Strategic Prioritization of Integrated Barriers to Industry 4.0 and Circular Supply Chain: Evidence From the Indian Manufacturing Sector

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Abstract

The transition toward Industry 4.0 (I4.0) and Circular Supply Chain (CSC) practices presents significant challenges for manufacturing firms seeking to achieve sustainable industrial transformation, particularly in emerging economy contexts. Organizations attempting to integrate digital technologies with CSC models often face complex technological, organizational, and institutional barriers that hinder successful implementation. Addressing this challenge, this study proposes a novel, expert-weighted hybrid decision-making framework that integrates Spherical Fuzzy DEMATEL and Spherical Fuzzy SWARA to identify, analyse, and prioritize the key barriers influencing the integrated adoption of I4.0 and CSC practices. A key methodological contribution of the study lies in incorporating differential expert weighting based on professional experience, which enhances the realism and robustness of decision-making under uncertainty-an aspect largely overlooked in previous studies. The proposed framework is empirically applied to the Indian manufacturing sector, where expert evaluations are used to model the causal relationships and relative importance of the identified barriers. The results reveal that barriers such as lack of global standards and technology transfer, shortage of skilled workforce, and high capital investment with uncertain returns exert the strongest influence on the adoption process. The study contributes methodologically by improving the accuracy of barrier prioritization under uncertainty and theoretically by extending the Resource-Based View (RBV) to explain how resource constraints and capability limitations affect the simultaneous adoption of I4.0 and CSC. From a practical perspective, the proposed framework offers a structured and replicable decision-support tool for managers and policymakers seeking to support digital-circular transformation within the Indian manufacturing context, while also providing insights that may inform similar initiatives in other emerging economies.

Keywords: *Industry 4.0, Circular Supply Chain, Barriers, Spherical Fuzzy Logic, DEMATEL, SWARA, Emerging Economies.*

1. Introduction

Globalisation and industrialisation have driven tremendous growth in manufacturing. However, this expansion has resulted in excessive consumption of natural resources and energy, leading to environmental and ecological imbalances, climate change, and ultimately, global warming

(Tseng et al., 2018). Increasing global pressure and regulatory requirements are compelling manufacturing firms to adopt sustainable practices to reduce their emissions (Chen et al., 2020). Since manufacturing is highly resource-intensive and contributes significantly to environmental pollution, prioritising sustainability is crucial to achieving SDG12 (Responsible Consumption and Production) and SDG9 (Industry, Innovation, and Infrastructure). The industrial sector remains one of the largest consumers of global energy, accounting for 37% of total usage in 2022 (IEA, 2022). A significant proportion of this energy demand is driven by the intensive processing, refining, and manufacturing of virgin raw materials. To mitigate this high energy footprint, industries are increasingly urged to transition toward circular economy (CE) models, such as the cradle-to-cradle (C2C) approach. While these models primarily target resource efficiency and material circularity, they are intrinsically linked to energy reduction; by extending product lifecycles and minimizing the need for energy-intensive virgin material production, circular strategies play a critical role in lowering the overall energy intensity of the manufacturing sector. Digitalisation within manufacturing plays a key role in advancing sustainability initiatives (Chen et al., 2020).

Over the past decade, industries have gradually shifted from traditional linear production systems to circular models (Guerra & Leite, 2021), reflecting a growing emphasis on reducing resource depletion and minimizing waste. The core objective of CE is to establish efficient material loops that lower pollution and waste generation while promoting responsible resource utilization (Provin et al., 2021). This study is framed within the CE model and the resource-based view (RBV) theory, offering a strategic perspective on sustainable industrial transformation.

Industry 4.0 (I4.0) refers to the integration of Cyber-Physical Systems (CPS) into industrial production, leveraging the Internet of Things (IoT) and services to create smart factories where machines, devices, sensors, and people connect and communicate with one another. The I4.0 technologies include artificial intelligence (AI), machine learning (ML), internet of things (IoT) and sensors, big data analytics (BDA), block chain technology (BCT), robotic systems (RS), cloud computing (CC), additive manufacturing (AM), virtual reality (VR), augmented reality (AR), autonomous vehicles (AV), and drones (Akhtar, 2022).

On a global scale, Industry 4.0 (I4.0) is revolutionising production systems, fostering sustainability by integrating circular processes (de Sousa Jabbour et al., 2018). By improving resource efficiency and reducing industrial emissions (Tseng et al., 2018), I4.0 contributes significantly to environmentally sustainable industrial growth. Leveraging cyber-physical networks, smart factories, and digitally interconnected supply chains, I4.0 enhances key operational areas such as equipment utilization, facility layout planning, product life-cycle management, and supply chain (SC) efficiency (Lopes de Sousa Jabbour et al., 2018). Emerging technologies—particularly advanced data analytics and IoT—are pivotal in optimizing resource allocation and facilitating circular supply chain (CSC) frameworks (Mastos et al., 2021), while AM can reduce material waste through on-demand production (Javaid et al., 2021). However, the environmental performance of these innovations is often challenged by the high energy intensity associated them. I4.0 technologies facilitate product tracking, reuse, and recycling, thereby strengthening both sustainability and CE efforts (Rosa et al., 2020; Gupta et al., 2021). Moreover, I4.0 technologies can drive sustainable manufacturing processes, providing firms with competitive advantages (Salam, 2021). Numerous barriers hinder I4.0 adoption despite its significant potential to enhance sustainability, circularity, and competitiveness within the manufacturing sector (Kamble et al., 2018).

I4.0 and CSC have each attracted considerable scholarly attention in recent years due to their potential to enhance operational efficiency and sustainability in manufacturing systems. While these paradigms have largely been examined independently, recent studies have begun exploring their interconnected adoption and the synergies between digital transformation and CE practices (e.g., Ozkan-Ozen et al., 2020; Shang et al., 2022; Taddei et al., 2024). However, understanding how the barriers associated with these two transformations interact remains an ongoing challenge, particularly in emerging economy manufacturing environments characterized by uncertainty and structural constraints. This highlights the need for analytical approaches capable of capturing the complex relationships among barriers influencing the simultaneous adoption of I4.0 and CSC.

Multi Criteria Decision Making (MCDM) techniques such as Decision Making Trial and Evaluation Laboratory (DEMATEL) and Step-wise Weight Assessment Ratio Analysis (SWARA) has been widely applied in many fields for causal relationship and weight determination. To address this gap, this study proposes a novel hybrid decision-making approach combining Spherical Fuzzy-DEMATEL (SF-DEMATEL) and Spherical Fuzzy-SWARA (SF-SWARA) to model both the interrelationships and priority levels of barriers. Unlike previous studies, this approach assigns differentiated weights to decision experts (DEs) based on experience, incorporates uncertainty using Spherical Fuzzy Sets (SFS), and visualises a cause–effect barrier structure that aids strategic intervention. Thus, the paper offers both methodological advancement and practical relevance for policy and industry.

The research objectives (ROs) are framed accordingly:

- RO1: To identify the key barriers affecting the integrated adoption of I4.0 and CSC practices through literature review and expert validation in the Indian manufacturing sector.
- RO2: To examine the causal relationships among the identified barriers using SF-DEMATEL method.
- RO3: To prioritize the barriers based on their relative importance using SF-SWARA to support managerial decision-making in Indian manufacturing firms.
- RO4: To address uncertainty and inconsistency in expert evaluations through SFS.
- RO5: To assign expert weights using the Spherical Fuzzy Weighted Geometric Average (SFWGA) operator.

The remainder of the paper is structured as follows. Section 2 presents the literature review and theoretical framework. Section 3 outlines the methodology. Section 4 discusses the case study, followed by results and discussion in Sections 5 and 6. Section 7 concludes and suggests directions for future research.

2. Literature Review

2.1 Theoretical background: Industry 4.0 and Circular Supply Chain

The transition from a linear economy to a CE has significantly increased the complexity of supply chain systems (Mangla et al., 2018). Due to circular flows and reverse logistics, the number of stakeholders involved in a CSC increases, and various new business models, previously absent in linear systems, emerge. This study is grounded in two key theoretical foundations: the CE model and RBV theory. The CE model emphasizes sustainable resource management by minimizing waste and maximizing reuse, recycling, and recovery throughout the product lifecycle (Fogarassy & Finger, 2020). In parallel, the RBV posits that firms gain sustained competitive advantage through the effective deployment of valuable, rare, inimitable, and non-substitutable internal resources, such as technology, expertise, and infrastructure (Barney, 1991). Furthermore, a firm's ability to adapt, innovate and reconfigure its resources in response to environmental changes contributes to its dynamic capabilities (Teece et al., 1997). These theoretical perspectives are critical for understanding how firms approach the integration of I4.0 and CSC under resource constraints typical of developing economies.

The 6R principles - redesign, reuse, refurbish, remanufacture, recycle, and recover (Jawahir & Bradley, 2016) - form the operational foundation of both CE and CSC systems. These principles aim to maximize resource utilisation throughout the entire product lifecycle, thereby minimizing waste generation and improving overall system sustainability. However, transforming traditional linear supply chains into circular models presents substantial challenges. This transition requires the development of innovative business models, the redesign of operational processes, and the adoption of new organizational practices to support circular resource flows (Schraven et al., 2019).

The adoption of I4.0 technologies can significantly enhance the performance and effectiveness of CSCs by enabling digital integration, real-time data exchange, and improved supply chain visibility. For example, the integration of renewable energy solutions such as solar photovoltaic systems can improve supply chain sustainability and reduce environmental impacts (Mastrocinque et al., 2022). Similarly, Artificial Intelligence (AI) has been shown to contribute to carbon emissions reduction when combined with enterprise green innovation initiatives (Chen & Jin, 2023). In addition, big data analytics supports more efficient resource allocation, predictive maintenance, and data-driven decision-making, thereby improving sustainability performance, operational efficiency, and competitiveness in modern industrial systems (Zhao et al., 2024). However, the realization of these benefits depends on the availability of adequate digital infrastructure and supporting technological capabilities.

