ME_08	Heavy costs due to unplanned breakdowns	Abidi et al. (2022); Jamwal et al. (2022); Legutko (2022); Li et al. (2022 a); Bhanji et al. (2021); Di Carlo et al. (2021); Franciosi et al. (2020); Reis & Campos (2020); Jasiulewicz-Kaczmarek & Gola (2019); Xenakis et al. (2019)
6	ME_13	The useful life of manufacturing equipment	Samadhiya et al. (2023); Abidi et al. (2022); Hien et al. (2022); Jamwal et al. (2022); Lambán et al.(2022); Legutko (2022); Li et al. (2022 a); Sharma et al. (2021); Çınar et al. (2020); Jasiulewicz-Kaczmarek & Gola (2019)

Table 4. Valid indicators for sustainable manufacturing performance (Social aspect)

No.	Code	Indicator	References
1	SM_S_04	Empowerment of human capital and development of employees' capabilities	Samadhiya et al. (2024); Bag & Pretorius (2022); Legutko (2022); Khanzode et al. (2021); Franciosi et al. (2020); Furstenau et al. (2020); Machado et al. (2020); Awan et al. (2018); Menon et al. (2018)
2	SM_S_09	Participation in the level of health and safety of employees	Samadhiya et al. (2024); Bag & Pretorius (2022); Ching et al. (2022); Javaid et al. (2022); Legutko (2022); Tortorella et al. (2022); Di Carlo et al. (2021); Khanzode et al. (2021); Nara et al. (2021); Jasiulewicz-Kaczmarek et al. (2020); Machado et al. (2020); Nissoul et al. (2020); Awan et al. (2018); Menon et al. (2018)
3	SM_S_14	Team spirit	Samadhiya et al. (2024); Khanzode et al. (2021); Jasiulewicz-Kaczmarek et al. (2020)

Table 5. Valid indicators for sustainable manufacturing performance (Environmental aspect)

No.	Code	Indicator	References
1	SM_E_01	Environmental pollutants and greenhouse gas emissions	Samadhiya et al. (2024); Bag & Pretorius (2022); Ching et al. (2022); Gadekar et al. (2022): Javaid et al. (2022); Legutko (2022); Enyoghasi & Badurdeen (2021); Harikannan et al. (2021); Sharma et al. (2021); Furstenau et al. (2020); Nissoul et al. (2020); Franciosi et al. (2018); Menon et al. (2018)
2	SM_E_04	Optimize and save resources	Samadhiya et al. (2024); Abidi et al. (2022); Ching et al. (2022); Gadekar et al. (2022); Hien et al. (2022); Jamwal et al. (2022); Javaid et al. (2022); Legutko (2022); Khanzode et al. (2021); Nara et al. (2021); Jasiulewicz-Kaczmarek et al.(2020); Leng et al. (2020); Nissoul et al. (2020); Menon et al. (2018); Rajput & Singh (2018)
3	SM_E_07	Recovery of resources and recycling of manufacturing waste	Samadhiya et al. (2023); Bag & Pretorius (2022); Hien et al. (2022); Jamwal et al. (2022); Javaid et al. (2022); Legutko (2022); Enyoghasi & Badurdeen (2021); Nara et al. (2021); Furstenau et al. (2020); Jasiulewicz-Kaczmarek et al. (2020); Machado et al. (2020); Menon et al. (2018); Rajput & Singh (2018)
4	SM_E_11	Use of organic raw materials	Sharma et al. (2021); Javaid et al. (2022)

Table 6. Valid indicators for sustainable manufacturing performance (Economic aspect)

No.	Code	Indicator	References
1	SM_EC_ 05	Risk for the organization and customers	Bag & Pretorius (2022); Gadekar et al. (2022); Bhanji et al. (2021); Enyoghasi & Badurdeen (2021); Nara et al. (2021); Jasiulewicz-Kaczmarek et al. (2020); Leng et al. (2020); Jasiulewicz-Kaczmarek & Gola (2019)
2	SM_EC_ 06	Operating costs	Samadhiya et al. (2024); Abidi et al. (2022); Ching et al. (2022); Javaid et al. (2022); Legutko (2022); Bhanji et al. (2021); Di Carlo et al. (2021); Harikannan et al. (2021); Nara et al. (2021); Franciosi et al. (2020); Machado et al. (2020); Gutschi et al. (2019); Menon et al. (2018)
3	SM_EC_ 13	Timely delivery	Bag & Pretorius (2022); Gadekar et al. (2022); Javaid et al. (2022); Lambán et al.(2022); Enyoghasi & Badurdeen (2021); Sharma et al. (2021); Markowski et al. (2020); Jasiulewicz-Kaczmarek & Gola (2019); Menon et al. (2018)
4	SM_EC_ 18	Flexibility in approaching customer requirements	Samadhiya et al. (2024); Bag & Pretorius (2022); Ching et al. (2022); Hien et al. (2022); Jamwal et al. (2022); Javaid et al. (2022); Tortorella et al. (2022); Sharma et al. (2021); Jasiulewicz-Kaczmarek et al.(2020)
5	SM_EC_ 22	More efficient customer-supplier interaction	Samadhiya et al. (2023); Bag & Pretorius (2022); Ching et al. (2022); Gadekar et al. (2022); Hien et al. (2022); Javaid et al. (2022); Legutko (2022); Sharma et al. (2021); Nissoul et al. (2020)
6	SM_EC_ 27	Identify worthless processes	Ching et al. (2022); Javaid et al. (2022); Legutko (2022); Jasiulewicz-Kaczmarek et al. (2020)

4.2 Fuzzy DEMATEL technique analysis

To establish causal relationships between the indicators and categorize the influencing and influenced indicators, a pairwise comparison questionnaire was developed utilizing 28 validated indicators. Subsequently, 10 managers and experts from the relevant plant of the company participated in the assessment. This group comprised 4 managers holding PhD degrees and 6 managers and experts with MSc degrees, each possessing diverse expertise in areas such as maintenance, digital transformation, and manufacturing. Participants were required to indicate the intensity of impact and relationships between the indicators by assigning a numerical value between zero and four in the questionnaire matrix. The sampling approach employed in this study was purposive, targeting individuals well-versed in the concepts under investigation and possessing significant work experience. While a limited number of experts are typically adequate for completing the Fuzzy DEMATEL technique questionnaire, this study involved the input of 10 experts to ensure comprehensive coverage.

To normalize the initial matrix of direct fuzzy relationships, the sum of the upper bounds of each indicator was calculated. Subsequently, the maximum value of the sum of the upper boundaries of the rows (r), amounting to 24,920, was determined by Eq. (5). Following this, all elements of the primary matrix of direct relationships were divided by 24,920 to obtain the normalized primary matrix by applying Eqs. (10) and (11), the intensity of cumulative and net effects of the indicators was determined (refer to Table 8), and a Fuzzy DEMATEL causal diagram was constructed (see Fig. 2).

Table 8. Intensity of cumulative and net effects of indicators.

