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ORIGINAL RESEARCH

A decision framework for SMEs to address sustainability issues with Industry 4.0 technologies

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Abstract
This study investigates the adoption of Industry 4.0 technologies in Small and Medium Enterprises (SMEs) within emerging economies, focusing on sustainability and resource efficiency. Extant research often targets larger firms or developed economies, leaving SMEs in emerging markets underexplored. This study proposes a holistic framework for SMEs to enhance Industry 4.0 adoption, addressing sustainability goals while improving competitiveness. Twenty-five enablers of Industry 4.0 adoption were identified through a systematic literature review and validated their significance through a survey of 233 Indian manufacturing SMEs. Using Exploratory Factor Analysis, the enablers were clustered into five groups: Digital and Physical Technologies, Organizational, Supply Chain, Environmental, and Social. Fuzzy-AHP prioritized the enablers, while Fuzzy-DEMATEL explored their interrelationships. Sensitivity analysis validated the results, ensuring robustness. Analyzed results highlight organizational readiness, such as dedicated R&D teams and managerial support. Inter-organizational factors, such as supply chain integration and social enablers with effective policies, were also found to be pivotal. Digital technologies and environmental strategies emerged as factors dependent on robust organizational and policy support. Practical recommendations include targeted resource allocation, skill development, and policy interventions to support digital transformation. This research bridges gaps in Industry 4.0 adoption and advances SME participation in sustainable global supply chains.

Keywords Industry 4.0 · Sustainability · Resource efficiency · Fuzzy AHP · Fuzzy-DEMATEL · Small and medium enterprises (SMEs)

1 Introduction

The advancement of Industry 4.0 offers the transformative potential to enhance productivity, resource efficiency, economic growth, and sustainability across industries. Extant literature has identified several factors influencing the adoption of Industry 4.0, such as physical and technological resources, technical skills, broader supply chain infrastructure, and effective

Extended author information available on the last page of the article organizational change management and the impact of these factors on sustainability. However, the majority of the literature has studied these factors in the context of developed economies and based on a larger organizational backdrop (Chauhan et al., 2021; Raj et al., 2020). Understanding of the adoption of Industry 4.0 technologies in small and medium-sized enterprises (SMEs) in emerging markets remains limited (Horváth & Szabó, 2019; Kumar et al., 2022, 2023; Mangla et al., 2024; Yadav et al., 2020). Active participation of SMEs from emerging markets, where infrastructural and organizational contexts differ significantly, is essential for achieving the broader objectives of sustainable manufacturing (Mishra & Pathak, 2024).

While some literature has examined the impact of different factors on Industry 4.0 adoption in emerging economies (Raj et al., 2020), a holistic interrelationship between these factors remains less understood. This restricts SMEs from developing effective Industry 4.0 adoption strategies and prioritizing their resources accordingly. A published McKinsey report argues that a transformation from a conventional production system to an automated one could improve productivity from around 45–55%[1]. Hence, examining how these factors interrelate is crucial to help SMEs develop effective strategies and optimize resource allocation to navigate the Industry 4.0 transition. Accordingly, this article aims to address the following two research objectives.

- **Research Objective 1**: To identify and validate the critical enablers of Industry 4.0 that contribute to improving manufacturing sustainability.
- **Research Objective 2**: To prioritize these enablers and uncover the causal interrelationships among the enablers within SMEs in emerging economies.

To achieve these objectives, this study conducted a systematic literature review and identified key enablers influencing Industry 4.0 adoption. Following this, a survey of 233 Indian SMEs was carried out to contextualize the significance of these factors. Using Exploratory Factor Analysis, the factors were grouped into clusters. Fuzzy-AHP was employed to rank their hierarchical importance, while Fuzzy-DEMATEL identified causal relationships, categorizing the clusters into cause-and-effect groups. These methodologies provided valuable insights into the interplay and prioritization of these enablers.

Consequently, the findings of this research will assist policymakers in creating a supportive environment for SMEs to adopt Industry 4.0 technologies. A deeper understanding of the specific challenges faced by SMEs in emerging markets like India—such as funding limitations, skill shortages, and technological readiness—can guide the development of targeted policies. Addressing these barriers comprehensively can enable SMEs to adopt sustainable manufacturing practices. This alignment with global supply chain objectives and sustainability targets can further enhance their competitiveness and resilience. The remainder of the paper is structured as follows: Sect. 2 presents a comprehensive literature review. Section 3 details the research methodology employed in the study. Section 4 discusses the findings and provides an in-depth discussion. Section 5 outlines the theoretical and managerial implications of the research. Finally, Sect. 6 concludes the paper, summarizing the key insights and contributions.

[1] https://www.infopulse.com/blog/the-main-benefits-and-challenges-of-industry-4-0-adoption-in-manufacturing.

2 Literature review

We conducted a systematic literature review on the enablers of Industry 4.0. The detailed protocols are outlined in Fig. 1. This review identified 25 enablers of Industry 4.0 adoption, summarised in Table 1 with the support of the relevant literature. This section examines key enablers in the literature and highlights limitations in the knowledge base. For more details on the 25 enablers, refer to Table 1.

Technology is identified as one of the key enablers for Industry 4.0. Some leading technologies like additive manufacturing are identified as facilitators of the development of practices leading to sustainability (Laskurain-Iturbe et al., 2021; Rai et al., 2021; Sonar et al., 2024; Vasileska et al., 2024). Other technologies, such as immersive technologies like Virtual and Augmented Reality (VAR) have been found to enable the simulation of real-life scenarios for employee training, risk mitigation planning, preventing hazardous situations, supporting decision-making, and practice procedures. Furthermore, VAR facilitates the development of augmented reality, where live direct or indirect views of physical environments are enhanced with computer-generated overlay images (Laskurain-Iturbe et al., 2021). Other technologies that gained attention in the extant literature include cyber-physical systems for improving machine utilization and human-machine interaction, networking and connectivity advancements, leveraging the Internet of Things (IoT) for convenience of data collection from multiple sources, cloud computing for time and place-independent access to data, RTLS technologies, and sensors, Big Data Analytics for gaining insights from a vast pool of gathered data, and Artificial Intelligence for various automated tasks among many others (Dubey et al., 2019; Frank et al., 2019; Galati & Bigliardi, 2019; Lu, 2017; Mittal et al., 2018; Strozzi et al., 2017). Despite the potential, organizations often struggle to implement these technologies successfully and get the most benefits out of these technologies due to high-cost outlay and lack of robust infrastructural support (Pachouri et al., 2024). Additional challenges include cybersecurity threats and integration complexity. These challenges are more prominent for SMEs in emerging economies where organiza-