At the same time, the implementation of I4.0 technologies requires secure and reliable information systems to ensure effective data sharing and system integration across supply chain partners. Information security concerns remain a significant barrier to digital transformation, particularly for small and medium-sized enterprises (SMEs) operating in developing economies, where technological infrastructure and cybersecurity capabilities may be limited (Arroyabe et al., 2024). Consequently, while the integration of I4.0 technologies with CSC principles offers considerable potential for achieving environmental and economic objectives, its successful implementation depends largely on firms' internal resource endowments, technological capabilities, and strategic orientation.

Although prior studies have explored I4.0 and CSC concepts independently, relatively few have examined the combined theoretical foundations explaining how internal firm resources influence their integrated adoption, particularly within emerging economy contexts. Building on the CE framework and RBV theory, this study therefore investigates the interrelated barriers that hinder the simultaneous implementation of I4.0 technologies and CSCS practices. A summary of key studies addressing barriers to I4.0 and CSC adoption is presented in Table 1.

Table 1. Key studies on the barriers of I4.0 and CSC

Authors	I4.0 Barriers	CSC Barriers	Description of Content	Location	Method
Ozkan-Ozen et al. (2020)	Y	Y	Prioritise the synchronized barriers of I4.0 and CSC in Turkey	Turkey	Fuzzy ANP
Narwane et al. (2021)	Y		Inter-relationship among the sustainable I4.0 barriers using	India	Fuzzy DEMATEL
Lahane & Kant (2021)		Y	Prioritise the barriers of CSC evaluation	India	Pythagorean fuzzy AHP-DEMATEL
Kumar, Raut, et al. (2021)	Y	Y	Prioritise Industry 4.0 and CE barriers in agricultural SC	India	ISM-ANP
Senna et al. (2022)	Y		Prioritise barriers for the adoption of I4.0 technologies	Portugal	ISM-MICMAC
Kumar, Bakshi et al. (2022).	Y		Prioritize barriers of I4.0 implementation in Indian SMEs	India	TOPSIS, VIKOR and PROMETHEE
Sayem et al. (2022)	Y		Prioritise the barriers of I4.0 adoption in Bangladesh manufacturing and mitigation strategies	Bangladesh	Integrated fuzzy-DEMATEL
Jena & Patel (2022)	Y		Prioritising the Barriers of I4.0 and requirements of Indian manufacturing industry	India	Trapezoidal Fuzzy functions and Factor Analysis
Shang et al. (2022)	Y	Y	Prioritise the barriers of CSC in the era of I4.0	NA	Q-Rung Orthopair fuzzy set-based CRITIC-CoCoSo method
Shaikh et al. (2022).		Y	Identify the contextual relationship among barriers of CSC in Pakistani FMCG sector	Pakistan	ISM- MICMAC
Kazancoglu et al. (2022)		Y	Determine the causal relationship among the barriers of CSC in Turkish textile industry	Turkey	Fuzzy DEMATEL
Govindan & Arampatzis (2023)	Y		Assess the firm level readiness and barriers of I4.0 implementation	Denmark	DEMATEL
Taddei et al. (2024)	Y	Y	Prioritise circular SC barriers in era of Industry 4.0	Italy	Design Research Methodology (DRM)
Cordeiro et al. (2024)	Y		Assessing the barriers impacting adoption of I4.0 in Brazilian companies	Brazil	Factor analysis and linear regression
Kumar, Mangla & Kumar (2024)	Y	Y	Determine causal relationship and critical barriers to I4.0 and CE adoption in sustainable food supply chain	India	Rough DEMATEL
Poddar, Priya, Ghosh, Singh & Pandey (2024).		Y	Prioritise the barriers hindering the implementation of CE within FMCG supply chains in India	India	Fuzzy-Delphi and Jaccard Similarity and Cosine Similarity metrics
Rayhan, Masum, & Karuppiah (2025).		Y	Develop causal relationship among the barriers to CE adoption in Textile and Apparel industry	Bangladesh	Fuzzy DEMATEL

2.2 qBarriers to Industry 4.0 Adoption

The implementation of I4.0 technologies presents several multifaceted challenges, many of which mirror the complexities encountered in previous technological transformations. These barriers are broadly categorized into organizational, technological, strategic, legal, and ethical dimensions (Sayem et al., 2022). Scholars across various domains have examined these barriers, identifying recurring factors that obstruct the smooth adoption of I4.0 in both developed and developing economies (Kamble et al., 2018).

A major organizational barrier lies in the lack of a clearly defined digital strategy, along with weak internal processes and limited alignment with I4.0 objectives (Mittal et al., 2018). Organizational culture and employee resistance to change further constrain adoption (Horváth & Szabó, 2019). Moreover, a shortage of skilled labour capable of working with advanced digital technologies remains a critical issue, especially in developing economies (Kamble et al., 2018; Müller et al., 2018).

Technological limitations also pose significant hurdles. The high initial investment required for deploying I4.0 solutions, such as automation systems, sensors, and integrated IT infrastructure, acts as a deterrent for many firms, particularly SMEs (Kamble et al., 2018). In addition, the absence of a digital-first mindset, coupled with underdeveloped communication and IT infrastructure, weakens the ability of firms to adopt and scale I4.0 systems effectively (Kamble et al., 2018; Karadayi-Usta, 2019).

Limited awareness and understanding of key technologies, such as the Internet of Things (IoT), cyber-physical systems, and artificial intelligence, also contribute to slow adoption (Stentoft et al., 2021). Many organizations are uncertain about the return on investment (ROI) associated with I4.0, which discourages decision-makers from committing to transformation efforts (Luthra & Mangla, 2018; Geissdoerfer et al., 2018). Additionally, concerns over data privacy, cybersecurity, and the integration of legacy systems with smart devices create further complications (Jbair et al., 2018; Kiraz et al., 2020).

Another significant challenge is the lack of seamless collaboration and interoperability across departments, suppliers, and partners. Successful I4.0 implementation requires interconnected systems and effective coordination across the supply chain, capabilities that are often underdeveloped in firms still operating under traditional models (Frank et al., 2019).

Taken together, these organizational and technological barriers hinder firms' ability to effectively transition to I4.0, especially in resource-constrained and infrastructure-deficient contexts (Luthra & Mangla, 2018). Addressing these issues requires not only technical upgrades but also strategic alignment, cultural readiness, and workforce development (Müller et al., 2018). In developing economies, these challenges are amplified, underscoring the need for holistic frameworks that can assess and prioritize such barriers in an integrated and context-sensitive manner (Luthra & Mangla, 2018).

2.3 Barriers to Circular Supply Chain Adoption

The adoption of CSC principles presents several operational and strategic challenges for firms, particularly in developing countries. As businesses increasingly integrate CSC practices to align economic growth with resource conservation and social welfare, they encounter multiple barriers that require targeted industrial and policy-level interventions. Poddar et al. (2024) used fuzzy Delphi and Jaccard Similarity and Cosine Similarity metrics to study the barriers hindering the implementation of CE within FMCG supply chains in India. Ho et al. (2025) carried out a qualitative analysis, based on in-depth interviews from the Dutch managers of medium-size organisations, of the drivers and barriers of circular business model transition. Rayhan et al. (2025) analysed the barriers to CE adoption in Textile and Apparel (T&A) industry using Fuzzy TISM and DEMATEL.

A critical obstacle lies in the lack of effective environmental regulations and enforcement mechanisms, which limits the institutional support necessary for CSC adoption (Goyal et al., 2018; Khandelwal & Barua, 2020). Even where policies exist, weak implementation hinders their practical impact on industrial transformation.

Human resource-related barriers also play a prominent role. Many organizations lack employees with the knowledge, skills, and motivation to implement greener practices and CSC-related initiatives (Govindan & Hasanagic, 2018; Ozkan-Ozen et al., 2020). Furthermore, consumer engagement is limited, as customers often show low levels of interest, understanding, or participation in circular activities (Taddei et al., 2024; Nyffenegger et al., 2024).

From an operational perspective, the absence of planning, cooperation, and coordination across supply chain stakeholders significantly impedes circular implementation (Mangla et al., 2018; Farooque et al., 2019). Many firms also lack the organizational infrastructure and digital capabilities needed to support reverse logistics, material recovery, and product lifecycle tracking (Govindan & Hasanagic, 2018; Bressanelli et al., 2019).

Technology availability and cost are other pressing challenges. Limited access to cost-effective, eco-efficient technologies, along with the higher production costs of recycled materials and circular processes, reduce incentives for firms to invest in CSC models (Mangla et al., 2018). These constraints are exacerbated by inadequate connectivity and traceability infrastructure, which restricts the visibility of material flows and product end-of-life (EOL) stages (Farooque et al., 2019; Urbinati et al., 2021).

In addition, firms often struggle with information gaps, such as lack of accurate data on materials or recycling processes, and concerns about data privacy and cybersecurity in shared circular systems (Nazam et al., 2020; Bressanelli et al., 2019; Ozkan-Ozen et al., 2020). Lack of monitoring mechanisms, such as follow-up on recycling efforts and performance, adds to the inefficiencies (Mangla et al., 2018).