Indicator Code	R	D	R + D	R - D	Rank
MC_01	1.3662	1.0812	2.4473	0.2850	**9**
MC_04	1.2364	0.9751	2.2116	0.2613	**10**
MC_06	1.4300	1.0827	2.5127	0.3473	**8**
MC_11	1.4311	0.7754	2.2065	0.6557	**2**
MC_12	1.4649	0.8638	2.3287	0.6011	**4**
MC_13	1.4763	1.0492	2.5255	0.4271	**7**
MC_25	1.5716	1.0385	2.6100	0.5331	**5**
MC_32	1.5653	0.9501	2.5154	0.6151	**3**
MC_48	1.7808	1.0860	2.8668	0.6948	**1**
ME_02	1.2683	1.1750	2.4433	0.0933	**12**
ME_03	1.2968	1.3977	2.6945	-0.1008	**15**
ME_04	0.9358	1.3256	2.2615	-0.3898	**23**
ME_05	1.1999	1.4404	2.6403	-0.2405	**19**
ME_08	1.1072	1.4388	2.5460	-0.3316	**22**
ME_13	1.3334	1.4872	2.8206	-0.1539	**16**
SM_S_04	1.7243	1.2400	2.9642	0.4843	**6**
SM_S_09	1.2077	1.2195	2.4272	-0.0118	**14**
SM_S_14	1.4564	1.2185	2.6749	0.2379	**11**
SM_E_01	0.8457	1.1031	1.9488	-0.2574	**20**
SM_E_04	0.9999	1.5449	2.5448	-0.5451	**25**
SM_E_07	0.9420	1.1754	2.1174	-0.2335	**18**
SM_E_11	0.8789	0.7894	1.6682	0.0895	**13**
SM_EC_05	0.9795	1.5849	2.5644	-0.6054	**26**
SM_EC_06	0.8347	1.6544	2.4891	-0.8196	**28**
SM_EC_13	0.8138	1.4759	2.2897	-0.6621	**27**
SM_EC_18	0.8822	1.3819	2.2642	-0.4997	**24**
SM_EC_22	1.0040	1.3090	2.3130	-0.3049	**21**
SM_EC_27	1.1420	1.3113	2.4534	-0.1693	**17**

Referring to Table 8, the position of each indicator is represented in the Fuzzy DEMATEL causal diagram (Fig. 2) through its corresponding coordinates. Analysis of the causal diagram derived from the Fuzzy DEMATEL technique (Fig. 2) yields the following key findings:

Indicators positioned above the horizontal line exhibit a positive net effect and are categorized as stimulating and influential indicators. These include Maintenance 4.0 capabilities (MC_01 to MC_48) and factors such as "Availability of spare parts and manufacturing equipment," "Empowerment of human capital and development of employees' capabilities," "Participation in the level of health and safety of employees," "Team spirit," and "Use of organic raw materials". Indicators located below the horizontal line demonstrate a negative net effect intensity and are classified as dependent. These indicators comprise ME_03, ME_04, ME_05, ME_08, ME_13, SM_E_01, SM_E_04, SM_E_07, SM_EC_05, SM_EC_06, SM_EC_13, SM_EC_18, SM_EC_22, and SM_EC_27. "Real-time communication and cooperation of humans, machines, and sensors" emerges as the most impactful indicator, possessing the highest R-D value, while "Operating costs" is identified as the most receptive indicator, characterized by the lowest R-D value. "Empowerment of human capital and development of employees' capabilities" exhibits the highest R + D value, indicating significant interactions with other indicators. Conversely, "Use of organic raw materials" registers the lowest R + D value, suggesting minimal interactions with other indicators.

Overall, the social dimension of sustainable manufacturing within the company exerts the most substantial influence on other sustainability aspects. Conversely, the economic aspect is identified as the most responsive to other sustainability dimensions.

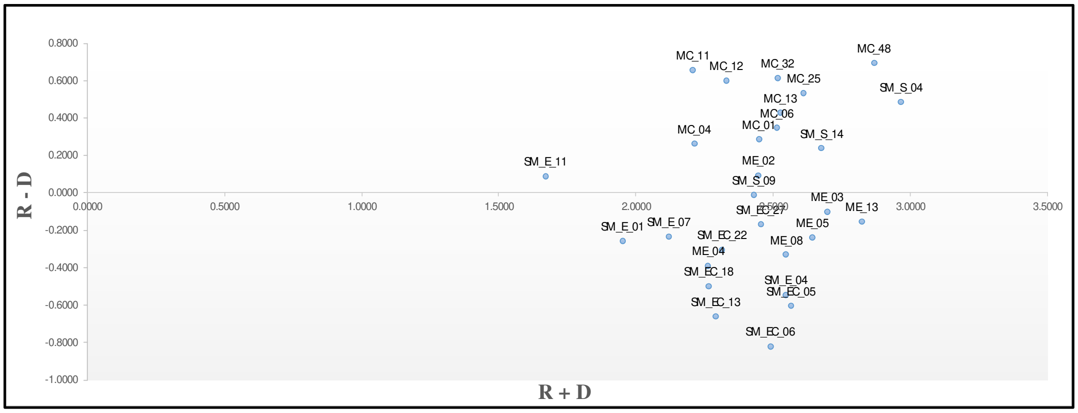


Fig.e 2. Fuzzy DEMATEL causal diagram.

4.3 ISM analysis

To construct the initial reachability matrix for ISM, the average value of the de-fuzzified total relations matrices was calculated, resulting in a value of 0.044. Subsequently, each element of the total de-fuzzified relation matrix was compared with this mean value to populate the initial reachability matrix. As per Eq. (12), if the value in the total de-fuzzified relations matrix is greater than or equal to the mean value, the corresponding entry in the initial reachability matrix is set to one; otherwise, it is set to zero.

In this research, consistency was attained after 3 iterations of the process (k = 4), as detailed in Table 9. Furthermore, following the categorization of indicators into 4 levels (refer to Table 10), the indicators were arranged from top to bottom based on their respective levels, and a directional diagram was created to illustrate the ISM model (Fig. 3).

Table 9. Consistent final access matrix

M_{ij}	MC_01	MC_04	MC_06	MC_11	MC_12	MC_13	MC_25	MC_32	MC_48	ME_02	ME_03	ME_04	ME_05	ME_08	ME_13	SM_S_04	SM_S_09	SM_S_14	SM_E_01	SM_E_04	SM_E_07	SM_E_11	SM_EC_05	SM_EC_06	SM_EC_13	SM_EC_18	SM_EC_22	SM_EC_27
MC_01	1*	1*	1	1*	1*	1	1	1	1	1	1	1	1	1	1	1*	1*	1*	1*	1	1*	1*	1	1	1	1	1	1*
MC_04	1	1*	1	1*	1*	1	1	1*	1	1	1	1	1	1	1	1*	1*	1*	1*	1	1*	1*	1	1	1*	1	1*	1*