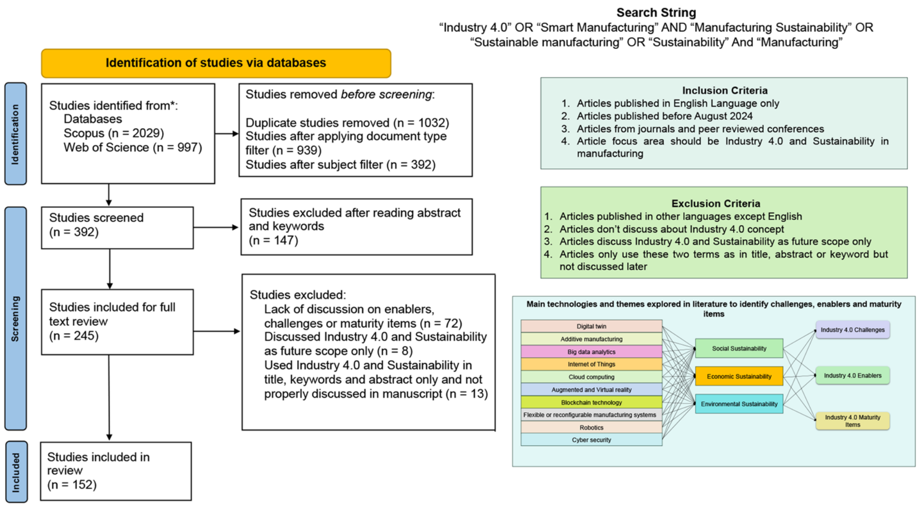

Fig. 1 Systematic literature review protocols

Table 1 Enablers for industry 4.0 implementation

S.NO.	Enabler name	Description	Reference
EN1	Additive manufacturing	It is an enabler of Industry 4.0 and leverages digital connectivity and data-driven processes to fabricate products layer by layer.	(Enyoghasi & Badurdeen, 2021; Jamwal et al., 2021; Karnik et al., 2022; Laskurain-Iturbe et al., 2021; Rai et al., 2021; Sonar et al., 2024; Vasileska et al., 2024; Vianna et al., 2020)
EN2	Cyber-physical systems	It is also an enabler of Industry 4.0, combining digital and physical elements to create smart, interconnected processes that enable real-time data exchange.	(Frank et al., 2019; Herterich et al., 2015; Karnik et al., 2022; Thiede, 2018; Vianna et al., 2020; Yadav et al., 2020)
EN3	Augmented and Virtual reality	It integrated physical entities into the digital world to enhance training, design, and maintenance processes. Also, it reduces the need for physical prototypes.	(Enyoghasi & Badurdeen, 2021; Frank et al., 2019; Laskurain-Iturbe et al., 2021; Menon et al., 2018; Wee et al., 2015)
EN4	Horizontal and Vertical integration	It facilitates the seamless communication within and between organizations. Horizontally, it links the departments for streamlined processes, and vertically, it connects the entire supply chain to improve resource efficiency.	(Arcuri & Giolli, 2022; Frank et al., 2019; Karnik et al., 2022; Orsdemir et al., 2019)
EN5	IoT and IoS-based platforms	It integrates devices and systems to gather and share real-time data to optimize processes and reduce resource consumption.	(Frank et al., 2019; Karnik et al., 2022; Mittal et al., 2018; Rajput & Singh, 2019; Tao et al., 2018; Vianna et al., 2020)
EN6	Dedicated R&D teams	It is an integral part of Industry 4.0 to drive innovation in processes and technology. It contributes to long-term sustainability in organizations.	(Bildirici & Ersin, 2023; de Sousa Jabbour et al., 2018; Marnewick & Marnewick, 2019; Mittal et al., 2018; Wang et al., 2023)
EN7	Top-level management support	It is important for Industry 4.0 success; a strong executive endorsement drives organizational alignment with its sustainability goals.	(Abdul-Rashid et al., 2017; Bag et al., 2021a, b; Behl et al., 2023; El Baz et al., 2022; Khan et al., 2024; Luthra & Mangla, 2018; Yadav et al., 2020)
EN8	Workforce knowledge and digital skills	A skilled workforce that uses digital technologies drives sustainability and innovation culture.	(Karnik et al., 2022; Li, 2022; Mittal et al., 2018; Wagire et al., 2020)
EN9	IT-based facilities and infrastructure	It is the core of Industry 4.0, which integrates digital technologies to optimize resource usage and process optimization.	(Karnik et al., 2022; Lasi et al., 2014; Luthra & Mangla, 2018; Mittal et al., 2018; Wagire et al., 2020)
EN10	Industry 4.0 supportive policies and budget	It is related to the funds and policies required for digital transformation and facilitates the integration of sustainable practices and technology.	(Banal-Estañol et al., 2015; Ghisetti & Rennings, 2014; Luthra & Mangla, 2018; Mittal et al., 2018; Yadav et al., 2020)
EN11	Supplier integration through digital platforms	Digital platforms connect suppliers and manufacturers, optimizing resource utilization and reducing waste. It also facilitates real-time communication and collaboration.	(Ardito et al., 2018; Karnik et al., 2022; Liu et al., 2022; Manavalan & Jayakrishna, 2019; Rahimi et al., 2024)

Table 1 (continued)

S.NO.	Enabler name	Description	Reference
EN12	Institutional Technology	Blockchain is an institutional technology and it is an enabler of Industry 4.0, which ensures secure and transparent data sharing across the value chain. Also, it enhances trust and traceability by minimizing fraud and providing ethical practices.	(Esmaeilian et al., 2020; Karnik et al., 2022; Khan et al., 2022; Leng et al., 2020; Saberi et al., 2019)
EN13	Real-time tracking in the supply chain	It is an I4.0 core capability that constantly monitors goods in transit. Minimizing delays and waste and optimizing logistics helps to improve resource utilization and transparency.	(Karnik et al., 2022; Manavalan & Jayakrishna, 2019; Soori et al., 2023; Yadav et al., 2020)
EN14	Supplier commitment to sustainability	It ensures reduced environmental impacts and ethical sourcing by fostering a culture of responsible production and supply chain management.	(Benzidia et al., 2021; Karnik et al., 2022; Luthra & Mangla, 2018; Shayganmehr et al., 2021; Yadav et al., 2020)
EN15	Reverse logistics	An important Industry 4.0 practice that ensures better management of product returns, remanufacturing, and recycling. It promotes CE principles by optimizing product recovery and waste minimization.	(Aljuneidi & Bulgak, 2020; Dev et al., 2020; Garrido-Hidalgo et al., 2019; Yadav et al., 2020)
EN16	Adopting Sustainable design strategies	It prioritizes eco-friendly and long-lasting products. It focuses on maximizing resource efficiency from the design phase, minimizing environmental impacts, and supporting a CE.	(Chou, 2024; Dahmani et al., 2021; Ghobakhloo, 2020; Kamble et al., 2018; Machado et al., 2020; Nayal et al., 2023; Yadav et al., 2020)
EN17	Adoption of renewable sources	It is a key Industry 4.0 practice that reduces reliance on fossil fuels. Adopting clean energy sources decreases the carbon footprints and contributes to a greener future.	(Ghobakhloo, 2020, 2021; Llopis-Albert et al., 2021; Scharl & Praktiknjo, 2019; Tsolakis et al., 2019; Yadav et al., 2020)
EN18	Life cycle thinking	It involves considering the entire product lifecycle. This assessment of environmental impacts from raw materials to disposal is done, which guides manufacturers to make sustainable decisions and foster responsible practices culture in their organizations.	(Behl et al., 2023; Mohan & Katakojwala, 2021; Yadav et al., 2020)
EN19	Sustainability awareness and training programs	These initiatives help to educate the workforce about sustainable practices. It ensures awareness and training of employees to integrate eco-friendly strategies and reduce resource waste.	(Bag et al., 2021a; Kumar et al., 2020; Luthra et al., 2020; Mittal et al., 2018; Schlegel et al., 2017)
EN20	Government policies for sustainability	It promotes eco-friendly practices through regulations and incentives. It also encourages technology adoption, responsible resource use in organizations.	(Harikannan et al., 2021; Luthra et al., 2020; Schwab et al., 2019; Yadav et al., 2020)
EN21	Data protection policies	It ensures secure handling of digital information and builds digital trust. It also safeguards sensitive manufacturing data and enables responsible technology adoption. These policies support sustainability practices while advancing digital transformation.	(Mittal et al., 2018; Trstenjak & Cosic, 2017; Ziebermayr, 2021)

Table 1 (continued)

S.NO.	Enabler name	Description	Reference
EN22	Human Resource Management 4.0	An essential Industry 4.0 aspect that focuses on aligning workforce skills with digital advancements. It supports innovation and sustainable growth by reducing skill gaps.	(Carlsson, 2023; Ghobakhloo, 2020; Hecklau et al., 2016; Kiel et al., 2017; Mukhuty et al., 2022; Rana & Sharma, 2019)
EN23	Customer response adoption	It involves addressing customer needs by using real-time data. It helps in minimizing overproduction, optimal resource allocation, and better market responsiveness.	(Ibarra et al., 2018; Manavalan & Jayakrishna, 2019; Müller & Däschle, 2018)
EN24	Man-machine interaction	It involves collaboration between humans and machines to optimize task efficiency and reduce resource waste. It can be considered a push button for digital twin-based manufacturing.	(Beltrami et al., 2021; Liu et al., 2019; Lu, 2017; Yadav et al., 2020)
EN25	Functional safety	It helps to reduce the unwanted risks that can be caused by malfunctioning physical entities and programmable technologies.	(Beltrami et al., 2021; da Anunciação et al., 2022; Habib & Chimsom, 2019; Liu et al., 2019)

tions are constrained by various factors, including limited budgets and restricted access to funds (Kumar et al., 2020; Masood & Sonntag, 2020).