Economic uncertainty further compounds these issues. High upfront investments, long payback periods, and unclear returns on CSC implementation limit organizational commitment to circular strategies (Kazancoglu et al., 2020; Ozkan-Ozen et al., 2020). In many cases, a lack of leadership support, motivation, and clear strategy prevents firms from fully transitioning to circular business models (Govindan & Hasanagic, 2018; Kumar, P. et al., 2021).

Finally, deeper systemic barriers include cultural resistance, low organizational readiness for change, and the absence of viable economic models that align circular principles with business profitability (Urbinati et al., 2021). These challenges highlight the need for a more structured approach to understanding and addressing CSC barriers, especially in economies where regulatory, technological, and cultural ecosystems are still evolving.

2.4 Integrated Barriers to I4.0 and CSC Adoption

While I4.0 and CSC practices have been studied extensively in isolation, relatively limited research has examined the integrated barriers associated with their simultaneous adoption, particularly within the context of developing economies. The concurrent implementation of I4.0 technologies and CSC practices introduces additional complexities arising from technological, organisational, infrastructural, and cultural misalignments across supply chain actors.

Several studies have begun to explore these combined challenges. For instance, Shang et al. (2022) identified thirteen significant barriers to the adoption of I4.0 and CSC, including lack of knowledge about circular approaches, limited understanding of data management, data security concerns, and insufficient awareness of the benefits of autonomous systems in EOL activities. Similarly, Ozkan-Ozen et al. (2020) examined thirteen barriers in the Turkish manufacturing context, highlighting coordination challenges and inadequate technological infrastructure as critical impediments to the integration of digital and circular practices.

Taddei et al. (2024) further consolidated seven key barriers affecting digital-circular transformation, including inadequate tax incentives, weak environmental regulations, high investment costs, limited technological infrastructure, and lack of integration among technical platforms in I4.0-enabled circular systems. These findings highlight the interconnected nature of I4.0 and CSC challenges, where technological limitations, institutional gaps, organisational readiness issues reinforce each other. In a similar vein, Kumar, Mangla, and Kumar (2024) identified technological immaturity, low eco-innovation, customer resistance, and financial uncertainty as major barriers affecting sustainable food supply chains transitioning toward integrated I4.0 and CE practices. Collectively, these studies indicate that integrated adoption involves the convergence of multiple, overlapping constraints that require a holistic, systems-oriented evaluation rather than isolated barrier assessments.

From a theoretical perspective, the adoption of I4.0 and CSC practices can be interpreted through the RBV. RBV posits that firms achieve sustained competitive advantage by acquiring and effectively deploying valuable, rare, inimitable, and non-substitutable resources (Barney, 1991). The integration of I4.0 technologies, like IoT, Big Data, Cyber-Physical Systems (CPS), and Artificial Intelligence, enhances productivity, efficiency, and innovation, creating unique value propositions that are difficult for competitors to replicate (Intezari and Gressel, 2017). I4.0 technologies are considered a source of resource heterogeneity, which can be leveraged to gain a competitive advantage in the following ways (Huang et al., 2023). I4.0 technologies facilitate iterative innovation and continuous improvement, which are crucial for maintaining competitiveness in dynamic markets (Gopal et al., 2025) which align with RBV.

In the context of digital and circular transformation, resources such as advanced technological infrastructure, skilled human capital, organizational learning mechanisms, and collaborative supply chain capabilities represent critical strategic assets. Differences in firms' resource endowments and resource heterogeneity influence their ability to undertake complex technological and sustainability transitions. Furthermore, the successful integration of I4.0 and CSC requires the development of organizational capabilities such as digital competencies, cross-functional coordination, and data-driven decision-making processes. From a dynamic capability perspective, firms must continuously sense emerging technological opportunities, seize circular business model innovations, and reconfigure internal resources to support digital–circular transformation (Teece, 2007). Consequently, deficiencies in technological, managerial, financial, or institutional resources may manifest as significant barriers that hinder firms' ability to adopt and integrate I4.0 technologies with CSC practices. Examining adoption barriers through the RBV lens therefore provides a useful theoretical foundation for understanding how resource constraints and capability limitations shape firms' transformation trajectories.

Following an extensive review of the literature, an initial set of barriers associated with the integrated adoption of I4.0 and CSC was identified. To ensure the relevance and practical validity of these barriers, a Delphi-based validation process was conducted with a panel of three industry experts possessing substantial experience in I4.0 and SCM. The participating experts were based in India and possessed an average of 13 years of professional experience in manufacturing operations and digital supply chain transformation initiatives. The Delphi approach enabled iterative evaluation and refinement of the initially identified barriers through expert feedback, ensuring that the final barrier set reflects both theoretical insights and practical industry perspectives.

Based on this combined process of literature synthesis and expert validation, eleven integrated barriers were confirmed. These barriers represent interconnected technological, organisational, and operational challenges that firms encounter when attempting to implement I4.0 technologies alongside CSC practices. Table 2 presents the final set of identified barriers, along with their descriptions and the supporting literature sources. In summary, the literature suggests that barriers to I4.0 and CSC adoption are not only persistent but also highly interdependent, reflecting complex interactions among technological capabilities, organizational readiness, financial constraints, and institutional conditions. Understanding the causal relationships among these resource-related barriers is therefore essential for supporting effective decision-making. This underscores the need for an integrated framework capable of modelling such interdependencies and prioritizing barriers under uncertainty, particularly in developing economy contexts where resource limitations and institutional challenges further complicate digital-circular transformation.

Table 2. Integrated barriers of I4.0 and CSC from the recent literature

Code	Barriers of I4.0 and CSC	Description	Author(s)
B1	High capital Investment requirement and uncertainty of ROI	High capital investments and uncertainty of ROI for transformation of the organisation to I4.0 and CSC.	Kamble et al. (2018); Kumar, S. et al. (2021); Laddha & Agrawal (2024); Taddei et al. (2024); Kumar, Mangla & Kumar (2024)
B2	Lack of awareness about potential benefits of I4.0 and CSC	Lack of awareness about potential benefits such as regular production and labour-related activities (like dismantling, disassembly and recycling) can easily be performed with automatic systems hampers implementation.	Luthra & Mangla (2018); Türkeş et al. (2019); Stentoft et al. (2021); Kumar, Raut et al. (2021); Amoozad Mahdiraji et al. (2022); Shang et al. (2022)
B3	Lack of smart equipment and network connectivity required for I4.0 and CSC implementation.	CSCs require sophisticated product tracking and recovery of products in the product life cycle. IoT and appropriate infrastructure will be required to implement circular transformations.	Luthra and Mangla (2018); Kamble et al. (2018); Taddei et al. (2024)
B4	Lack of data transfer, interoperability and safety among different systems and SC stakeholders	Large data transfer, safety and interactivity of systems across all stakeholders are required to transform the organisations from linear to circular. This is barrier in a developing country.	Luthra and Mangla (2018); Stentoft et al. (2019); Türkeş et al. (2019); Ozkan-Ozen et al. (2020); Jankowska et al. (2023).
B5	Lack of skilled workforce for I4.0 and CSC	Skilled workforce and capability required for the transformation of traditional to I4.0 and CSCs simultaneously, which is lacking.	Stentoft et al. (2019); Türkeş et al. (2019); Kumar, Raut et al. (20021)
B6	Lack of support from top management, employees and stakeholder for I4.0 and CSC adoption	Transition from linear to CSC requires redesigning the process. Due to lack of proven evidence of its benefits, top management, employees and stakeholder lack to support I4.0 and CSC adoption.	Ratner et al.(2021); Sarja et al. (2021)
B7	Lack of coordination and collaboration among supply chain stakeholders	Lack of communication setup, cooperation and coordination with suppliers and stakeholders in developing countries in adopting I4.0 for enhancing supply chain sustainability and transparency.	Kazancoglu et al. (2020); Taddei et al. (2024)
B8	Lack of global standards, integration and technology transfer in CSC processes	Lack of standard protocol for technology transfer among stakeholders and integration of various processes in CSC. Also lack of technology transfer particularly developing countries.	Khandelwal & Barua (2020); Lahane & Kant (2021); Kumar, Raut et al. (2021); Taddei et al. (2024)
B9	Complexity of I4.0 and CSC integration	Practitioners are unaware of complex resource management and precise effects on I4.0 and CSC sustainability objectives.	Kazancoglu et al. (2020); Taddei et al. (2024)
B10	Lack of government policies and incentives for circular model adoption	Lack of government rules and regulations, preferential loans and tax benefits policy related to I4.0 and CSC is a significant barrier to the implementation of circular concepts.	Kamble et al. (2018); Khandelwal & Barua (2020) ; Kumar, Raut et al. (2021); Laddha & Agrawal (2024)
B11	Lack of digital culture and circular model adoption	I4.0 and CSC necessitate digitisation to link various network components for smooth and secure data transfer, which is lacking in developing countries.	Luthra & Mangla, 2018; Isensee et al. (2020); Kumar, Raut et al. (2021); Shang et al. (2022)

2.5 Research Gap and Contribution

Although a substantial body of literature has examined I4.0 and CSC adoption barriers independently (Kamble et al., 2018; Govindan & Hasanagic, 2018), research on their integrated adoption is comparatively recent and methodologically heterogeneous. Existing integrated studies differ in analytical depth, treatment of interdependencies, and handling of uncertainty, indicating the need for more robust and context-sensitive modelling approaches.