M_{ij}	MC_01	MC_04	MC_06	MC_11	MC_12	MC_13	MC_25	MC_32	MC_48	ME_02	ME_03	ME_04	ME_05	ME_08	ME_13	SM_S_04	SM_S_09	SM_S_14	SM_E_01	SM_E_04	SM_E_07	SM_E_11	SM_EC_05	SM_EC_06	SM_EC_13	SM_EC_18	SM_EC_22	SM_EC_27
MC_06	1	1	1*	1*	1*	1	1	1	1*	1	1	1	1	1	1	1	1	1	1	1	1	1*	1	1	1	1	1*	1
MC_11	1	1	1	1*	1*	1	1	1	1	1	1	1	1	1	1	1	1	1	1*	1	1	1*	1	1	1	1	1	1
MC_12	1	1	1	1*	1*	1	1	1	1	1	1	1	1	1	1	1	1	1	1*	1	1	1*	1	1	1	1	1	1
MC_13	1	1*	1	1*	1*	1*	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1*	1*	1	1	1	1	1*	1
MC_25	1	1	1	1	1	1	1*	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1*	1	1	1	1	1*	1
MC_32	1	1	1	1*	1	1	1	1*	1	1	1	1	1	1	1	1	1*	1	1*	1	1*	1*	1	1	1	1	1*	1
. . . .																											. .	
SM_E_01	0	0	0	0	0	0	0	0	0	1*	1*	1*	1*	1*	1*	0	0	0	1*	1*	0	0	1	1*	1*	1*	1*	0
SM_E_04	0	0	0	0	0	0	0	0	0	1	1*	1	1*	1*	1	0	0	0	0	1*	0	0	1	1	1*	1*	1*	0
SM_E_07	0	0	0	0	0	0	0	0	0	1*	1*	1*	1*	1*	1*	0	0	0	0	1	1*	0	1	1*	1*	1*	1*	0
SM_E_11	1*	1*	1*	1*	1*	1*	1*	1*	1*	1*	1*	1*	1*	1*	1*	1*	1	1*	1	1	1	1*	1	1	1*	1*	1*	1*
SM_EC_05	0	0	0	0	0	0	0	0	0	1*	1*	1	1*	1*	1	0	0	0	0	1	0	0	1*	1	1	1*	1*	0

M_{ij}	MC_01	MC_04	MC_06	MC_11	MC_12	MC_13	MC_25	MC_32	MC_48	ME_02	ME_03	ME_04	ME_05	ME_08	ME_13	SM_S_04	SM_S_09	SM_S_14	SM_E_01	SM_E_04	SM_E_07	SM_E_11	SM_EC_05	SM_EC_06	SM_EC_13	SM_EC_18	SM_EC_22	SM_EC_27
SM_EC_06	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1*	0	0	0	0
SM_EC_13	0	0	0	0	0	0	0	0	0	1*	1*	1*	1*	1*	1*	0	0	0	0	1*	0	0	1	1*	1*	1	1	0
SM_EC_18	0	0	0	0	0	0	0	0	0	1*	1*	1*	1*	1*	1*	0	0	0	0	1*	0	0	1	1*	1	1*	1	0
SM_EC_22	0	0	0	0	0	0	0	0	0	1	1*	1	1*	1*	1*	0	0	0	0	1*	0	0	1	1*	1	1	1*	0
SM_EC_27	0	0	0	0	0	0	0	0	0	1*	1*	1	1	1*	1	0	0	0	0	1	0	0	1	1	1*	1*	1*	1*

Table 10. Segmentation of final accessibility matrix levels

Code	No.	Input Set	Output Set	Subscription Set	Level
MC_01	1	1-2-3-4-5-6-7-8-9-16-17-18-22	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-24-25-26-27-28	1-2-3-4-5-6-7-8-9-16-17-18-22	**4**
MC_04	2	1-2-3-4-5-6-7-8-9-16-17-18-22	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-24-25-26-27-28	1-2-3-4-5-6-7-8-9-16-17-18-22	**4**
MC_06	3	1-2-3-4-5-6-7-8-9-16-17-18-22	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-24-25-26-27-28	1-2-3-4-5-6-7-8-9-16-17-18-22	**4**
MC_11	4	1-2-3-4-5-6-7-8-9-16-17-18-22	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-24-25-26-27-28	1-2-3-4-5-6-7-8-9-16-17-18-22	**4**
MC_12	5	1-2-3-4-5-6-7-8-9-16-17-18-22	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-24-25-26-27-28	1-2-3-4-5-6-7-8-9-16-17-18-22	**4**
MC_13	6	1-2-3-4-5-6-7-8-9-16-17-18-22	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-24-25-26-27-28	1-2-3-4-5-6-7-8-9-16-17-18-22	**4**
MC_25	7	1-2-3-4-5-6-7-8-9-16-17-18-22	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-24-25-26-27-28	1-2-3-4-5-6-7-8-9-16-17-18-22	**4**
MC_32	8	1-2-3-4-5-6-7-8-9-16-17-18-22	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-24-25-26-27-28	1-2-3-4-5-6-7-8-9-16-17-18-22	**4**
MC_48	9	1-2-3-4-5-6-7-8-9-16-17-18-22	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-24-25-26-27-28	1-2-3-4-5-6-7-8-9-16-17-18-22	**4**

Code	No.	Input Set	Output Set	Subscription Set	Level
ME_02	10	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-25-26-27-28	10-11-12-13-14-15-20-23-24-25-26-27	10-11-12-13-14-15-20-23-25-26-27	**2**
ME_03	11	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-25-26-27-28	10-11-12-13-14-15-20-23-24-25-26-27	10-11-12-13-14-15-20-23-25-26-27	**2**
ME_04	12	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-25-26-27-28	10-11-12-13-14-15-20-23-24-25-26-27	10-11-12-13-14-15-20-23-25-26-27	**2**
ME_05	13	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-25-26-27-28	10-11-12-13-14-15-20-23-24-25-26-27	10-11-12-13-14-15-20-23-25-26-27	**2**
ME_08	14	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-25-26-27-28	10-11-12-13-14-15-20-23-24-25-26-27	10-11-12-13-14-15-20-23-25-26-27	**2**
ME_13	15	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-25-26-27-28	10-11-12-13-14-15-20-23-24-25-26-27	10-11-12-13-14-15-20-23-25-26-27	**2**

Table 10. Segmentation of final accessibility matrix levels (continued)