Apart from the technologies and associated infrastructure, organizational factors have been identified as other key foundational enablers for successful Industry 4.0 implementation. One such factor is top management support. It is a critical determinant of successful Industry 4.0 adoption and sustainability, serving as a pivotal catalyst for organizational transformation in the rapidly evolving technological landscape. Extensive research demonstrates that strategic leadership engagement significantly enhances employee motivation, technological integration, and organizational readiness for digital transformation (Bag et al., 2021a; Baz et al., 2022; Behl et al., 2023; Khan et al., 2024). The absence of top management support has been found to act as a barrier to successful Industry 4.0 implementation (Bag et alb., 2021b). This type of support prepares the workforce with the necessary knowledge and skills required for Industry 4.0 adoption (Li, 2022). Despite these advantages, workforce upskilling is often neglected, particularly in resource-constrained SMEs (Roy Ghatak & Garza-Reyes, 2024). Research and development (R&D) is another organizational facet that has been found to be a key enabler in the literature. Any investment in digital transformation linked to R&D enhances improvements in carbon performance and sustainability (Wang et al., 2023). However, this need for investment could impede access to R&D and act as a barrier for organizations that are financially constrained (Bildirici & Ersin, 2023). To this end, government funding schemes have been identified to enhance technological advancement and diversification (Ghisetti & Rennings, 2014) through financial support and collaboration opportunities, influenced by funding intensity (Banal-Estañol et al., 2015). However, research evidence has often underscored that these types of support mechanisms may be limited due to various challenges in emerging regions of the world (Kumar et al., 2020; Reza et al., 2024).

Alongside the organizational enablers, certain inter-organizational factors have also been identified in extant literature to play an integral role in the successful implementation of Industry 4.0 such as the existence of a supply chain and the way the supply chain is mapped

(Mubarik et al., 2021). Extant research has argued for the need for transformation of the supply chain along the lines of cleaner production to achieve sustainability in the era of Industry 4.0 (Ivanov & Dolgui, 2021; Manavalan & Jayakrishna, 2019). Supply chain integration, particularly close collaboration with suppliers, has been considered to be one such supply chain phenomenon that can facilitate the supply chain mapping required for Industry 4.0 (Ardito et al., 2018; Rahimi et al., 2024). In this context, supplier integration through digital platforms and the adoption of institutional technologies (e.g. blockchain technology) have been found to improve transparency and accountability in sourcing and procurement practices (Khan et al., 2022; Saberi et al., 2019). These efforts can ensure that sustainability is embedded throughout the supply chain and address system-level sustainability. These efforts are supported by real-time tracking capabilities, which can allow manufacturers to proactively manage resources and waste (Soori et al., 2023). To improve overall sustainability, reverse logistics and sustainable design strategies provide a holistic approach for manufacturers to achieve resource efficiency and carbon neutrality (Aljuneidi & Bulgak, 2020). With these strategies manufacturing organizations not only meet regulatory demands but also respond to the growing consumer preference for sustainable products. Such practices also help them gain a competitive edge in the global market. However, these practices of reverse logistics and sustainable design are often marred by infrastructural and financial challenges that require smart budget allocations (Yadav et al., 2020). This makes successful implementation challenging for SMEs, as they are often constrained by significant financial challenges.

Furthermore, factors relevant to the sustainability considerations (e.g. sustainable design, need for holistic thinking such as product lifecycle approach, adopting sustainable alternative choices such as renewable sourcing, and governmental support and regulations) play a pivotal role in determining the successful implementation of Industry 4.0 technologies that can facilitate sustainable choices (Ameknassi et al., 2016; Sindhwani et al., 2023; Zhang et al., 2022). Integrating sustainability aspects into product design has been found to improve market performance, address changing customer needs (Dahmani et al., 2021; Nayal et al., 2023), and foster agile, responsive, resource-efficient, and sustainability-conscious design processes (Chou, 2024). These design efforts are further strengthened by enhancing the understanding of sustainability's impact across the entire product lifecycle. This helps organizations to make effective decisions during the production and consumption stages to drive sustainability initiatives (Behl et al., 2023). Furthermore, adopting renewable sourcing has been found to enhance these sustainability efforts. Extant literature has focused on applications of renewable sourcing in the car industry (Llopis-Albert et al., 2021; Tsolakis et al., 2019), and chemical industries, among others. These practices can be accelerated through strategic guidelines and increased governmental support (Liu et al., 2020a, b; Reza et al., 2024). Moreover, generating this sustainability awareness requires dedicated training programs, which have been found to be a key enabler of Industry 4.0. Continuous training programs help to facilitate upskilling of employees (Schlegel et al., 2017). This ensures that employees are making an effort to utilize these new tools and methodologies. These efforts help to foster a culture of sustainability within organizations (Müller et al., 2018) and enhance competitiveness in digitalized production (Schlegel et al., 2017). However, these efforts often remain rudimentary due to various issues associated with greening (decarbonization) of the supply chains (Sindhwani et al., 2023). The authors further iterated the reasons including limited access to funds, lack of awareness, lack of expertise, and resistance to change as notable barriers. These challenges are especially pronounced in SMEs.

Extant literature has also explored certain additional human-centric enablers (e.g. integrating human resources practices with technology and managing this human-machine interaction, consideration of customer feedback to the decision making, responsible usage of data by having rigorous data protection policies, and having a proper working environment that ensures the safety) that influence the implementation of Industry 4.0. Transforming the workforce to be ready to embrace advanced technologies has garnered attention in the literature as these advanced HRM practices are essential for addressing digitalization challenges in the industrial value chain. Extant literature highlighted various relevant aspects such as transferring senior engineers' expertise to intelligent systems and novices (Carlsson, 2023), emphasizing job enrichment, rotation, and enlargement to enhance worker autonomy in computerized production (Cirillo et al., 2021), and incentives to boost AI interaction in key industries like automotive and electronics (Pillai et al., 2022). These attempts to integrate the existing human resources with advanced technology facilitate the human-machine interaction that is necessary for the effective implementation of Industry 4.0 (Kiel et al., 2017). Research further suggested that these improved man-machine interaction initiatives are becoming important from moral, ethical, and legal requirements to ensure functional workplace safety of interacting with advanced technologies (Beltrami et al., 2021; Liu et al., 2019).