These literature remains fragmented in three important respects: First, while several studies prioritize barriers using conventional or fuzzy multi-criteria decision-making (MCDM) methods, relatively few model the causal interdependencies among integrated I4.0–CSC barriers. Given that technological, organizational, financial, and institutional constraints interact dynamically, analysing them in isolation may oversimplify the systemic nature of digital-circular transformation. Second, most prior studies assume homogeneity in expert judgments, assigning equal weights to decision-makers regardless of experience or domain expertise. This assumption may reduce robustness, particularly in complex transformation contexts characterized by uncertainty and information asymmetry. The incorporation of differential expert weighting within advanced fuzzy environments remains underexplored. Third, although integrated analyses are emerging, limited attention has been devoted to emerging economy contexts such as India, where structural constraints including infrastructural deficiencies, capability gaps, regulatory inconsistency, and financial limitations significantly influence adoption trajectories. Manufacturing firms in emerging economies face compounded challenges when simultaneously pursuing digital transformation and circular restructuring. Empirical evidence from such contexts remains comparatively limited and calls for context-sensitive analytical frameworks.

From a theoretical standpoint, the joint adoption of I4.0 and CSC can be interpreted through the RBV, which emphasizes the role of valuable, rare, inimitable, and non-substitutable resources in achieving sustained competitive advantage. However, existing empirical studies seldom connect identified adoption barriers explicitly to RBV constructs such as resource heterogeneity, capability development, and dynamic capability formation. Understanding how technological infrastructure, skilled human capital, managerial support, and institutional alignment function as strategic resources is essential for explaining differential adoption outcomes across firms.

To address these gaps, this study makes three primary contributions:

1. Theoretical Contribution: It extends the RBV by linking integrated I4.0–CSC barriers to firm-level resource endowments and dynamic capability development in manufacturing firms operating in emerging economies.
2. Methodological Contribution: It proposes a hybrid framework integrating Spherical Fuzzy DEMATEL and Spherical Fuzzy SWARA to simultaneously model causal interdependencies and prioritize barriers under uncertainty. The framework incorporates differential expert weighting and captures hesitancy using spherical fuzzy sets, advancing beyond conventional fuzzy or crisp MCDM approaches.
3. Contextual Contribution: It provides empirical insights from the Indian manufacturing sector, illustrating how emerging economy structural conditions influence digital-circular transformation.

By combining advanced uncertainty modelling, causal analysis, and theory-driven interpretation within an emerging economy context, this study advances the understanding of integrated I4.0-CSC adoption beyond fragmented or methodologically limited assessments.

3. Methodology

3.1 Methodological Framework

This study adopts a novel hybrid MCDM framework integrating SF-DEMATEL and SF-SWARA to systematically analyse and prioritise the barriers affecting the joint adoption of I4.0 and CSC. The proposed framework is designed to address two key analytical requirements: (i) identifying the causal relationships among barriers and (ii) determining their relative importance under conditions of uncertainty.

The methodological procedure consists of two complementary phases:

Phase 1: Identifying Causal Relationships with SF-DEMATEL. In the first phase, SF-DEMATEL is applied to identify and model the causal interdependencies among the barriers. This technique enables the classification of barriers into driving (cause) and dependent (effect) groups, providing insights into how barriers influence one another within the system.

Phase 2: Prioritizing Barriers with SF-SWARA: In the second phase, SF-SWARA is employed to determine the relative importance of the identified barriers based on expert evaluations, allowing the prioritisation of critical obstacles to I4.0 and CSC implementation.

Unlike conventional fuzzy DEMATEL–SWARA frameworks, the present study incorporates spherical fuzzy sets (SFS) to capture expert hesitation, neutrality, and uncertainty more effectively. The integration of SFS enhances the reliability of linguistic evaluations by allowing decision-makers to express judgments within a three-dimensional membership space. This provides greater flexibility in modelling ambiguity compared with traditional fuzzy, intuitionistic, Pythagorean or Neutrosophic fuzzy approaches.

By combining causal structure analysis and priority weighting within a unified spherical fuzzy environment, the proposed hybrid framework offers a comprehensive approach for analysing complex adoption barriers. The overall research process is illustrated in Figure 1, which summarises the sequential steps of the methodology.

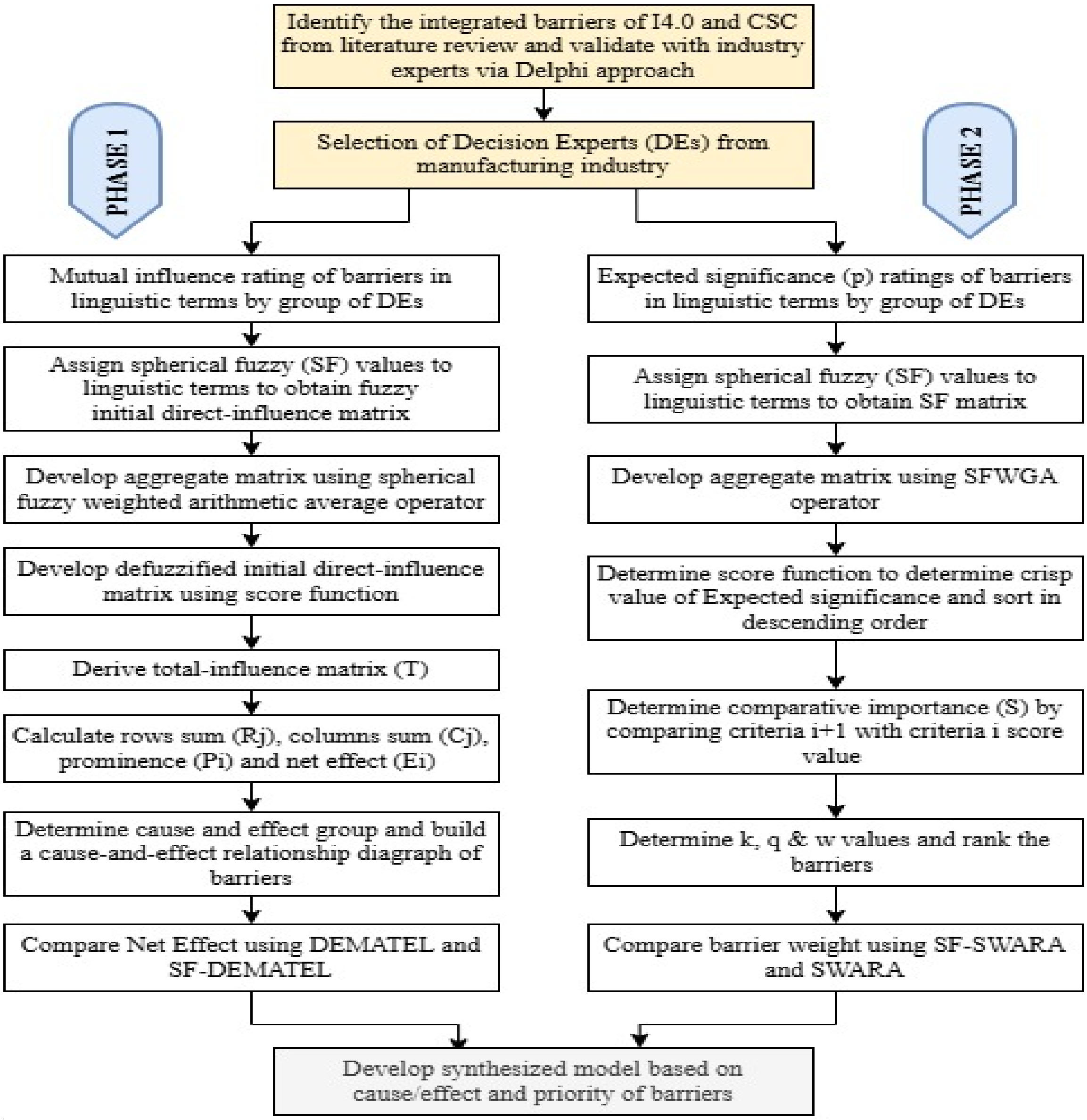
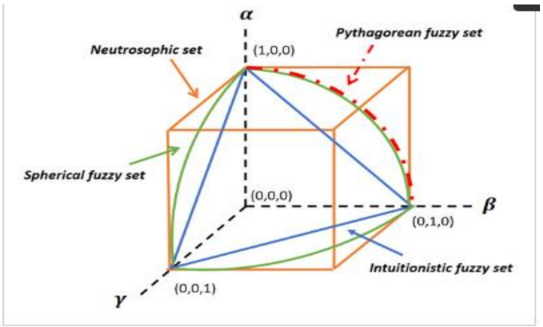


Figure 1. Proposed Research Methodology

3.2 Spherical Fuzzy Set

SFS introduced by Kutlu Gündoğdu & Kahraman (2020), represent an advanced extension of traditional fuzzy set theories for modelling uncertainty in decision-making environments. Unlike conventional fuzzy approaches, SFS allow decision-makers to simultaneously express membership, non-membership, and hesitancy degrees, enabling a more flexible representation of ambiguous and uncertain information. The conceptual structure of SFS is illustrated in Figure 2.



Source: adopted from Gundogdu and Kahraman (2020)

Figure 2. Geometric Representation of SFS

Definition 1*:* The SFS *S* of the universe *X* is denoted as follows:

$$S = \{x, (\mu_S(x), \nu_S(x), \pi_S(x)) \mid x \in X\};$$

where $\mu_{S(x)}, \nu_{S(x)}, \pi_{S(x)} : X \rightarrow [0, 1]$ and

$$0 \leq \mu_S^2(x) + \nu_S^2(x) + \pi_S^2(x) \leq 1$$

where, $\mu_S(x)$ represents membership (or truth), $\nu_S(x)$ non-membership (or falsify), and $\pi_S(x)$ indeterminacy (or hesitancy or abstinence) function of x to *S.*

For simplicity, let $S = (\mu_s, \nu_s, \pi_s)$

where $\mu_s, \nu_s, \pi_s \in [0, 1]$

$$0 \leq \mu_s^2 + \nu_s^2 + \pi_s^2 \leq 1 \qquad (1)$$

The degree of refusal = $\sqrt{(1 - \mu_s^2 - \nu_s^2 - \pi_s^2)}$

Definition 2: SFWGA operator for aggregation of SF decision matrix X_i (Mahmood et al., 2019) can be obtained as:

$$\text{SFWGA} = \left(\prod_{j=1}^{k} \left(\mu_j\right)^{u_j}, \sqrt[2]{1 - \prod_{j=1}^{k} \left(1 - \nu_j^2\right)^{u_j}}, \sqrt[2]{1 - \prod_{j=1}^{k} \left(1 - \pi_j^2\right)^{u_j}} \right) \qquad (2)$$

where μ^k, ν^k, and π^k are the k^th^ DEs rating and *k* is the number of DEs. u_j is the weight of DEs.