Code	No.	Input Set	Output Set	Subscription Set	Level
SM_S_04	16	1-2-3-4-5-6-7-8-9-16-17-18-22	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-24-25-26-27-28	1-2-3-4-5-6-7-8-9-16-17-18-22	**4**
SM_S_09	17	1-2-3-4-5-6-7-8-9-16-17-18-22	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-24-25-26-27-28	1-2-3-4-5-6-7-8-9-16-17-18-22	**4**
SM_S_14	18	1-2-3-4-5-6-7-8-9-16-17-18-22	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-24-25-26-27-28	1-2-3-4-5-6-7-8-9-16-17-18-22	**4**
SM_E_01	19	1-2-3-4-5-6-7-8-9-16-17-18-19-22	10-11-12-13-14-15-19-20-23-24-25-26-27	19	**3**
SM_E_04	20	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-25-26-27-28	10-11-12-13-14-15-20-23-24-25-26-27	10-11-12-13-14-15-20-21-23-25-26-27	**2**
SM_E_07	21	1-2-3-4-5-6-7-8-9-16-17-18-21-22	10-11-12-13-14-15-20-21-23-24-25-26-27	21	**3**
SM_E_11	22	1-2-3-4-5-6-7-8-9-16-17-18-22	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-24-25-26-27-28	1-2-3-4-5-6-7-8-9-16-17-18-22	**4**
SM_EC_05	23	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-25-26-27-28	10-11-12-13-14-15-20-23-24-25-26-27	10-11-12-13-14-15-20-23-25-26-27	**2**
SM_EC_06	24	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-24-25-26-27-28	24	24	**1**
SM_EC_13	25	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-25-26-27-28	10-11-12-13-14-15-20-23-24-25-26-27	10-11-12-13-14-15-20-23-25-26-27	**2**
SM_EC_18	26	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-25-26-27-28	10-11-12-13-14-15-20-23-24-25-26-27	10-11-12-13-14-15-20-23-25-26-27	**2**
SM_EC_22	27	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-25-26-27-28	10-11-12-13-14-15-20-23-24-25-26-27	10-11-12-13-14-15-20-23-25-26-27	**2**
SM_EC_27	28	1-2-3-4-5-6-7-8-9-16-17-18-28	10-11-12-13-14-15-20-23-24-25-26-27-28	28	**3**

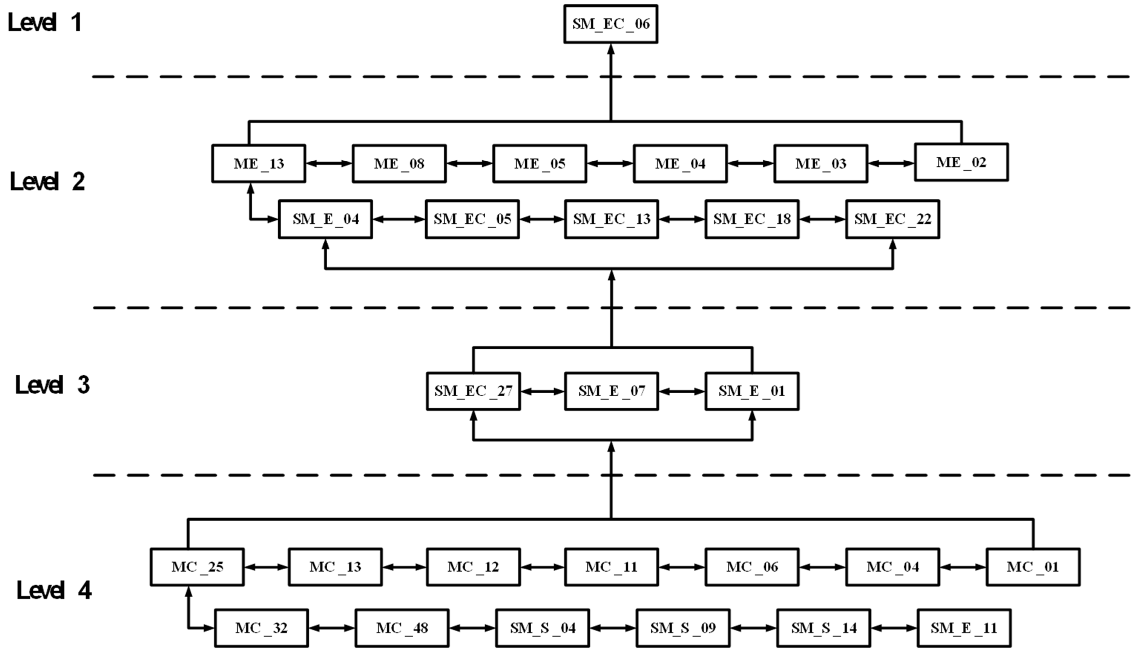


Fig. 3. Interpretive Structural Model (ISM)

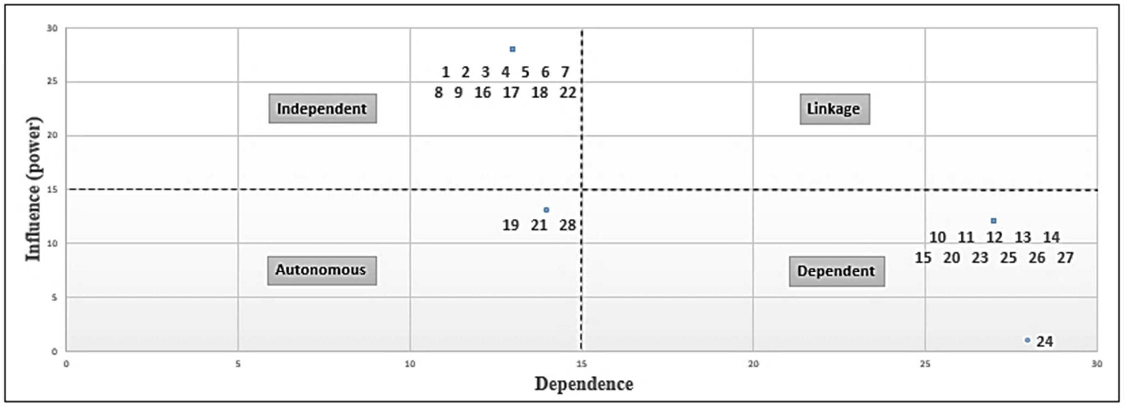
Based on the model derived from the ISM methodology (Fig. 3), the following key insights emerge:

Indicators situated at the lowest tier of the depicted model (fourth level) exhibit the most substantial influence on other indicators while being the least influenced by them. Notable factors include Maintenance 4.0 capabilities (MC_01 to MC_48) and aspects such as "Empowerment of human capital and development of employees' capabilities," "Participation in employee health and safety initiatives," "Fostering team spirit," and "Utilization of organic raw materials". Third-level indicators are influenced by fourth-level indicators and, in turn, influence second-level indicators. These indicators, including "Environmental pollutants and greenhouse gas emissions," "Resource recovery and manufacturing waste recycling," and "Identification of inefficient processes," wield significant influence in the model. Second-level indicators, impacted by the third-level indicators, play a pivotal role in influencing first-level indicators. Noteworthy indicators in this category encompass Maintenance 4.0 outcomes, "Resource optimization and conservation," "Risk assessment for organizational and customer well-being," "Timely delivery," "Adaptability to customer requirements," and "Enhanced customer-supplier interactions". Positioned at the pinnacle of the model (first level), "Operating costs" are influenced by other indicators while exerting the least impact on other variables. The interconnected relationships within the Interpretive Structural Model underscore the entanglement, interdependence, and synergy among the study indicators, echoing findings from prior research studies conducted by Mishra et al. (2021), Singh et al. (2021), Vinodh (2021), Sonar et al. (2020), and Rajput & Singh (2018).