Despite these developments, the current research landscape reveals substantial methodological limitations, primarily characterized by a pronounced geographic and organizational bias that constrains a comprehensive understanding of Industry 4.0 dynamics. Predominantly, existing studies have concentrated on economically advanced regions, effectively marginalizing insights from emerging economies where infrastructural, technological, and organizational contexts fundamentally differ (Mishra & Pathak, 2024). This research myopia creates significant knowledge gaps, particularly regarding how smaller enterprises—often the economic backbone of developing nations—navigate complex technological transitions. While some scholarly efforts have attempted to explore Industry 4.0 and Sustainable manufacturing adoption in contexts like India (Yadav et al., 2020) and Malaysia (Abdul-Rashid et al., 2017), these investigations predominantly focused on larger organizational structures, thereby overlooking the nuanced challenges and unique adaptation strategies of small and medium enterprises (SMEs). Examining localized challenges, such as resource constraints and cultural resistance, can offer broader insights into overcoming barriers to technological advancement. This expansion can enable the development of more inclusive strategies that address global Industry 4.0 implementation challenges.

3 Research methodology

This article employs a multi-method approach to explore the factors influencing Industry 4.0 implementation in SMEs within emerging economies. It assesses the relevance of these factors and ranks them based on their significance. A systematic literature review was conducted (outlined in the previous section) and identified 25 factors associated with Industry 4.0 adoption. Based on the identified factors, a survey was administered to SMEs in India to gather 233 valid responses regarding their perspectives on the importance of these factors in the Indian context. The survey data underwent Exploratory Factor Analysis, which grouped the 25 factors into five broader clusters. Following this, the Fuzzy Analytical Hierarchy Process was applied to rank the factors by assigning weights and determining priorities. To investigate the causal relationships among the clusters and categorize them into cause and effect groups, the Fuzzy-DEMATEL technique was employed. The proposed methodological framework is described in Fig. 2. Sensitivity analyses were performed to validate the robustness of the findings. In the next section, we discuss the details of the survey conducted, followed by the details of the Fuzzy Analytical Hierarchy Process (Fuzzy AHP), and finally the details of Fuzzy DEMATEL.

3.1 Survey details and data collection

In this study, we identified potential manufacturing SMEs using online industry directories. Stratified random sampling yielded 1,147 active SMEs in India's manufacturing sector. A pre-tested questionnaire was developed with input from two professors and four industry experts specializing in digitalization and sustainability. The finalized questionnaire was shared via email, along with the study's purpose and enabler descriptions. It included three sections: (1) General Information, (2) Main Questions, and (3) Demographics. In the first three months, 157 responses were collected. To enhance participation, experts from these firms were contacted through various social media channels, adding 87 responses. After data cleaning, 11 invalid responses were excluded, leaving valid data for analysis. The survey

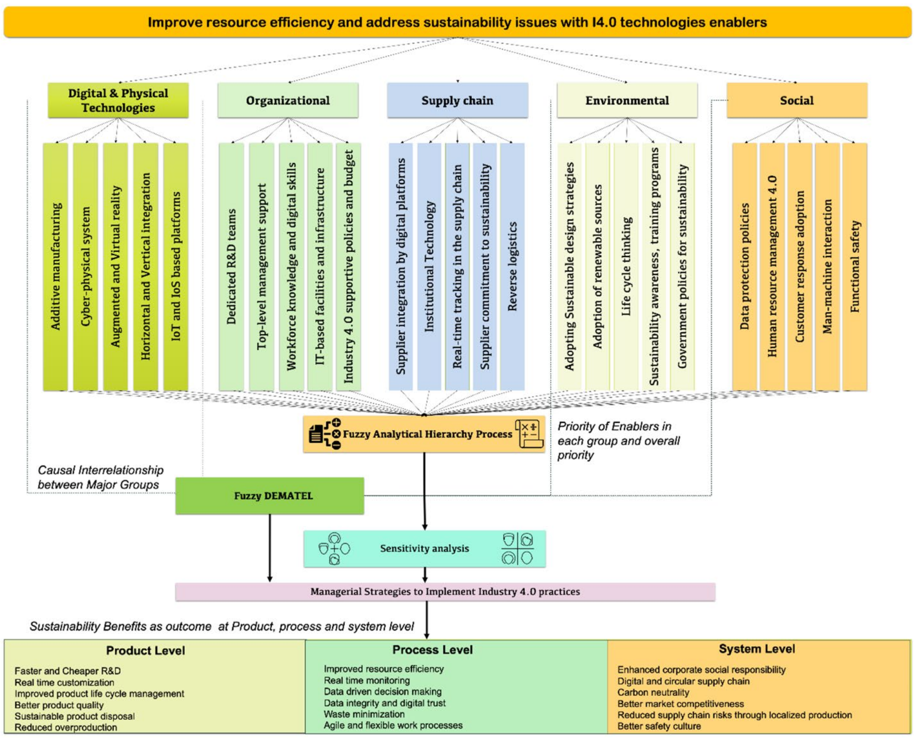

Fig. 2 Framework to achieve manufacturing sustainability in I4.0

achieved a 21.3% response rate, acceptable for I4.0 research in India (Luthra & Mangla, 2018; Yadav et al., 2020). Demographics of the SMEs are detailed in Table 2. Enablers were categorized through expert consultation and validated using exploratory factor analysis (see Supplementary Material). The 25 enablers were grouped into five categories: (1) Physical and Digital Technologies, (2) Organizational, (3) Supply Chain, (4) Environmental, and (5) Social. Survey findings confirmed the significance of all enablers in the Indian context. The mean scores for each enabler are shown in Table 3. In the analysis, we found that each variable involved in the study had more than a factor loading of more than 0.5, demonstrating the data's convergent validity. In this case, the Kaiser-Meyer-Olkin (KMO) value was 0.781, indicating that the data was suitable for factor analysis (Field, 2013). In order to rank these 25 enablers, we performed the Fuzzy AHP technique. This is discussed in the next section.

3.2 Triangular fuzzy AHP

In the literature, the Analytic Hierarchy Process (AHP) is widely recognized for its effectiveness in multicriteria decision-making. However, the traditional AHP approach has notable limitations, particularly in addressing vagueness and uncertainty (Chang, 1996). To overcome these limitations, this study employed a Triangular Fuzzy AHP approach, as suggested by previous research (Liu et al., 2020a, b). This integration enhances the decision-making process by providing a more nuanced evaluation of criteria and alternatives (Kubler et al., 2016). Given its suitability for decision-making in similar contexts, the Fuzzy AHP methodology was adopted for this study. To implement this approach, experts from an electronics manufacturing SME located in northern India were selected as the case organization. The firm has a broader customer base across India and other international destinations, including Nepal, Hong Kong, and the UAE. Based on the experts' inputs, pairwise comparisons were conducted for the identified criteria and sub-criteria. It is worth noting that the choice of sampling approach should align with the specific context and research objectives (Stratton, 2021). For Industry 4.0 (I4.0) adoption in emerging economies like India, convenience sampling is particularly useful due to its resource efficiency and alignment with time constraints

Table 2 Demographic summary of SMEs respondents

Indicator	Response	Frequency
Industry sector	Manufacturing	84
	Chemical and Pharmaceutical	40
	Mineral Industries	23
	Agriculture and Food processing	28
	Electrical and Electronics	58
Organizational Function	Finance and HR	21
	Information Technology	7
	R&D	29
	Production and Supply Chain	176
Experience	Less than 5 Years	34
	Between 5–10 years	91
	More than 10 years	108
Respondent profile	Top management	22
	Middle management	147
	Others	64