In case of multiple experts, aggregated matrix is obtained using SFWGA.

Definition 3: Score function (ϑ) is given in a unit interval [0,1].

$$\vartheta = \sqrt{\left|100 * \left[\left(\mu_{\tilde{A}_x} - \pi_{\tilde{A}_x}\right)^2 - \left(v_{\tilde{A}_x} - \pi_{\tilde{A}_x}\right)^2\right]\right|} \quad (3)$$

The ability of SFS to capture higher levels of uncertainty makes them particularly suitable for analysing complex socio-technical systems such as the adoption of I4.0 and CSC practices. In such contexts, expert judgments often involve incomplete information, subjective perceptions, and varying levels of confidence. By incorporating SFS within both the DEMATEL and SWARA methods, this study ensures a consistent treatment of uncertainty throughout the decision-making process (Gul, 2020).

A comparative overview of commonly used fuzzy frameworks and the advantage of the proposed spherical fuzzy approach is presented in Table 3.

Table 3: Comparison of Methodological Approaches

Method	**Type of Fuzziness**	**Interdependency Analysis**	**Weighting Sensitivity**	**Advantage**
Traditional Fuzzy AHP	Triangular	✗	Moderate	Simpler, but limited expert modelling
IF-DEMATEL & SWARA	Intuitionistic	✓	Moderate	Captures some uncertainty
SF-DEMATEL & SF-SWARA (This study)	Spherical	✓	High	Superior in modelling expert hesitancy, handles ambiguity and neutrality simultaneously.

3.3 SF-DEMATEL Method

The causal model such as ISM and TISM, assess the mutual relationship in binary options (0,1) while the DEMATEL provides more options (0-4) and are able to quantify the strength of causal relationships, thus overcoming the drawbacks of the above techniques. The technique can be applied in following steps:

1. Selection of the barrier and the DEs.
2. Construction of the linguistic direct influence matrix

Each expert evaluates the direct influence of i^{th} barrier on j^{th} barrier in the linguistic scale using Table 4. Four-point and five-point SFS scales have been used in many applications. Authors have devised a modified 5-point scale meeting the criteria (Eq. 1) as shown in table 4. Then SFN are assigned to linguistic ratings. The direct relationship matrix is obtained $X^k = [x^k_{ij}]$, where k is number of DEs. In the direct inflectional matrix, diagonal element (i = j) is zero (0,0).

Table 4. Linguistic and Spherical Fuzzy Scale

Linguistic Scale	**Crisp Value**	**Spherical Fuzzy Number (μ, ν, π)**
No influence (N)	0	(0.00, 0.80, 0.05)
Low influence (L)	1	(0.25, 0.60, 0.15)
Medium influence (M)	2	(0.50, 0.40, 0.30)
High influence (H)	3	(0.75, 0.20, 0.15)
Very High influence (VH)	4	(0.90, 0.05, 0.05)

3. Develop a spherical fuzzy initial direct-relation matrix.

Assign a spherical fuzzy number to the linguistic scale from Table 4 to obtain the fuzzy initial direct-influence matrix for each decision expert.

4. Develop the aggregate fuzzy initial direct-influence matrix using SFWGA given in Eq. (1).
5. Develop the non-fuzzy initial direct-influence matrix using the score function given in Eq. (2).

   $A = [a_{ij}]_{nxn}$

6. Obtain the normalised initial direct-influence matrix using Eq. (4).

   $$N = m \times A \tag{4}$$

   where, $m = \min [(1/ \max \Sigma a_{ij} \text{ for } j = 1,..,n), (1/ \max \Sigma a_{ij} \text{ for } i = 1,..,n)]$

7. Develop the total-influence matrix (T) using Eq. (5)

   $$T = N*[I-N]^{-1} \tag{5}$$

   where, I: the identity matrix, and

   $T = [t_{ij}]_{nxn}$

8. Calculate the sum of rows (R) and the sum of column (C) from the Total-influence matrix (T):

   $$R_i = \Sigma t_{ij} \text{ for } i = 1,..,n \tag{6}$$

   $$C_j = \Sigma t_{ij} \text{ for } j = 1,..,n \tag{7}$$

9. Determine prominence (Pi) and net effect (Ei) using Eq. (8 and 9).

   $$P_i = R_i + C_j \tag{8}$$

   $$E_i = R_i - C_j \tag{9}$$

The P_i signifies the degree of importance that factor *i* plays in the entire system. The E_i indicates the net effect; that factor *i* contribute to the system. If E_i is positive, factor *i* is a net cause; if E_i is negative, factor is a net receiver.

10. Develop a Causal Diagraph by plotting P_i on the x-axis and E_i on the y-axis, the structural cause-effect relationship can be visualised in a causal diagram.

3.4 SF-SWARA Method

Step-wise Weight Assessment Ratio Analysis (SWARA), developed by Kersuliene et al. (2010), to calculate the weight of selection criteria based on expert's knowledge and experience. One criterion may be higher or lower in significance than other. The significance ratio of criteria is determined in this method for making decisions. Pair-wise comparison is reduced in this method in comparison to others method, AHP, BWM. The evaluation process incorporated DEs' preferences, user-friendly and easy to implement. The relative weight of barriers can be determined in following steps:

1. Identified barriers are rated based on their expected significance (p_i^r) in linguistic scale by groups of DEs, where *i* criteria (1, 2,…,n) and *r* decision-makers (1,2,…,r).
2. Assign SFS value to linguistic scale as per Table 5.

Table 5. Linguistic and Spherical Fuzzy Scale (Kutlu Gündoğdu & Kahraman, 2020)

Linguistic Scale	**Crisp**	**Spherical Fuzzy Number (μ, v, π)**		
Absolutely more significant (AM)	9	0.90	0.10	0.05
Very high significant (VH)	8	0.80	0.20	0.10
High significant (H)	7	0.70	0.30	0.20
Slightly more significant (SM)	6	0.60	0.40	0.30
Almost Equal significant (E)	5	0.50	0.50	0.40
Slightly low significant (SL)	4	0.40	0.60	0.30
Low significant (L)	3	0.30	0.70	0.20
Very low significant (VL)	2	0.20	0.80	0.10
Absolutely low significant (AL)	1	0.10	0.90	0.05

3. Determine aggregate fuzzy expected significance ($\bar{p}_i$) using SFWGA given in Eq. (2).
4. Determine non-fuzzy (crisp) expected significance using the Score function (ϑ_i) given in Eq. (3) and sort in descending order of score value.
5. Determine comparative importance (S_i). Compare the criterion i+1 in relation to the previous criterion i starting from the second criterion for all the criteria.

$$S_i = \vartheta_i - \vartheta_{i+1} \qquad (10)$$

6. Compute coefficient (ki):

$$k_i = 1 \qquad \text{if } i = 1$$

$$k_i = S_i + 1 \qquad \text{if } i > 1 \qquad (11)$$

7. Determine the recalculated weight (q_i) of the criteria

$$q_i = 1 \quad \text{if } i = 1$$

$$q_i = q_{i-1} / k_i \quad \text{if } i > 1 \tag{12}$$

8. Determine the relative weight of criteria (w_i)

$$w_i = q_i / \sum q_i \quad i = 1 \ldots n \tag{13}$$

4. Empirical Context: The Indian Manufacturing Sector

The adoption of I4.0 technologies in the Indian manufacturing industry has been slow, with only a limited number of companies implementing a few of these I4.0 technologies. The DEs were carefully selected from a small pool of manufacturing firms for this study. The study follows these steps:

Step 1: Identify the integrated I4.0 and CSC barriers and Instrument design

Barriers to I4.0 and CSC adoption were identified through a literature review and discussions with industry experts, as summarised in Table 2. The research instrument consisted of a two-part structured questionnaire: Part A: Collected demographic and professional data to categorize experts based on their length of service and institutional role. Part B: Facilitated the pairwise comparison of the identified barriers using the linguistic spherical fuzzy scale.

Step 2: Expert Selection and Data Collection

The decision-makers (DEs) from manufacturing companies those implemented I4.0 were identified using purposive sampling technique. The selection criteria required a minimum of 5 years of experience in manufacturing, I4.0 technologies and circular models. The expert panel comprised representatives from five large manufacturing companies. Through questionnaire, the DEs were asked to: (i) Assess the barriers based on their mutual influence using linguistics terms, and (ii) Rate the barriers in terms of their relative significance using linguistics terms. After repeated follow-ups, nine valid responses (DE1,…,DE9) were received.

The expertise is often correlated with professional longevity. An Expert weighting factor **(w_j)** was assigned to each DE based on their years of experience such as: 10%, 5–10 years (Mid-level managers): 12%, 10+ years (Senior managers). The detailed profiles of these DEs are provided in Annexure I.

5. Result and Analysis

The analysis is carried out in two steps as per the methodology explained in section 3.