Beyond the realm of Maintenance 4.0 capabilities, the outcomes of sustainable manufacturing practices, such as "Empowerment of human capital and development of employees' capabilities," "Participation in employee health and safety initiatives," "Fostering team spirit," and "Utilization of organic raw materials," also impact Maintenance 4.0 results. This underscores the intricate interplay, interdependence, and synergy between emerging Maintenance 4.0 technologies and sustainability metrics within the organizational framework.

4.4 MICMAC analysis

The position of each of the available indicators is plotted using its coordinate point in the MICMAC diagram (Fig. 4).



Determining boundaries = $(\frac{n}{2}) + 1 = (\frac{28}{2}) + 1 = 15$

Fig. 4. MICMAC graph

Based on Fig. 4, the following insights can be gleaned:

"Environmental pollutants and greenhouse gas emissions," "Resource recovery and recycling of manufacturing waste," and "Identification of inefficient processes" are identified as autonomous indicators within the model. The outcomes of Maintenance 4.0 and factors such as "Resource optimization and conservation," "Risk assessment for organizational and customer well-being," "Operating costs," "Timely delivery," "Adaptability to customer requirements," and "Enhanced customer-supplier interactions" are categorized as dependent indicators. No indicators in the third quarter exhibit linkage characteristics. Indicators depicted in the fourth quarter of the chart are deemed independent and serve as key indicators due to their significant penetration rate and low dependency rate, exerting a strong influence on the system processes. These pivotal indicators, encompassing Maintenance 4.0 capabilities and aspects like "Empowerment of human capital and development of employees' capabilities," "Participation in employee health and safety initiatives," "Fostering team spirit," and "Utilization of organic raw materials," warrant focused attention to driving sustainability objectives effectively.

5. Discussion

The insights garnered from the Fuzzy DEMATEL and ISM analyses offer valuable perspectives on the technological capabilities of Maintenance 4.0, the tangible outcomes of Maintenance 4.0, and the performance indicators for sustainable manufacturing across social, environmental, and economic dimensions. These findings have the potential to guide decision-making processes, shape strategic initiatives, and pave the way for further exploration in the realms of maintenance, digital transformation, and sustainable manufacturing. In the Fuzzy DEMATEL analysis, the most impactful indicator identified is "Real-time communication and cooperation among humans, machines, and sensors," while the most responsive indicator is "Operating costs". Moreover, the analysis underscores the significant interplay and influence of the social dimension of sustainable manufacturing, particularly concerning indicators related to human capital and employee development, on other sustainability facets. Conversely, the economic dimension emerges as the most responsive and susceptible to the influence of other sustainability dimensions. This outcome aligns with prior research by Legutko (2022), Li et al. (2022b), Samadhiya et al. (2024), Ching et al. (2022), emphasizing the importance of these findings.

The ISM technique reveals the critical importance of Maintenance 4.0 capabilities within the company and demonstrates how certain sustainable manufacturing outcomes, such as human capital empowerment, employee health and safety participation, team cohesion, and the use of organic materials, impact Maintenance 4.0 results. This underscores the intricate interconnectedness and synergy between the evolving technologies of Maintenance 4.0 and sustainability indicators within the company, as also highlighted in previous studies (e.g., Mishra et al., 2021; Sonar et al., 2020; Singh et al., 2021; Vigneshvaran & Vinodh, 2020; Rajput & Singh, 2018). Furthermore, the high level of agreement among the results obtained from Fuzzy DEMATEL, ISM, and MICMAC methodologies indicates a significant overlap in identifying effective and affected indicators. This convergence underscores the consistency and reliability of the findings, with no discrepancies observed among the results.

5.1 Theoretical implications

The integration of Industry 4.0 technologies in maintenance processes is crucial for enhancing manufacturing sustainability. The study focuses on mapping the effects and capabilities of Maintenance 4.0 on sustainable manufacturing performance indicators within a company. The research highlights the significance of incorporating sustainability performance indicators and the impact of Industry 4.0 technologies on decision-making processes in maintenance.

The study emphasizes the relationship between maintenance 4.0 capabilities and sustainable manufacturing performance indicators, shedding light on previously unexplored areas. By utilizing a combination of Fuzzy DEMATEL and Interpretive Structural Modeling (ISM), the intensity and direction of effects between indicators are elucidated.

5.2 Managerial implications

Prioritization of indicators: The analyses help in identifying the most influential indicators and their impact on sustainable manufacturing performance. Managers can prioritize their efforts and resources by focusing on the indicators that have a positive net effect, such as real-time communication and cooperation among humans, machines, and sensors. These indicators can be targeted for improvement and investment to enhance overall sustainability.

Emphasizing human capital and employee development: The strong influence of indicators related to human capital and employee development on other aspects of sustainability highlights the importance of investing in training, empowerment, and skill development of the workforce. Managers should focus on fostering a culture of learning, teamwork, and employee engagement to drive sustainable manufacturing practices.

Integration of digital technologies: Maintenance 4.0 capabilities play a significant role in sustainable manufacturing performance. Organizations should prioritize the integration of digital technologies, such as sensors, data analytics, and real-time communication systems, to enable proactive maintenance, reduce downtime, and enhance overall operational efficiency.

Environmental impact reduction: The analyses highlight the negative net effect of indicators related to environmental pollutants, greenhouse gas emissions, and unplanned breakdowns. Managers should implement strategies to minimize these impacts, such as adopting cleaner production processes, improving energy efficiency, and implementing preventive maintenance practices to reduce emissions and waste generation.

Cost optimization: The analysis identifies operating costs as a receptive indicator influenced by other aspects of sustainability. Managers should focus on optimizing costs through efficient resource utilization, effective maintenance planning, and adopting sustainable practices that can lead to long-term cost savings.

Strategy development: The findings can inform the development of comprehensive strategies for sustainable manufacturing. Managers can use the insights gained from the analyses to set performance targets, define action plans, and align their efforts with the social, environmental, and economic dimensions of sustainability.

Continuous improvement and monitoring: The interdependencies and hierarchy among indicators depicted in the ISM model highlight the need for continuous improvement and monitoring of sustainable manufacturing practices. Managers should establish performance metrics, conduct regular assessments, and leverage feedback mechanisms to drive ongoing improvements and ensure the effectiveness of sustainability initiatives.

By considering these practical and managerial implications, organizations can enhance their understanding of Maintenance 4.0, optimize their sustainable manufacturing performance, and contribute to a more environmentally responsible and socially conscious approach to production.

6. Conclusions

The study delves into the integration of Industry 4.0 technologies in maintenance processes to bolster sustainable manufacturing practices within organizations. By emphasizing the interplay between Maintenance 4.0 capabilities and sustainable manufacturing performance indicators, this research sheds light on previously unexplored territories. The study's contribution lies in mapping a comprehensive model that elucidates the impact of Maintenance 4.0 on sustainability within a company, paving the way for informed decision-making processes and enhanced operational efficiency. Furthermore, the societal impact of this research is significant as it aligns with the growing emphasis on sustainable production practices in the era of the fourth industrial revolution.