Table 3 Significance of enabling factors based on mean score

Enabler group	Enabling factor	Mean	Significance
Digital and Physical Technologies	Additive manufacturing	2.76	Yes
	Cyber-physical system	3.11	Yes
	Augmented and Virtual reality	2.91	Yes
	Horizontal and Vertical integration	2.94	Yes
	IoT and IoS-based platforms	2.97	Yes
Organizational	Dedicated R&D teams	4.00	Yes
	Top-level management support	3.94	Yes
	Workforce knowledge and digital skills	3.90	Yes
	IT-based facilities and infrastructure	3.87	Yes
	Industry 4.0 supportive policies and budget	3.96	Yes
Supply chain	Supplier integration through digital platforms	3.58	Yes
	Institutional technology	3.72	Yes
	Real-time tracking in the supply chain	3.77	Yes
	Supplier commitment to sustainability	3.58	Yes
	Reverse logistics	3.80	Yes
Environmental	Adopting Sustainable design strategies	3.30	Yes
	Adoption of renewable sources	3.36	Yes
	Life cycle thinking	3.62	Yes
	Sustainability awareness and training programs	3.18	Yes
	Government policies for sustainability	3.53	Yes
Social	Data protection policies	3.97	Yes
	Human Resource Management 4.0	3.88	Yes
	Customer response adoption	4.08	Yes
	Man-machine interaction	3.87	Yes
	Functional safety	3.97	Yes

(Luthra & Mangla, 2018). The selected organization was actively pursuing its I4.0 journey, incorporating technologies such as IoT, additive manufacturing, and machine learning. Eight experts from the company were initially approached. Following discussions with the executive members and top management, five experts agreed to participate and provide their insights. The details of these experts are presented in Table 4. To overcome any subjectivity in expert opinion, we performed sensitivity analysis on the results of the Fuzzy AHP (See

Table 4 Details of experts

Expert No.	Expert Designation	Experience (In Years)	Expertise
Expert 1	Plant Head	17	Production planning, Quality, and predictive maintenance
Expert 2	Production Manager	14	Mass production, batch production,
Expert 3	Head Production and IT	10	Automation, supply chain management
Expert 4	R&D Manager	12	R&D, product development
Expert 5	Digital Consultant	9	I4.0 pilot projects, Shop floor digitalization

Sect. 3.2.1). The steps followed in the Triangular Fuzzy-AHP approach, as suggested by Kumar et al. (2023), which is based on (Chang, 1996; Zhu et al., 1999) are discussed below:

Step 1 Fuzzy synthetic extent (FSE) value for i^{th} object was calculated as follows (Eq. 1).

$$X_i = \sum_{j=1}^{m} A_{gi}^{j} \odot \left[\sum_{i=1}^{n} \sum_{j=1}^{m} A_{gi}^{i} \right]^{-1} \tag{1}$$

In the provided equation, “ A_{gi}^{i}” denotes the extent analysis value acquired for each criterion within the context of the goal set represented by “ gi” Additionally, all the TFNs were represented as described in Eq. (2).

$$\sum_{j=1}^{m} A_{gi}^{j} \tag{2}$$

The computation for Eq. 1 can be done as follows:

$$\sum_{j=1}^{m} A_{gi}^{j} = \left(\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j \right) \tag{3}$$

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} A_{gi}^{i} \right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} \sum_{j=1}^{m} u_{ij}}, \frac{1}{\sum_{i=1}^{n} \sum_{j=1}^{m} m_{ij}}, \frac{1}{\sum_{i=1}^{n} \sum_{j=1}^{m} l_{ij}} \right) \tag{4}$$

Step 2 The calculation of the degree of possibility of superiority for each FSE value over the others was determined using Eq. (5).

$$D_P\left(A_2 \geq A_1\right) = \begin{cases} 1, & m_2 \geq m_1 \\ 0, & l_1 \geq u_2 \\ \frac{l_1 - u_2}{(m_2 \geq u_2) - (m_1 \geq l_1)}, & otherwise \end{cases} \tag{5}$$

Step 3 For a convex fuzzy number that was larger than the fuzzy number k, then the degree of possibility was computed using Eqs. (6) and (7).

$$D_P\left(A \geq A_1, A_2, \ldots \ldots ., A_k\right) = \min D_P\left(A \geq A_i\right) \tag{6}$$

where

$$i \in 1{,}2, \ldots ., k \text{ or } y'\left(Z_i\right) = \min D_P(X_i \geq X_k) \tag{7}$$

Step 4 The normalized weight vectors, which played a critical role in the analysis, were precisely represented as outlined in Eq. (8)

$$W = \left(y\left(Z_1\right), y\left(Z_2\right), \ldots ., y\left(Z_n\right)\right)^T \tag{8}$$

Here, W is the non-fuzzy number weight which can be used to rank the enablers.

Further, Fig. 3 shows the global weights of enablers of I4.0 technologies identified from the Triangular Fuzzy AHP employed in this study.

The results from the Fuzzy AHP method rely on expert opinions. These opinions may be subjective, and influenced by personal experiences. To ensure robust and reliable decisions, a sensitivity analysis was conducted. This analysis examines how expert inputs, such as pairwise comparisons, affect the rankings. It also addresses uncertainty and improves the model's transparency. These steps enhance trust among stakeholders and help generalize the findings. Details of this analysis are provided in Sect. 3.2.1.

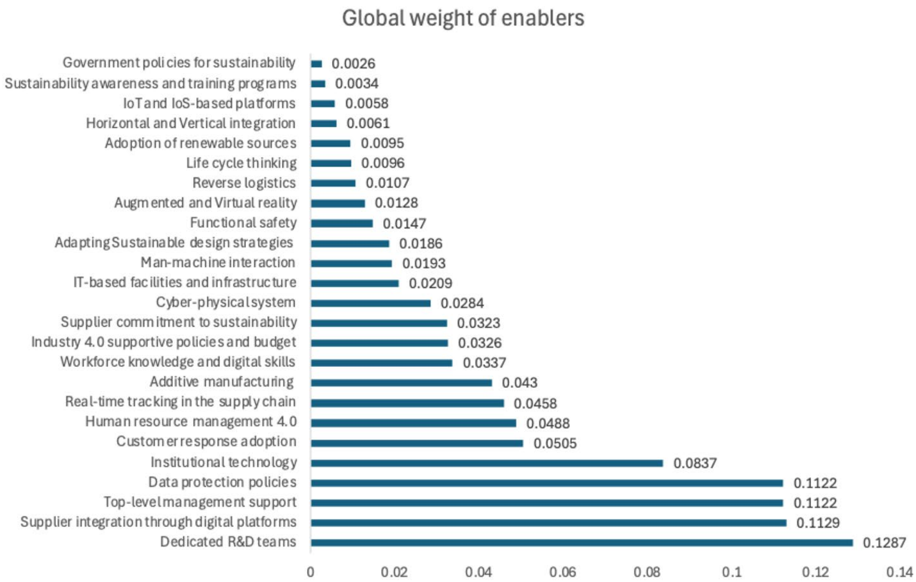

Fig. 3 Global weight of Enablers based on Fuzzy-AHP

3.2.1 Sensitivity analysis of enablers ranks

Sensitivity analysis was conducted to explore how variations in the weights of enablers impact the overall ranking of these enablers. The analysis involved adjusting the expert-assigned weights. The summarized outcomes of the sensitivity analysis are presented in Fig. 4. It was found that the ranking of most of the enablers was stable and remained stable and unchanged. However, minor fluctuations in the results were observed in the results. Therefore, the proposed framework for Industry 4.0 practices is comprehensive and robust, demonstrating consistency in the enablers' weights.

In this study, prioritization of enablers was done based on Fuzzy-AHP to determine their relative importance within the framework. However, the prioritization does not help to capture the complex interactions among the different enabler groups. Moreover, Fuzzy-AHP does not consider how these enablers interact. Therefore, in the next section, we performed Fuzzy-DEMATEL techniques to investigate the causal inter-relationship among the enabler groups.