5.1 Causal relationship of barriers using SF-DEMATEL

Step 1: SF values were assigned to the ratings in linguistic terms from Table 4 to obtain a fuzzy initial direct-influence matrix.

Step 2: Aggregated spherical fuzzy initial direct-influence matrix was obtained using SFWGA operator given in Eq. (2). The DEs were assigned different weight based on their experience.

Step 3: Using score function given in Eq. (3), non-fuzzy initial direct-influence matrix was obtained as shown in Table 6 and Total influence matrix (T) was obtained as shown in Table 7.

Step 4: Prominence (Pi), Net Effect (Ei) and cause/effect barriers were obtained using Eq. (8 and 9) as shown in Table 8. Causal digraph is shown in Figure 3.

Table 6. Non-fuzzy (crisp) initial direct-influence matrix of Barriers of I4.0 and CSC

Barriers	**B1**	**B2**	**B3**	**B4**	**B5**	**B6**	**B7**	**B8**	**B9**	**B10**	**B11**
B1	0.00	2.26	5.89	3.83	2.30	1.91	3.91	0.48	3.59	2.62	3.68
B2	2.26	0.00	2.22	1.53	0.58	0.19	3.01	2.38	3.36	2.03	2.75
B3	1.11	4.29	0.00	2.45	2.76	4.19	1.50	3.91	2.68	3.65	0.83
B4	3.97	2.02	4.91	0.00	3.90	3.65	0.30	2.46	4.33	2.05	2.38
B5	1.91	2.39	3.46	2.50	0.00	2.39	4.53	3.57	3.17	1.42	0.47
B6	2.92	0.40	3.17	2.25	3.29	0.00	3.45	4.20	3.01	3.77	1.84
B7	3.08	1.55	3.90	2.17	4.13	1.96	0.00	1.42	3.08	3.72	2.32
B8	2.46	3.21	0.62	1.13	3.31	3.27	3.46	0.00	0.58	2.21	2.06
B9	2.37	1.35	2.12	4.03	3.18	4.53	1.00	5.45	0.00	4.55	0.53
B10	4.14	3.90	1.49	0.92	0.50	3.36	2.00	4.49	1.94	0.00	4.14
B11	4.29	1.27	2.48	2.39	4.08	2.55	3.56	3.67	4.14	1.59	0.00

Table 7. Total influence matrix (T) of Barriers of I4.0 and CSC

Barrier	**B1**	**B2**	**B3**	**B4**	**B5**	**B6**	**B7**	**B8**	**B9**	**B10**	**B11**	**R**
B1	-0.48	-0.11	0.11	0.04	-0.17	-0.16	-0.17	-0.32	-0.03	-0.13	-0.04	**-1.467**
B2	-0.04	-0.31	-0.10	-0.06	-0.20	-0.24	-0.04	-0.11	0.04	-0.08	0.06	**-1.074**
B3	-0.18	0.12	-0.50	-0.11	-0.13	-0.01	-0.13	0.01	-0.12	-0.01	-0.11	**-1.178**
B4	-0.09	-0.12	0.02	-0.35	-0.05	0.00	-0.34	-0.12	-0.02	-0.17	-0.15	**-1.396**
B5	-0.18	-0.03	-0.03	-0.05	-0.37	-0.10	0.06	-0.05	-0.07	-0.13	-0.23	**-1.184**
B6	-0.09	-0.23	-0.11	-0.12	-0.05	-0.41	-0.02	-0.05	-0.14	-0.03	-0.10	**-1.340**
B7	-0.09	-0.12	-0.02	-0.08	-0.02	-0.15	-0.44	-0.22	-0.07	-0.03	-0.08	**-1.322**
B8	-0.05	0.00	-0.18	-0.14	0.01	-0.10	0.11	-0.47	-0.18	-0.11	-0.01	**-1.107**
B9	-0.11	-0.16	-0.22	-0.01	-0.09	0.05	-0.21	0.08	-0.50	0.01	-0.17	**-1.321**
B10	0.07	0.00	-0.21	-0.19	-0.27	-0.14	-0.08	-0.08	-0.14	-0.45	0.19	**-1.296**
B11	-0.05	-0.24	-0.12	-0.05	0.03	-0.13	-0.06	-0.13	-0.03	-0.22	-0.44	**-1.434**
C	**-1.290**	**-1.203**	**-1.329**	**-1.128**	**-1.299**	**-1.358**	**-1.323**	**-1.472**	**-1.273**	**-1.362**	**-1.082**	

Table 8. Prominence (Pi) and Net Effect (Ei) and Cause/Effect of Barriers of I4.0 and CSC

Barrier	**R**	**C**	**P(R+C)**	**E(R-C)**	**Cause**
B1	-1.467	-1.290	-2.757	-0.177	Effect
B2	-1.074	-1.203	-2.277	0.129	Cause
B3	-1.178	-1.329	-2.507	0.151	Cause
B4	-1.396	-1.128	-2.524	-0.268	Effect
B5	-1.184	-1.299	-2.482	0.115	Cause
B6	-1.340	-1.358	-2.698	0.018	Effect
B7	-1.322	-1.323	-2.645	0.001	Cause
B8	-1.107	-1.472	-2.578	0.365	Cause
B9	-1.321	-1.273	-2.594	-0.048	Effect
B10	-1.296	-1.362	-2.658	0.067	Cause
B11	-1.434	-1.082	-2.516	-0.352	Effect

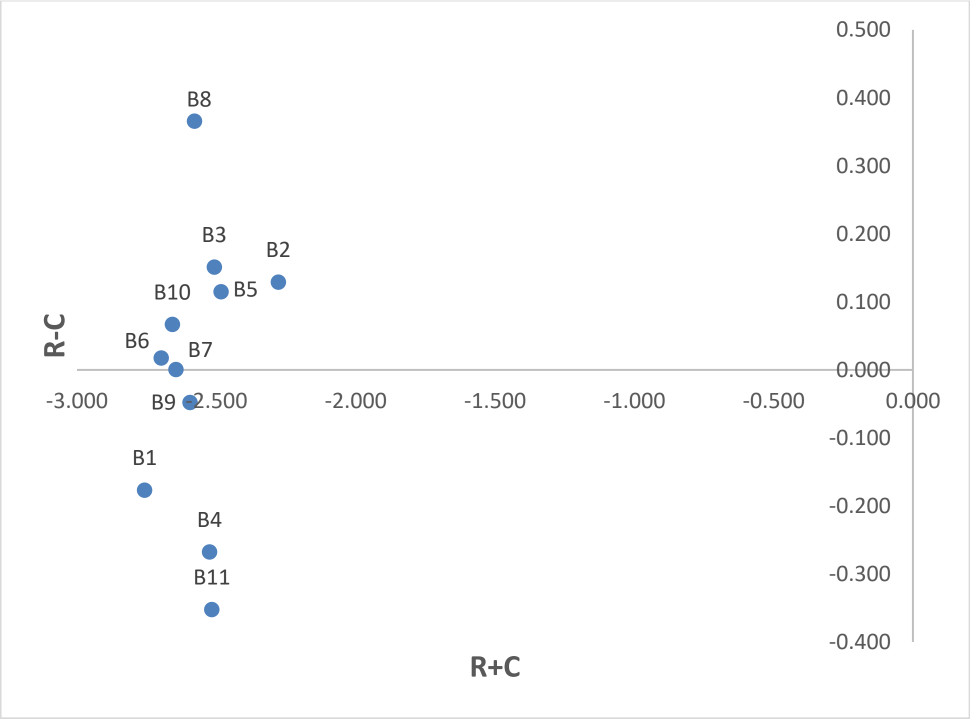


Figure 3. Causal Diagram of Barriers of I4.0 and CSC

5.2 Barrier weight using SF-SWARA

Step 1: Barriers expected significance rating (p_i) was done by group of DEs. The linguistic ratings were assigned SF values from Table 5.

Step 2: Aggregate fuzzy expected significance rating for all DEs the was obtained using SFWGA operator given in Eq. (2), as shown in Annexure III. The DEs with more than 12 years of experience were assigned 12% weight, while the rest 10% weight. Weights to DEs are assigned (0.12, 0.10, 0.10, 0.12, 0.10, 0.10, 0.12, 0.12, and 0.12) respectively.

Step 3: Using the Score function (ϑi) given in Eq. (3), non-fuzzy (crisp) expected significance are computed as shown in Annexure III.

Step 4: Barriers are sorted in descending order of Score function (ϑi). Comparative importance (S_i) of barriers is computed using Eq. 10 as shown in Table 9.

Step 5: The values of *k, q and w* (weight) of the barriers were calculated using Eq. (11, 12, &13) as shown in Table 9.

Table 9. Non-fuzzy S, k, q, weight (w) and rank of barriers

Barrier	**Score value**	***S***	***k***	***q***	***w* (weight)**	**Rank**
B1	3.380		1	1	0.168	1
B5	3.310	0.070	1.070	0.934	0.157	2
B8	3.240	0.070	1.070	0.873	0.147	3
B9	3.008	0.232	1.232	0.709	0.119	4
B10	2.388	0.619	1.619	0.438	0.073	5
B11	2.383	0.005	1.005	0.436	0.073	6
B4	2.293	0.090	1.090	0.400	0.067	7
B2	2.240	0.054	1.054	0.379	0.064	8
B6	2.196	0.044	1.044	0.363	0.061	9
B3	1.577	0.619	1.619	0.224	0.038	10
B7	1.452	0.126	1.126	0.199	0.033	11

5.3 Comparison of spherical fuzzy and traditional Method

A comparison of the Net effect (E) obtained by SF-DEMATEL and traditional DEMATEL is shown in Figure 4. In traditional DEMATEL, experts might have overemphasised certain relationships due to rigid expert inputs. Spherical fuzzy sets capture uncertainty and hesitancy much better, which played a significant role in expert opinions. Spherical fuzzy sets also reduce bias by allowing experts to express hesitation, making the results more representative of real-world uncertainty (Gul, 2020). The difference in net effect (Pi) by both the methods is due to mainly two reasons. The SFS scale captures uncertainty and hesitancy of expert's rating and assigning different weights to experts' evaluation based on their experience, which is more rational than the traditional method, in which equal weightage is given to all experts.