This study provides a structured framework for understanding the relationship between Maintenance 4.0 capabilities and sustainable manufacturing performance indicators. It also offers insights into the crucial role of Industry 4.0 technologies in driving sustainability within production enterprises. Furthermore, this research highlights the importance of integrating sustainability performance indicators in maintenance decision-making processes.

The findings have the potential to revolutionize maintenance practices in industrial organizations, fostering a shift towards more sustainable and efficient manufacturing processes. By leveraging Maintenance 4.0 capabilities, companies can optimize resource utilization, reduce costs, and enhance overall sustainability. This research contributes to the broader societal goal of promoting environmentally conscious and socially responsible business practices, aligning with the global trend towards sustainable production.

6.1 Research limitations and future study agenda

The study focuses on a subset of Maintenance 4.0 capabilities and results, omitting certain factors such as continuous improvement, less skilled operators, and marketing strategies. This limitation stems from the need to streamline the analysis process and may impact the comprehensiveness of the findings. The study primarily considers IoT technologies, big data analytics, and cloud computing as Industry 4.0 technologies, neglecting the examination of other essential technological components crucial for Maintenance 4.0 implementation. The conceptual model assumes a constant timeframe, overlooking the dynamic nature of indicators over time. This limitation restricts the exploration of evolving effects and trends in sustainable manufacturing performance indicators.

Future research could expand the scope of analyzed capabilities and results to encompass a broader range of factors influencing Maintenance 4.0 and sustainable manufacturing practices. Further investigation into additional Industry 4.0 technologies beyond the core components considered in this study could provide a more holistic understanding of Maintenance 4.0 implementation. Subsequent studies should explore the temporal dynamics of indicators to capture the evolving effects and relationships over time, enhancing the predictive capabilities of maintenance strategies in the context of sustainability.

References

Abidi, M. H., Mohammed, M. K., & Alkhalefah, H. (2022). Predictive Maintenance Planning for Industry 4.0 Using Machine Learning for Sustainable Manufacturing. *Sustainability*, 14 (6), 3387. https://doi.org/10.3390/su14063387.

Assad, F., Konstantinov, S., Nureldin, H., Waseem, M., Rushforth, E., Ahmad, B., & Harrison, R. (2021). Maintenance and digital health control in smart manufacturing based on condition monitoring. *Procedia CIRP*, 97, 142-147.

Awan, U., Kraslawski, A., & Huiskonen, J. (2018). Understanding influential factors on implementing social sustainability practices in Manufacturing Firms: An interpretive structural modelling (ISM) analysis. *Procedia Manufacturing*, 17, 1039-1048. https://doi.org/10.1016/j.promfg.2018.10.082.

Baboli, A. (2020). Introduction to Industry 4.0, *[PowerPoint Presentation]. Lyon, France*. armand.baboli@insa-lyon.fr.

Bag, S., & Pretorius, J. H. C. (2022). Relationships between industry 4.0, sustainable manufacturing and circular economy: proposal of a research framework. *International Journal of Organizational Analysis*, 30(4), 864-898. https://doi.org/10.1108/IJOA-04-2020-2120.

Bhanji, S., Shotz, H., Tadanki, S., Miloudi, Y., & Warren, P. (2021). Advanced Enterprise Asset Management Systems: Improve Predictive Maintenance and Asset Performance by Leveraging Industry 4.0 and the Internet of Things (IoT). *In ASME/IEEE Joint Rail Conference* (Vol. 84775, p. V001T12A002). American Society of Mechanical Engineers. https://doi.org/10.1115/JRC2021-58346.

Ching, N. T., Ghobakhloo, M., Iranmanesh, M., Maroufkhani, P., & Asadi, S. (2022). Industry 4.0 applications for sustainable manufacturing: A systematic literature review and a roadmap to sustainable development. *Journal of Cleaner Production*, 334, 130133. https://doi.org/10.1016/j.jclepro.2021.130133.

Çınar, Z. M., Abdussalam Nuhu, A., Zeeshan, Q., Korhan, O., Asmael, M., & Safaei, B. (2020). Machine learning in predictive maintenance towards sustainable smart manufacturing in Industry 4.0. *Sustainability*, 12(19), 8211. https://doi.org/10.3390/su12198211.

Di Carlo, F., Mazzuto, G., Bevilacqua, M., & Ciarapica, F. E. (2021). Retrofitting a process plant in an Industry 4.0 perspective for improving safety and maintenance performance. *Sustainability*, 13(2), 646. https://doi.org/10.3390/su13020646.

Drakaki, M., Karnavas, Y. L., Tzionas, P., & Chasiotis, I. D. (2021). Recent Developments Towards Industry 4.0 Oriented Predictive Maintenance in Induction Motors. *Procedia Computer Science*, 180, 943-949. https://doi.org/10.1016/j.procs.2021.01.345.

Enyoghasi, C., & Badurdeen, F. (2021). Industry 4.0 for sustainable manufacturing: Opportunities at the product, process, and system levels. *Resources, conservation and recycling*, 166, 105362. https://doi.org/10.1016/j.resconrec.2020.105362.

Eschen, H., Kötter, T., Rodeck, R., Harnisch, M., & Schüppstuhl, T. (2018). Augmented and virtual reality for inspection and maintenance processes in the aviation industry. *Procedia manufacturing*, 19, 156-163. https://doi.org/10.1016/j.promfg.2018.01.022.

Franciosi, C., Iung, B., Miranda, S., & Riemma, S. (2018). Maintenance for sustainability in the Industry 4.0 context: A scoping literature review. *IFAC-PapersOnLine*, 51(11), 903-908. https://doi.org/10.1016/j.ifacol.2018.08.459.

Franciosi, C., Voisin, A., Miranda, S., & Iung, B. (2020). Integration of I4. 0 technologies with maintenance processes: what are the effects on sustainable manufacturing?. *IFAC-PapersOnLine*, 53(3), 1-6. https://doi.org/10.1016/j.ifacol.2020.11.001.

Furstenau, L. B., Sott, M. K., Kipper, L. M., Machado, E. L., Lopez-Robles, J. R., Dohan, M. S., ... & Imran, M. A. (2020). The link between sustainability and Industry 4.0: trends, challenges and new perspectives. *Ieee Access*, 8, 140079-140096. https://doi.org/10.1109/ACCESS.2020.3012812.

Gadekar, R., Sarkar, B., & Gadekar, A. (2022). Investigating the relationship among Industry 4.0 drivers, adoption, risks reduction, and sustainable organizational performance in manufacturing industries: An empirical study. *Sustainable Manufacturing and Consumption*, 31, 670-692. https://doi.org/10.1016/j.spc.2022.03.010.

Gutschi, C., Furian, N., Pan, J., & Vössner, S. (2019). A conceptual modelling framework for evaluating the performance of predictive maintenance for modern, real-world manufacturing systems using potentials and risks of Industry 4.0. *In 2019 4th International Conference on System Reliability and Safety (ICSRS)* (pp. 267-274). IEEE. https://doi.org/10.1109/ICSRS48664.2019.8987658.

Harikannan, N., Vinodh, S., & Gurumurthy, A. (2021). Sustainable Industry 4.0 – an exploratory study for uncovering the drivers for integration. *Journal of Modelling in Management*, 16(1), 357-376. https://doi.org/10.1108/JM2-11-2019-0269.