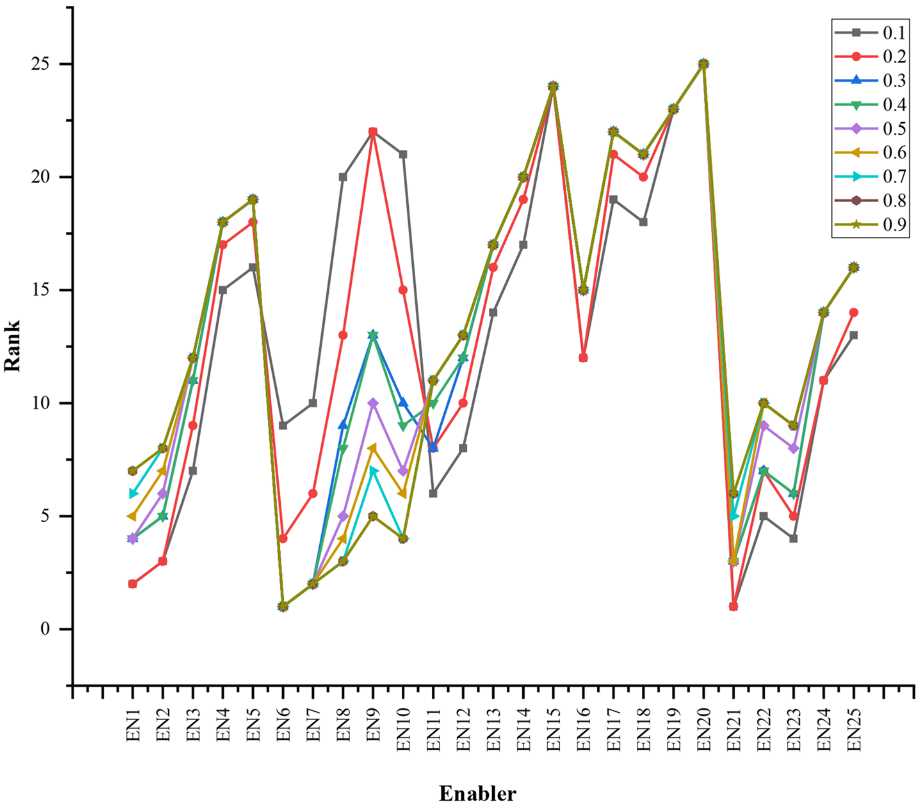

Fig. 4 Sensitivity analysis results

3.2.2 Fuzzy-DEMATEL approach

The DEMATEL approach was used in the literature to determine the causal interrelationship among factors (Si et al., 2018). However, the traditional DEMATEL approach faces challenges in addressing uncertainty during decision-making. To overcome these issues, the Fuzzy-DEMATEL approach was introduced (Wu & Lee, 2007). This method enhances the decision-making process by effectively handling uncertainty and determining the causal interrelationships among the major criteria involved in decision-making problems. In the present study, the Fuzzy-DEMATEL approach was employed to identify the causal interrelationship between the major enabler groups. The steps involved in Fuzzy DEMATEL approach used in this study are discussed as below:

3.2.2.1 Step 1: generate a fuzzy direct-relationship matrix among the enablers To identify the relationship between n criteria of a problem, a $n \times n$ matrix was generated (See Eq. 9). In our case, with five clusters, n=5. The fuzzy numbers in the matrix represent the influence of each enabler. If multiple experts were involved, their opinions were considered individually, and the matrix was completed by each expert. Then, the arithmetic mean of all expert opinions was then calculated to obtain the direct relationship matrix, denoted as a.

$$a = \begin{bmatrix} 0 & \cdots & \tilde{a}_{n1} \\ \vdots & \ddots & \vdots \\ \tilde{a}_{1n} & \cdots & 0 \end{bmatrix} \tag{9}$$

Further, Table 5 represents the fuzzy scale used in Fuzzy-DEMATEL.

The direct relation matrix was derived based on the pairwise comparisons made by the experts. Table 6 shows the direct relation matrix.

3.2.2.2 Step 2: normalization of fuzzy direct relationship matrix The normalization of the fuzzy direct relationship matrix was applied (Eq. 10 and Eq. 11) as follows:

$$\tilde{n}_{xy} = \frac{\tilde{a}_{xy}}{r} = \left(\frac{l_{xy}}{r}, \frac{m_{xy}}{r}, \frac{u_{xy}}{r}\right) \tag{10}$$

where,

Table 5 Fuzzy scale for DEMATEL approach

Response	Linguistic term	U	M	L
1	No influence	0.25	0	0
2	Lower influence	0.5	0.25	0
3	Medium influence	0.75	0.5	0.25
4	Higher influence	1	0.75	0.5
5	Very high influence	1	1	0.75

Table 6 Direct relation matrix

	Digital and Physical Technologies	Organizational	Supply Chain	Environmental	Social
Digital and Physical Technologies	(0.000,0.000,0.000)	(0.000,0.200,0.450)	(0.000,0.050,0.300)	(0.000,0.200,0.450)	(0.000,0.100,0.350)
Organizational	(0.250,0.500,0.750)	(0.000,0.000,0.000)	(0.200,0.450,0.700)	(0.300,0.550,0.800)	(0.100,0.350,0.600)
Supply Chain	(0.250,0.500,0.750)	(0.050,0.300,0.550)	(0.000,0.000,0.000)	(0.150,0.400,0.650)	(0.000,0.250,0.500)
Environmental	(0.000,0.250,0.500)	(0.000,0.250,0.500)	(0.000,0.100,0.350)	(0.000,0.000,0.000)	(0.000,0.250,0.500)
Social	(0.150,0.400,0.650)	(0.100,0.350,0.600)	(0.000,0.250,0.500)	(0.100,0.350,0.600)	(0.000,0.000,0.000)

$$r = \max_{x,y}\left\{\max_{x}\sum_{y=1}^{N} u_{xy}, \max_{y}\sum_{x=1}^{N} u_{xy}\right\} \quad x \in \{1,2,3,\ldots,N\}\ and\ y \in \{1,2,3,\ldots,N\} \tag{11}$$

3.2.2.3 Step 3: fuzzy total relation matrix (FTRM) Based on the pairwise comparisons, a Fuzzy Total Relation Matrix (FTRM) was developed and computed using Eq. 12. This matrix represents the relationship between the factors.

$$\tilde{T} = \lim_{k \to +\infty}\left(\tilde{n}^{1} \oplus \tilde{n}^{2} \oplus \ldots \oplus \tilde{n}^{k}\right) \tag{12}$$

If each factor in the fuzzy total relation matrix was represented as: $\tilde{t}_{\mathrm{xy}} = (\mathrm{l}''_{\mathrm{xy}}, \mathrm{m}''_{\mathrm{xy}}, \mathrm{u}''_{\mathrm{xy}})$, then it could be computed as (Eq. 13, Eq. 14, Eq. 15):

$$\left[l''_{xy}\right] = n_l \times (I - n_l)^{-1} \tag{13}$$

$$\left[m''_{xy}\right] = n_m \times (I - n_m)^{-1} \tag{14}$$

$$\left[u''_{xy}\right] = n_u \times (I - n_u)^{-1} \tag{15}$$

In this scenario, we first calculated the inverse of the normalized matrix and subtracted it from the identity matrix (I). Subsequently, we multiplied the normalized matrix by the resulting matrix to complete the computation.