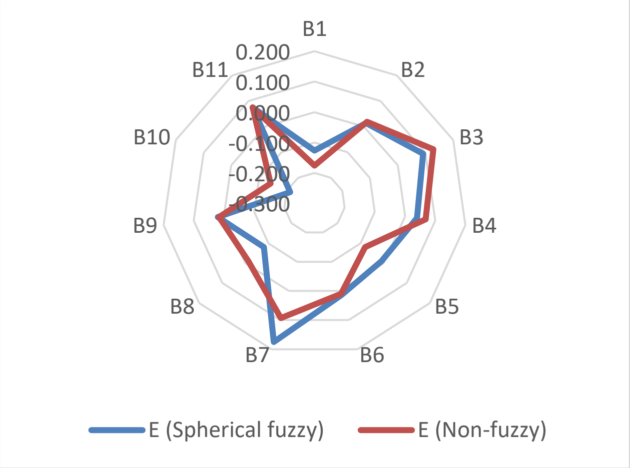


Figure 4. Comparison of Net effect (E) by SF-DEMATEL and traditional DEMATEL

A similar comparison of barriers weight by SF-SWARA and traditional SWARA is shown in Figure 5. The barriers weights are varying more particularly B5, B7, B8 and B9 by two methods of SF-SWARA and traditional SWARA. This is due to higher rating and higher weightage assigned to DE1, DE7, DE8 and DE9. SF-SWARA. SF-SWARA has advantage in that it captures uncertainty and hesitancy of expert's rating and assigns different weights to experts' evaluation based on their experience, whereas traditional SWARA does not consider this hesitancy of experts and equal weights are assigned to DE's rating.

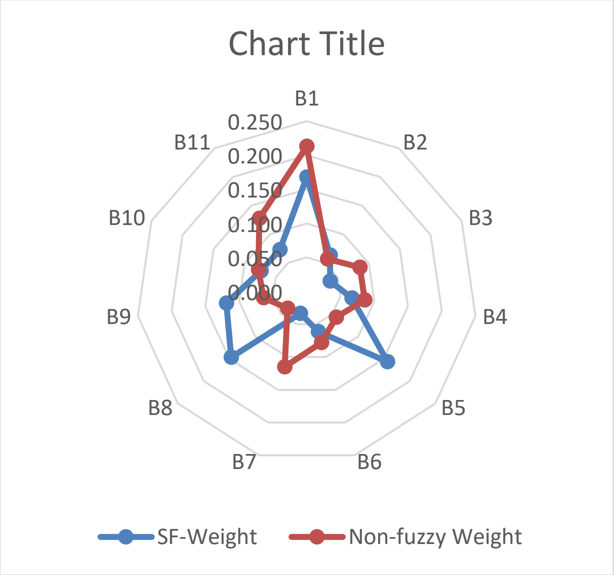


Figure 5. Comparison of Barrier Weight by SF-SWARA and traditional SWARA

6. Discussions and Implications

The results obtained from the SF-DEMATEL analysis provide insights into the causal relationships among the barriers of I4.0 and CSC adoption in the Indian manufacturing industry. The analysis reveals that lack of global standards, integration, and technology transfer in CSC processes (B8) exerts the highest degree of causal influence within the system. Other barriers belonging to the cause group include lack of smart equipment and network connectivity required for I4.0 and CSC implementation (B3), lack of awareness about potential benefits of I4.0 and CSC (B2), lack of skilled workforce for I4.0 and CSC (B5), Lack of government policies and incentives for circular model adoption (B10), Lack of support from top management, employees and stakeholder for I4.0 and CSC adoption (B6), and lack of coordination and collaboration among supply chain stakeholders (B7). These barriers act as driving factors that influence the occurrence and intensity of other barriers within the adoption system.

These findings are consistent with prior studies that highlight technological infrastructure and digital capability constraints as major challenges in implementing I4.0 and CE initiatives. For example, lack of smart equipment and network connectivity required for I4.0 and CSC implementation (B3) has been widely acknowledged as a major barrier to digital transformation (Jena & Patel, 2022; Kamble et al., 2018). Similarly, issues related to Lack of awareness about potential benefits of I4.0 and CSC (B2) have been emphasised as key barriers in transitioning towards circular business models (Kandasamy et al., 2023; Dwivedi & Paul, 2022). Lack of skilled workforce for I4.0 and CSC (B5) also remain a critical concern in digitalized circular supply chains (Bag et al., 2022), while Shang et al. (2022) highlighted challenges associated with data security in relationship management within circular flows.

Furthermore, barriers such as complexity of I4.0 and CSC integration (B9), High capital Investment requirement and uncertainty of ROI (B1), Lack of data transfer, interoperability and safety among different systems and SC stakeholders (B4) and Lack of digital culture and circular model adoption (B11) are also consistent with earlier research. Shang et al. (2022), for example, highlighted the lack of awareness regarding the potential benefits of autonomous systems in labour-intensive EOL activities during for the transition to I4.0-enabled CSCs.

From a theoretical perspective, these findings can be interpreted through the lens of the RBV. RBV suggests that firms achieve sustainable competitive advantage by acquiring and deploying valuable and difficult-to-imitate resources and capabilities. Several barriers identified in this study reflect limitations in firms' access to such strategic resources. For instance, barriers related to technological infrastructure, such as lack of smart equipment and network connectivity (B3), represent constraints in acquiring essential digital resources required for I4.0 implementation. Similarly, barriers associated with high capital investment requirement and uncertainty of ROI (B1) indicate challenges in mobilizing financial resources necessary for technological transformation. These constraints highlight the role of resource heterogeneity, as firms with greater access to financial and technological resources may be better positioned to adopt digital and circular practices.

In addition to resource availability, the results also highlight the importance of capability development within organizations. Barriers such as lack of skilled workforce (B5) and Lack of awareness about potential benefits of I4.0 and CSC (B2) indicate deficiencies in organizational capabilities required to effectively utilize advanced technologies and circular practices. Developing digital competencies, training employees, and fostering knowledge-sharing mechanisms are therefore essential for enabling successful adoption of these innovations.

Moreover, barriers such as Lack of coordination and collaboration among supply chain stakeholders (B7), lack of digital culture and circular model adoption (B11), and organizational resistance reflected in lack of support from top management, employees, and stakeholders for I4.0 and CSC adoption (B6) point to the importance of dynamic capabilities. These capabilities enable firms to reconfigure existing resources, integrate new technologies, and adapt organizational processes in response to rapidly changing technological and sustainability requirements. The presence of these barriers suggests that many manufacturing firms may still lack the dynamic capabilities necessary to integrate digital technologies with circular supply chain practices effectively.

The cause group is therefore considered as a set of controlling barriers, as these barriers exert a strong influence on other barriers within the system. Addressing these foundational barriers can significantly facilitate the adoption process. By leveraging the causal model (cause-and-effect grouping) obtained through SF-DEMATEL, managers can develop targeted strategies to mitigate these root barriers before addressing dependent barriers.

The weight and priority of the barriers calculated using SF-SWARA, as presented in Table 8 and Figure 4. The barriers ranked in decreasing order of priority are: B1>B5>B8>B9>B10>B11>B4>B2>B6>B3>B7. The highest-priority barriers, each scoring more than 7% weight include: High capital investment requirement and uncertainty of ROI (B1) (Ozkan-Ozen et al., 2020; Taddei et al., 2024; Kumar, Mangla et al., 2024)), lack of skilled workforce for I4.0 and CSC (B5) (Kumar, Raut et al., 2021), lack of global standards, integration and technology transfer in CSC processes (B8) (Taddei et al., 2024), and complexity of I4.0 and CSC integration (B9) (Taddei et al., 2024), Lack of government policies and incentives for circular model adoption (B10) and Lack of digital culture and circular model adoption (B11). These barriers represent the most critical challenges that organisations must address to enable successful adoption of integrated digital and CSC practices.

6.1 Causal and Priority Matrix

To better understand the relationship between different barriers, a classification system was developed that simultaneously considers their causal influence and priority level. In this framework, barriers are plotted along two axes: the x-axis represents the cause-effect relationship derived from the SF-DEMATEL, while the y-axis indicates priority based on the weights obtained from the SF-SWARA method, as illustrated in Figure 6.

Priority	Effect	Cause
Higher	B1, B9, B11	B5, B8, B10
Lower	B4	B2, B3, B6, B7

Figure 6. Barrier classification based on the Cause-Effect and Priority

Among the most influential barriers, those that drive other barriers, three stand out as high priority: Lack of skilled workforce for I4.0 and CSC (B5) (Isensee et al., 2020; Kandasamy et al., 2023), and lack of global standards, integration and technology transfer in CSC processes (B8) and Lack of government policies and incentives for circular model adoption (B10). These barriers occupy a critical position because they simultaneously exert strong causal influence and possess high priority levels, indicating that they should be addressed at the earliest stages of implementation.