Hermann, M., Pentek, T., & Otto, B. (2016). Design Principles for Industrie 4.0 Scenarios .In 2016 49th Hawaii International Conference on System Sciences (HICSS) (pp. 3928– 3937). IEEE.

Hien, N. N., Lasa, G., Iriarte, I., & Unamuno, G. (2022). An overview of Industry 4.0 Applications for Advanced Maintenance Services. *Procedia Computer Science*, 200, 803-810. https://doi.org/10.1016/j.procs.2022.01.277.

Jamwal, A., Agrawal, R., & Sharma, M. (2022). Deep learning for manufacturing sustainability: Models, applications in Industry 4.0 and implications. *International Journal of Information Management Data Insights*, 2(2), 100107. https://doi.org/10.1016/j.jjimei.2022.100107.

Jasiulewicz-Kaczmarek, M., & Gola, A. (2019). Maintenance 4.0 Technologies for Sustainable Manufacturing Overview. *IFAC-PapersOnLine*, 52(10), 91-96. https://doi.org/10.1016/j.ifacol.2019.10.005.

Jasiulewicz-Kaczmarek, M., Legutko, S., & Kluk, P. (2020). Maintenance 4.0 technologies – new opportunities for sustainability-driven maintenance. *Management and Manufacturing Engineering Review*, 11. https://doi.org/10.24425/mper.2020.133730.

Javaid, M., Haleem, A., Singh, R. P., Khan, S., & Suman, R. (2022). Sustainability 4.0 and its applications in the field of manufacturing. *Internet of Things and Cyber-Physical Systems*, 2, 82-90. https://doi.org/10.1016/j.iotcps.2022.06.001.

Kamble, S. S., Gunasekaran, A., & Gawankar, S. A. (2018). Sustainable Industry 4.0 framework: A systematic literature review identifying the current trends and future perspectives. *Process Safety and Environmental Protection*, 117, 408–425. https://doi.org/10.1016/j.psep.2018.05.009.

Khan, S., Khan, M. I., & Haleem, A. (2019). Evaluation of barriers in the adoption of halal certification: a fuzzy DEMATEL approach. *Journal of Modelling in Management*, 14(1), 153-174. https://doi.org/10.1108/JM2-03-2018-0031.

Khanzode, A. G., Sarma, P. R., Mangla, S. K., & Yuan, H. (2021). Modelling the Industry 4.0 adoption for sustainable manufacturing in Micro, Small & Medium Enterprises. *Journal of Cleaner Manufacturing*, 279, 123489. https://doi.org/10.1016/j.jclepro.2020.123489.

Lambán, M. P., Morella, P., Royo, J., & Sánchez, J. C. (2022). Using Industry 4.0 to face the challenges of predictive maintenance: A key performance indicators development in a cyber-physical system. *Computers & Industrial Engineering*, 171, 108400. https://doi.org/10.1016/j.cie.2022.108400.

Legutko, S. (2022). Industry 4.0 Technologies for the Sustainable Management of Maintenance Resources. In *International Conference Innovation in Engineering* (pp. 37-48). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-031-09360-9_4.

Leng, J., Ruan, G., Jiang, P., Xu, K., Liu, Q., Zhou, X., & Liu, C. (2020). Blockchain-empowered sustainable manufacturing and product lifecycle management in industry 4.0: A survey. *Renewable and sustainable energy reviews*, 132, 110112. https://doi.org/10.1016/j.rser.2020.110112.

Li, J., Schaefer, D., & Milisavljevic-Syed, J. (2022 a). A Decision-Based Framework for Predictive Maintenance Technique Selection in Industry 4.0. *Procedia CIRP*, 107, 77-82. https://doi.org/10.1016/j.procir.2022.04.013.

Li, Q., Yang, Y., & Jiang, P. (2022 b). An Industry 4.0 Platform for Equipment Monitoring and Maintaining in Carbon Anode Manufacturing. *IFAC-PapersOnLine*, 55(2), 37-41. https://doi.org/10.1016/j.ifacol.2022.04.166.

Liu, G., Yang, H., Fu, Y., Mao, C., Xu, P., Hong, J., & Li, R. (2020). Cyber-physical system-based real-time monitoring and visualization of greenhouse gas emissions of prefabricated construction. *Journal of Cleaner Manufacturing*, 246 ,119059. https://doi.org/10.1016/j.jclepro.2019.119059.

Im, S. J., Viet, N. D., & Jang, A. (2021). Real-time monitoring of forward osmosis membrane fouling in wastewater reuse process performed with a deep learning model. *Chemosphere*, 275, 130047.

Lu, Y. (2017). Industry 4.0: A survey on technologies, applications and open research issues .*Journal of Industrial Information Integration* ,6 ,1–10.

Lukač, D. (2015). The fourth ICT-based industrial revolution" Industry 4.0"—HMI and the case of CAE/CAD innovation with EPLAN P8 .In 2015 23rd *Telecommunications Forum Telfor (TELFOR)* (pp. 835-838). IEEE.

Luthra, S., & Mangla, S. K. (2018). Evaluating challenges to Industry 4.0 initiatives for supply chain sustainability in emerging economies .*Process Safety and Environmental Protection* ,117 ,168–179.

Machado, C. G., Winroth, M. P., & Ribeiro da Silva, E. H. D. (2020). Sustainable manufacturing in Industry 4.0: an emerging research agenda. *International Journal of Manufacturing Research*, 58(5), 1462-1484. https://doi.org/10.1080/00207543.2019.1652777.

Maddikunta, P.K.R., Pham, Q.V., Prabadevi, B., Deepa, N., Dev, K., Gadekallu, T.R., ... & Liyanage, M. (2022). Industry 5.0: A survey on enabling technologies and potential applications .*Journal of Industrial Information Integration* ,26 ,100257.

Markowski, K., Wojakowski, K., Pokropek, E., & Marzęcki, M. (2020). Numerical and experimental performance analysis of the chirped fibre Bragg grating-based abrasion sensor for maintenance applications in Industry 4.0. *Sensors*, 20(3), 770. https://doi.org/10.3390/s20030770.

Menon, S., Shah, S., & Coutroubis, A. (2018). Impacts of I4. 0 on sustainable manufacturing to achieve competitive advantage. https://core.ac.uk/download/pdf/301021995.pdf.

Mirhosseini, S. S., Azar, A., & Jahanyan, S. (2019). Examining the Risks and Obstacles to the Success of ERP implementation using the Critical System Heuristics (CSH) Approach. *Modern Research in Decision Making*, 4(4), 31-58. https://doi.org/20.1001.1.24766291.1398.4.4.2.2.

Mishra, R. P., Gupta, G., & Sharma, A. (2021). Development of a Model for Total Productive Maintenance Barriers to Enhance the Life Cycle of Productive Equipment. *Procedia CIRP*, 98, 241-246. https://doi.org/10.1016/j.procir.2021.01.037.