3.2.2.4 Step 4: defuzzification The conversion of the fuzzy crisp score method was applied to derive precise values for the factors in the total relation matrix using Eqs. 16, 17, 18, and 19.

$$l^{N}_{xy} = \frac{\left(l^{t}_{xy} - \min l^{t}_{xy}\right)}{\Delta^{max}_{min}} \tag{16}$$

$$m^{N}_{xy} = \frac{\left(m^{t}_{xy} - min\ l^{t}_{xy}\right)}{\Delta^{max}_{min}} \tag{17}$$

$$u^{N}_{xy} = \frac{\left(u^{t}_{xy} - min\ l^{t}_{xy}\right)}{\Delta^{max}_{min}} \tag{18}$$

So that

$$\Delta^{max}_{min} = \max u^{t}_{xy} - \min l^{t}_{xy} \tag{19}$$

The upper and lower bounds for each normalized value were calculated using Eqs. (20) and (21)

$$l_{xy}^{s} = m_{xy}^{N} \Big/ (1 + m_{xy}^{N} - l_{xy}^{N}) \tag{20}$$

$$u_{xy}^{s} = u_{xy}^{N} \Big/ (1 + u_{xy}^{N} - l_{xy}^{N}) \tag{21}$$

Total normalized crisp values in the matrix can be calculated as (Eq. 22):

$$n_{xy} = \frac{\left[l_{xy}^{s}\left(1 - l_{xy}^{s}\right) + u_{xy}^{s} \times \ u_{xy}^{s}\right]}{\left[1 - l_{xy}^{s} + u_{xy}^{s}\right]} \tag{22}$$

Table 7 shows the total relation matrix.

3.2.2.5 Step 5: threshold value To determine the threshold value for the internal relation matrix, partial relations within the matrix were excluded. A network relationship map was then plotted, including only relations with values exceeding the threshold. Values below the threshold were set to zero. In this study, the threshold value was determined to be 0.220, and all values below this were computed as zero. The total relation matrix, adjusted for the threshold, is presented in Table 8.

3.2.2.6 Step 6: causal relationship diagram At this stage, the sum of each column in the crisp total relation matrix was calculated. The sum of the columns is represented as 'R,' while the sum of the rows is represented as 'D.' These values were computed using Eqs. (23) and (24).

$$D = \sum_{x=1}^{N} T_{xy} \tag{23}$$

$$R = \sum_{y=1}^{N} T_{xy} \tag{24}$$

The values of D+R represent the degree of importance, whereas the values of D-R indicate the net effect of a specific factor within the system (Raj et al., 2020). The Final output matrix containing D and R values is displayed in Table 9.

Table 7 The crisp total relation matrix

	Digital and Physical Technologies	Organizational	Supply Chain	Environmental	Social
Digital and Physical Technologies	0.11	0.163	0.109	0.183	0.13
Organizational	0.375	0.177	0.283	0.375	0.269
Supply Chain	0.344	0.244	0.125	0.306	0.221
Environmental	0.231	0.198	0.143	0.134	0.19
Social	0.314	0.254	0.209	0.29	0.134

Table 8 Total relationship matrix after considering threshold value

	Digital and Physical Technologies	Organizational	Supply Chain	Environmental	Social
Digital and Physical Technologies	0	0	0	0	0
Organizational	0.375	0	0.283	0.375	0.269
Supply Chain	0.344	0.244	0	0.306	0.221
Environmental	0.231	0	0	0	0
Social	0.314	0.254	0	0.29	0

Table 9 Final output

	R	D	D+*R*	D-*R*
Digital and Physical Technologies	1.375	0.695	2.07	-0.679
Organizational	1.036	1.48	2.516	0.445
Supply Chain	0.869	1.24	2.109	0.37
Environmental	1.288	0.896	2.184	-0.391
Social	0.945	1.201	2.146	0.256

The significant relations in the decision-making problem are visually represented in Fig. 5, where D+R values are plotted along the horizontal axis, and D-R values are plotted along the vertical axis.

4 Findings and discussions

The causal interrelationship among the five major clusters: Digital and Physical Technologies, Organizational, Supply Chain, Environmental, and Social was obtained from Fuzzy DEMATEL analysis. Each cluster's role was evaluated using four metrics: degree of influence (R), degree of dependence (D), total prominence (D+R), and net effect (D−R), offering insights into their importance and interdependencies within the framework. In the Fuzzy-DEMATEL approach, negative D-R values indicate impact factors, while positive values denote causal factors. In our study (as illustrated in Fig. 5; Table 9), Organizational, Supply Chain, and Social factors have emerged as causal, whereas Digital and Physical Technologies and Environmental factors have emerged as effects. This result aligns with previous studies that identify these factors as critical drivers in facilitating Industry 4.0 implementation, emphasizing their proactive roles in shaping policies and practices (Raj & Jeyaraj, 2023).

Total prominence (D+R) identifies the most influential cluster, with higher values indicating a greater impact. As illustrated in Table 9, Organizational factors rank highest (2.516), followed by Environmental (2.184), Social (2.146), Supply Chain (2.109), and Digital and Physical Technologies (2.07). This highlights the critical role of Organizational factors in Industry 4.0 adoption for sustainability and resource efficiency. They guide strategic decisions, align resources with sustainability goals, and support technology implementation. These findings align with the findings of McKinsey which emphasize that robust organizational frameworks improve energy management, waste reduction, and sustainability by reducing carbon footprints (Hammer & Somres, 2021).

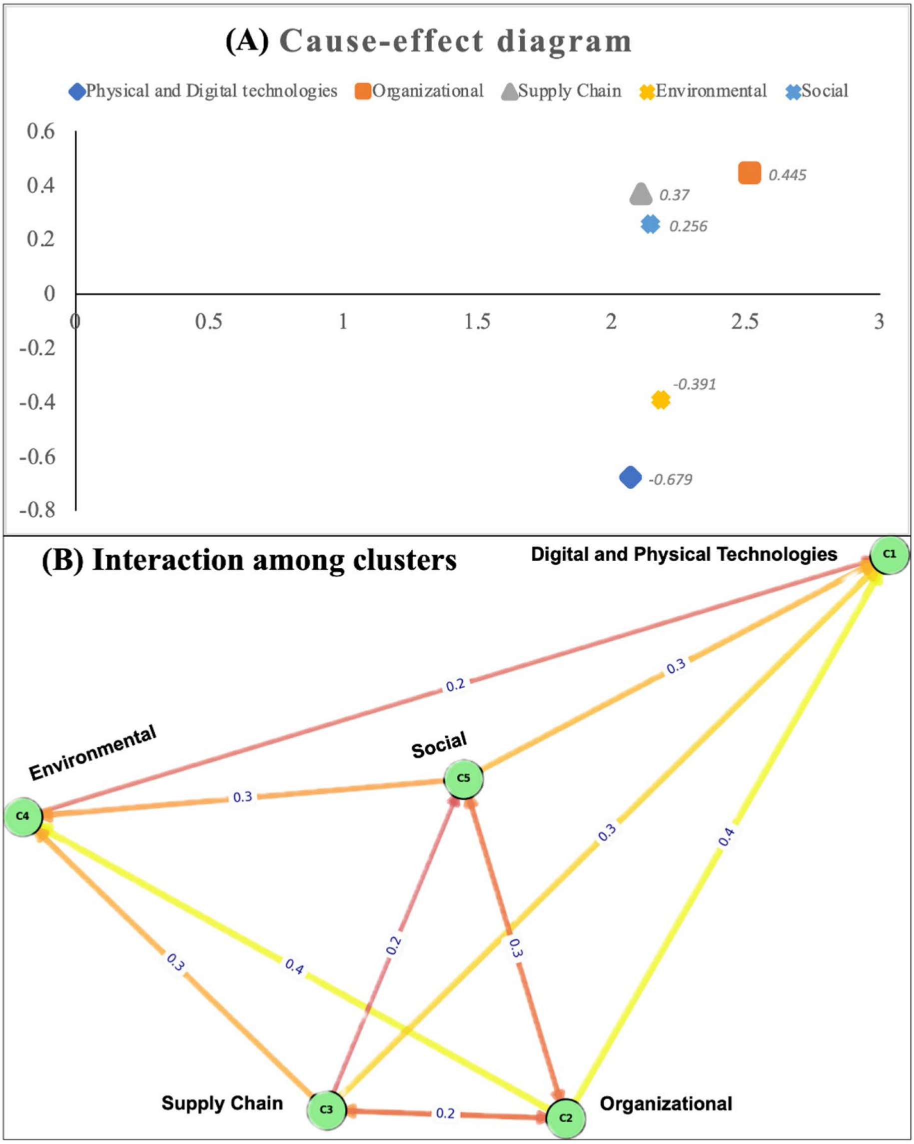

Fig. 5 Cause-effect diagram and interaction among clusters

Organizational, Supply Chain, and Social clusters (causing clusters), are crucial for driving change in Industry 4.0 adoption. The Social factor cluster was found to have a positive net effect, but it has been found to be less significant in comparison to other causal clusters (Organizational and Supply Chain). These findings align with studies emphasizing Organizational and Supply Chain readiness as key drivers in Industry 4.0 adoption (Stentoft et al., 2021). Social considerations, such as data protection, customer response adoption, and human resource management 4.0, play a supportive yet responsive role within the Industry 4.0 ecosystem. Digital and Physical Technologies and Environmental clusters are effect clusters, influenced by the actions of other clusters rather than driving change. This aligns with findings that these aspects rely on organizational and policy frameworks for progress. The dependency of Digital and Physical Technologies highlights the need for organizational and supply chain support to maximize their impact and align them with strategic goals. Strengthening the causing clusters can support the integration of technologies by providing a solid foundation for adoption and policy alignment. Research suggests that without cohesive strategies and infrastructure, technological advancements face integration challenges, particularly in resource-constrained developing economies (Kumar et al., 2020). As shown in Fig. 5b, the dependency of Environmental and Technological factors highlights the need for regulatory support, with policies focusing on funding and infrastructure to advance digital transformation and sustainability.

We further analyzed critical factors in each cluster using the Fuzzy-AHP to examine the importance of each factor within the cluster. In the Digital and Physical Technologies cluster (0.0964), "Additive Manufacturing" emerged as the key enabler. Enyoghasi and Badurdeen (2021*)* highlighted its role in promoting sustainable product development, enhancing product quality, accelerating R&D, and reducing supply chain risks by minimizing lead times. In the Organizational cluster (0.3283), "Dedicated R&D Teams" was the most significant enabler. (Marnewick & Marnewick, 2019) emphasized that such teams improve digital culture and readiness. Similarly, de Sousa Jabbour et al. (2018) noted the importance of effective project teams for integrating smart manufacturing with Industry 4.0 technologies, addressing resource efficiency in manufacturing. In the Supply Chain cluster (0.2856), "Supplier Integration through Digital Platforms" was critical. These findings were supported by the findings of the extant literature. Manavalan and Jayakrishna (2019) suggested mobile devices and digital applications for seamless supply chain integration. Liu et al. (2022) also highlighted the need for SMEs and large enterprises to adopt collaborative approaches and align systems with business processes, ensuring financially sustainable supply chain participation. In the Environmental cluster (0.0440), "Adapting Sustainable Design Strategies" emerged as the key enabler. Machado et al. (2020) also emphasized minimizing environmental impact through sustainable manufacturing practices, focusing on energy efficiency, resource optimization, and reduced carbon emissions. To achieve these, industries usually focus on sustainable design strategies during the manufacturing stage (Ghobakhloo, 2020). For the Social cluster (0.2457), "Data Protection Policies" was identified as a key enabler. Trstenjak and Cosic (2017) and Ziebermayr (2021) highlighted safeguarding data from Industry 4.0 activities to prevent theft and ensure sustainability. Additionally, Human Resource Management 4.0 fosters a socially responsible digital environment, enhancing value creation through advanced HR solutions (Mukhuty et al., 2022). "Customer Response Adoption" is also crucial, as adapting to customer feedback improves product quality, pricing, and sustainability (Schlaepfer & Koc, 2015).

5 Theoretical and managerial implications

This paper offers significant contributions to the understanding of Industry 4.0 adoption, particularly within the context of Indian SMEs. It analyzes 25 factors identified in the existing literature as critical to Industry 4.0 adoption, providing valuable insights for SMEs in emerging economies. By examining these factors, the study helps SMEs understand their roles and the extent of their influence in driving Industry 4.0 adoption. The research further organizes these factors into five distinct clusters using exploratory factor analysis. Employing Fuzzy DEMATEL techniques, the study investigates the causal relationships among these clusters, which are subsequently classified into “cause” and “effect” categories. This classification enhances understanding of the interconnections between various factors and the influence each cluster exerts on others. By addressing uncertainties and clarifying these relationships, the research provides a robust framework for decoding the complexities surrounding Industry 4.0 adoption.

Beyond theoretical insights, the findings have practical implications for policy-making and industrial development in emerging economies. The study emphasizes the importance of organizational culture and commitment, supply chain integration, technical infrastructure, establishing standards, and implementing regulations to facilitate Industry 4.0 adoption. Such measures are crucial for enabling SMEs to adapt to technological advancements effectively. These insights can guide policymakers and industrial clusters in developing countries to create supportive environments that promote the integration of Industry 4.0 principles. This research offers valuable guidance for firms in formulating effective strategies to enhance the success of Industry 4.0 implementation while contributing to sustainability-related goals. The findings underscore the need for managers to prioritize strengthening their firms’ internal capabilities to address the challenges associated with Industry 4.0 adoption. Enhancing these capabilities requires a focused approach by top management, including the establishment of dedicated R&D teams, fostering supplier integration through digital platforms, and ensuring robust support from senior leadership. Overall, this research contributes to a deeper understanding of the dynamics of Industry 4.0 adoption and provides actionable recommendations for SMEs, policymakers, and industrial stakeholders in emerging economies.

6 Conclusion

This study provides a comprehensive analysis of Industry 4.0 adoption, emphasizing the unique challenges faced by SMEs in emerging markets like India. A systematic literature review identified 25 Industry 4.0 adoption factors. A survey of 233 Indian SMEs contextualized their importance and was analyzed using Exploratory Factor Analysis to form five clusters. Fuzzy-AHP ranked the factors, while Fuzzy-DEMATEL revealed causal relationships and categorized clusters into cause-and-effect groups. The application of Fuzzy DEMATEL and Fuzzy-AHP methodologies offered valuable insights into the causal relationships and hierarchical importance of these enablers. By identifying and prioritizing critical enablers across Digital and Physical Technologies, Organizational, Supply Chain, Environmental, and Social clusters, the research highlights the interconnected nature of these factors and their role in fostering sustainable manufacturing practices. The findings underscore the centrality of organizational readiness, supply chain integration, and a supportive policy environment in facilitating this transition. Practical implications include targeted strategies for SMEs to optimize resource allocation and align technological adoption with sustainability objectives. Additionally, policymakers are encouraged to address funding constraints, skill gaps, and infrastructural deficiencies to create a conducive environment for Industry 4.0 integration. This research contributes to bridging the Industry 4.0 adoption gap, enabling SMEs to enhance their participation in global supply chains and align with broader sustainability goals. By fostering a holistic approach to adoption, this study supports the advancement of SMEs in emerging economies, ensuring their growth and alignment with the principles of sustainable industrial development.

Future research can validate findings in other markets, compare SMEs in different economies, and explore temporal changes in factor impacts. Integrating qualitative approaches, such as case studies, could uncover nuanced interconnections between clusters, enriching the quantitative results. Additionally, longitudinal research may examine the evolving impact of these factors over time as SMEs progress in their adoption journey.

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