Nara, E. O. B., da Costa, M. B., Baierle, I. C., Schaefer, J. L., Benitez, G. B., do Santos, L. M. A. L., & Benitez, L. B. (2021). Expected impact of industry 4.0 technologies on sustainable development: A study in the context of Brazil's plastic industry. *Sustainable Production and Consumption*, 25, 102-122. https://doi.org/10.1016/j.spc.2020.07.018.

Newman, I., Lim, J., & Pineda, F. (2013). Content validity using a mixed methods approach: Its application and development through the use of a table of specifications methodology. *Journal of Mixed Methods Research*, 7(3), 243-260. https://doi.org/10.1177/1558689813476922.

Nissoul, H., El Harrouti, T., Serrou, D., & Abouabdellah, A. (2020). Impact of maintenance 4.0 on the performance of the manufacturing function: Application to the automotive industry in Morocco. In *2020 5th International Conference on Logistics Operations Management (GOL)* (pp. 1-5). IEEE. https://doi.org/10.1109/GOL49479.2020.9314737.

Paudel, N., & Neupane, R. C. (2021). A general architecture for a real-time monitoring system based on the Internet of Things. *Internet of Things*, 14(5), 100367. https://doi.org/10.1016/j.iot.2021.100367.

Rajput, S., & Singh, S. P. (2018). Identifying Industry 4.0 IoT enablers by integrated PCA-ISM-DEMATEL approach. *Management Decision*, 57(8), 1784-1817. https://doi.org/10.1108/MD-04-2018-0378.

Reis, T. A., & Campos, F. C. (2020). Industry 4.0 influences on maintenance operation: a bibliometric analysis. *IFAC-PapersOnLine*, 53(2), 10633-10638. https://doi.org/10.1016/j.ifacol.2020.12.2823.

Sahba, R., Radfar, R., Ghatari, A. R., & Ebrahimi, A. P. (2021). Development of Industry 4.0 predictive maintenance architecture for broadcasting chain. *Advanced Engineering Informatics*, 49, 101324

Sahli, A., Evans, R., & Manohar, A. (2021). *Predictive Maintenance in Industry 4.0: Current Themes. Procedia CIRP*, 104, 1948-1953

Samadhiya, A., Agrawal, R., & Garza-Reyes, J. A. (2024). Integrating Industry 4.0 and total productive maintenance for global sustainability. *The TQM Journal*, 36(1), 24-50. https://doi.org/10.1108/TQM-05-2022-0164.

Samadhiya, A., Agrawal, R., Luthra, S., Kumar, A., Garza-Reyes, J. A., & Srivastava, D. K. (2023). Total productive maintenance and Industry 4.0 in a sustainability context: exploring the mediating effect of the circular economy. *The International Journal of Logistics Management*, 34(3), 818-846. https://doi.org/10.1108/IJLM-04-2022-0192.

Shafiee, S., Ghatari, A. R., Hasanzadeh, A., & Jahanyan, S. (2022). Developing a model for smart tourism destinations: an interpretive structural modelling approach. *Information Technology & Tourism*, 24(4), 511-546. https://doi.org/10.1007/s40558-022-00236-7.

Sharma, R., Jabbour, C. J. C., & Lopes de Sousa Jabbour, A. B. (2021). Sustainable manufacturing and industry 4.0: what we know and what we don't. *Journal of Enterprise Information Management*, 34(1), 230-266. https://doi.org/10.1108/JEIM-01-2020-0024.

Silvestri, L., Forcina, A., Introna, V., Santolamazza, A., & Cesarotti, V. (2020). Maintenance transformation through Industry 4.0 technologies: a systematic literature review. *Computers in Industry*, 123, 103335. https://doi.org/10.1016/j.compind.2020.103335.

Sindhwani, R., Afridi, S., Kumar, A., Banaitis, A., Luthra, S., & Singh, P.L. (2022). Can industry 5.0 revolutionize the wave of resilience and social value creation? A multi-criteria framework to analyze enablers .*Technology in Society* ,68 ,101887.

Singh, C., Singh, D., & Khamba, J. S. (2021). Developing a conceptual model to implement green lean practices in Indian manufacturing industries using the ISM-MICMAC approach. *Journal of Science and Technology Policy Management*, 12(4), 587-608. https://doi.org/10.1108/JSTPM-08-2019-0080.

Singh, P. K., & Sarkar, P. (2020). A framework based on fuzzy Delphi and DEMATEL for sustainable product development: A case of Indian automotive industry. *Journal of Cleaner Manufacturing*, 246, 118991. https://doi.org/10.1016/j.jclepro.2019.118991.

Soldatos, J., Gusmeroli, S., Malo, P., & Di Orio, G. (2016). Internet of Things Applications in Future Manufacturing. Digitising the Industry . *Internet of Things Connecting the Physical and Virtual World* ,(July), 153–183.

Sonar, H., Khanzode, V., & Akarte, M. (2020). Investigating additive manufacturing implementation factors using integrated ISM-MICMAC approach. *Rapid Prototyping Journal*, 26(10), 1837-1851. https://doi.org/10.1108/RPJ-02-2020-0038.

Tortorella, G., Saurin, T. A., Fogliatto, F. S., Tlapa, D., Moyano-Fuentes, J., Gaiardelli, P., ... & Forstner, F. F. (2022). The impact of Industry 4.0 on the relationship between TPM and maintenance performance. *Journal of Manufacturing Technology Management*, 33(3), 489-520. https://doi.org/10.1108/JMTM-10-2021-0399.

Trivedi, A., Jakhar, S. K., & Sinha, D. (2021). Analyzing barriers to inland waterways as a sustainable transportation mode in India: a DEMATEL-ISM based approach. *Journal of Cleaner Production*, 295, 126301. https://doi.org/10.1016/j.jclepro.2021.126301.

Uhlmann, E., Laghmouchi, A., Geisert, C., & Hohwieler, E. (2017). *Decentralized data analytics for maintenance in industrie 4.0. Procedia Manufacturing*, 11, 1120-1126

Vinodh, S. (2021). Development of a structural model based on ISM for analysis of barriers to integration of lean with industry 4.0. *The TQM Journal*, 33(6), 1201-1221. https://doi.org/10.1108/TQM-07-2020-0151.

Vishwakarma, A., Dangayach, G. S., Meena, M. L., & Gupta, S. (2022). Analysing barriers of sustainable supply chain in apparel & textile sector: A hybrid ISM-MICMAC and DEMATEL approach. *Cleaner Logistics and Supply Chain*, 5, 100073. https://doi.org/10.1016/j.clscn.2022.100073.

Xenakis, A., Karageorgos, A., Lallas, E., Chis, A. E., & González-Vélez, H. (2019). Towards distributed IoT/cloud-based fault detection and maintenance in industrial automation. *Procedia Computer Science*, 151, 683-690. https://doi.org/10.1016/j.procs.2019.04.091.

Xu, X., Lu, Y., Vogel-Heuser, B., & Wang, L. (2021). Industry 4.0 and Industry 5.0—Inception, conception and perception .*Journal of Manufacturing Systems* ,61 ,530-535.