The next set of barriers, lack of awareness about potential benefits of I4.0 and CSC (B2), lack of smart equipment and network connectivity required for I4.0 and CSC implementation (B3), lack of support from top management, employees, and stakeholders for I4.0 and CSC adoption (B6), and lack of coordination and collaboration among supply chain stakeholders (B7) also belong to the cause group but have comparatively lower priority levels. After addressing the most critical barriers, organizations should focus on these secondary drivers to further facilitate the transition toward integrated digital and CSC practices.

In contrast, High capital Investment requirement and uncertainty of ROI (B1), complexity of I4.0 and CSC integration (B9), and lack of digital culture and circular model adoption (B11) fall within the effect group but possess relatively high priority levels. These barriers are strongly influenced by the cause barriers and should therefore be addressed in the subsequent stages of implementation once the foundational drivers have been mitigated.

Finally, Lack of data transfer, interoperability and safety among different systems and SC stakeholders (B4) is categorised as low-priority effect barriers. These barriers have relatively lower direct influence on the adoption process and can be addressed in the later phases once more fundamental barriers have been resolved. By prioritizing barriers in this structured manner, decision-makers can adopt a systematic approach that resolves foundational challenges before tackling less critical ones, thereby facilitating a more efficient and sustainable transition toward integrated I4.0-CSC adoption.

The contemporary business environment has become increasingly volatile, uncertain and susceptible to disruptions due to multiple black swan events, such as the COVID-19 pandemic, the U.S.-China trade war, and geopolitical tensions such as the Russia-Ukraine conflict. Manufacturing supply chains face mounting competitive pressure arising from globalisation and the growing urgency of climate change mitigation. In this context, I4.0 technologies can enhance supply chain efficiency by optimising resource utilisation, minimising waste, and reducing energy and water consumption. Technologies such as blockchain and the Internet of Things (IoT) can further enhance transparency and traceability across the product life cycle. Consequently, addressing the key causal barriers identified in this study is essential for facilitating the adoption of integrated I4.0-CSC practices and achieving broader sustainability objectives, including the Sustainable Development Goals (SDG).

6.2 Theoretical Implication

The SFSs, known for their flexibility and ability to provide more accurate results in handling uncertainty and imprecision, were adopted in this study. The spherical fuzzy-based DEMATEL technique was employed to develop a causal model illustrating the interrelationships among eleven barriers of I4.0 and CSC adoption. Additionally, the SF-SWARA method was applied to establish their priority. A key novelty of the proposed method lies in assigning different weights to DEs based on their knowledge and experience, whereas most studies assume equal weighting for DEs. Furthermore, a novel approach was developed to categorise the integrated barriers of I4.0 and CSC by combining the causal model with priority weights. To the best of the authors' knowledge, this is the first study to apply the hybrid SF-DEMATEL and SF-

SWARA model to the manufacturing industry within a developing economy context. This research significantly contributes to the existing body of knowledge.

6.3 Managerial Implication

The study offers several important implications for managers. It helps identify key barriers to I4.0 and CSC adoption in a developing country, recognising that all barriers do not hold equal significance. Many practitioners, particularly in developing economies like India, may be unfamiliar with these barriers and their impact. The proposed model enables managers to develop a causal framework, prioritise barriers based on their cause-and-effect grouping, and set priority so as to pay attention to them accordingly. By integrating this approach, managers can focus on eliminating the most critical barriers, particularly those in the cause group, which require the highest priority for resolution. For instance, Managers must align digital transformation initiatives with CE goals (Ozkan-Ozen et al., 2020; Kumar, Raut et al., 2021). Managers should invest in digital technologies like IoT, AI, big data, and automation as a precursor to circular business model innovation, which are often underdeveloped in emerging markets (Shang et al., 2022; Kumar, Mangla & Kumar, 2024). Firms should invest in upskilling the workforce in both digital technologies and sustainability concepts (Ozkan-Ozen et al., 2020; Taddei et al., 2024). Managers should build transparent digitally connected data-sharing platforms across suppliers, customers, and recyclers to achieve circularity (Kumar, Raut et al., 2021; Taddei et al., 2024). Structured assessment models can help firms identify critical barriers and systematically allocate resources (Kumar, Raut et al., 2021; Kumar, Mangla & Kumar, 2024). Firms should engage in policy discussions to shape favorable ecosystems (Shang et al., 2022; Taddei et al., 2024).

6.4 Policy Implication

To facilitate the adoption of I4.0 and CSC, it is essential to establish standardized frameworks and reference models that ensure seamless integration across industries (Kamble et al., 2018). These standards not only improve compatibility but also contribute to economies of scale, making I4.0 adoption more accessible for businesses. Governments can play a vital role in this process by encouraging collaboration among industries, technology providers, and policymakers to create guidelines that support digital transformation.

A key area of government intervention should be the development of information and communication technology infrastructure. Expanding broadband access, enhancing wireless connectivity, and improving internet speeds will provide the necessary foundation for smart manufacturing systems to function efficiently (Kim, 2018). Additionally, ensuring the availability of adequate spectrum and reliable communication networks will enable real-time data exchange, which is essential for I4.0 operations. Cybersecurity and interoperability among different systems must also be prioritized. Governments should introduce policies that promote secure data transfer and safeguard supply chains from cyber threats (Lee, 2019). Ensuring the protection of sensitive industrial data will build confidence among businesses, fostering wider adoption of I4.0 technologies (de Bruijn & Janssen, 2017).

Another critical policy consideration is workforce development. The success of I4.0 relies heavily on skilled professionals who can operate and manage advanced technologies. Governments should work closely with educational institutions and industry leaders to design training programs that equip workers with the skills required for automation, data analytics, and smart manufacturing. Providing incentives for upskilling initiatives and integrating I4.0-related subjects into academic curricula will help prepare the workforce for the evolving industrial landscape (Schneider, 2018). By focusing on standardization, infrastructure development, cybersecurity, and workforce education, policymakers can create an environment that supports sustainable and scalable I4.0 and CSC adoption. These measures will ensure that industries remain competitive while contributing to long-term economic growth and innovation.

7. Conclusion, Limitations, and Future Research

The integration of I4.0 technologies with CE principles represents a critical pathway for enhancing sustainability, resource efficiency, and long-term competitiveness in modern manufacturing sector. Despite the growing recognition of its potential, the simultaneous adoption of digital technologies and CSC practices remains challenging due to presence of multiple interrelated technological, organizational, and institutional barriers. Addressing this gap, the present study developed and applied a novel hybrid MCDM framework integrating SF-DEMATEL and SF-SWARA to systematically identify, analyse, and prioritize the key barriers affecting the integrated adoption of I4.0 and CSC practices.

The empirical analysis, conducted within the Indian manufacturing sector, identified several critical barriers that significantly influence the adoption processes. The results reveal that the identified barriers are highly interconnected and collectively shape the adoption environment within manufacturing supply chains. The causal analysis further distinguishes between cause-and-effect barriers, highlighting a subset of barriers that exert greater driving influence within the system. These are not complicated, where addressing key driving barriers is essential for facilitating the broader adoption of I4.0-enabled circular supply chain practices.

From a methodological standpoint, the study contributes to the literature by proposing a novel hybrid spherical fuzzy decision-making framework capable of modelling complex interdependencies among barriers while addressing uncertainty and expert hesitancy in the evaluation process. The incorporation of differential expert weighting based on experience further enhances the robustness and realism of the assessment compared to conventional MCDM approaches that assume homogeneous expert judgments. From a theoretical perspective, the findings also contribute to the RBV by illustrating how limitations in critical organizational resources, such as technological infrastructure, skilled human capital, and managerial capabilities, can hinder the ability of firms to develop and deploy the capabilities required for digital–circular transformation.

Practically, the findings provide a strategic decision-support tool for manufacturing firms and policymakers aiming to accelerate sustainable transformation. By identifying the most influential barriers, the study helps stakeholders focus their efforts where they are likely to have the most impact.

Despite these contributions, the study has several limitations that should be acknowledged. This study is based on expert evaluations drawn exclusively from the Indian manufacturing sector, and therefore the findings reflect the institutional, technological, and economic conditions specific to India. While the identified barriers may also be relevant to other emerging economies with similar structural characteristics, caution should be exercised when generalizing the results beyond the Indian context. Future research may replicate the proposed framework in other emerging economies to validate and compare the barrier structures across different industrial environments.

Furthermore, the analysis relied on a relatively small panel of industry experts, which is consistent with expert-based MCDM studies but may limit the diversity of perspectives captured in the evaluation process. Future studies may expand the number of experts and include participants from different stakeholder groups, such as policymakers, technology providers, and sustainability practitioners, to further strengthen the robustness of the findings. In addition, future research could apply the proposed analytical framework to different industrial sectors or regional contexts to examine how variations in institutional environments and technological readiness influence the structure and prioritization of adoption barriers.

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APPENDICES

Appendix I: Profile of the Decision Experts (DEs) from Indian Manufacturing Sector

Role	Qualification	Experience (years)	Sector
Department Head	B. Tech	16	Automobile
Lead Engineer	B. Tech	12	Automobile
Sr. Engineer	B. Tech	8	Automobile
Sr. Engineer-PP	M. Tech	19	Consumer durable
Dy. General Manager	B. Tech	20	Electronics
Logistics Planning	MBA	20	Electronics
SC Planning	MBA	11	Electronics
SC Planning	MBA	11	Food Processing
Sr. Engineer	B. Tech	10	Pharmaceutical

Appendix II*:* Aggregated Initial Direct Relationship Matrix

Barrier	DE1			DE2			DE3			DE4			DE5			DE6			DE7			DE8			DE9		
B1	0.00	0.00	0.00	0.46	0.56	0.24	0.76	0.27	0.16	0.31	0.60	0.20	0.57	0.48	0.23	0.50	0.44	0.15	0.31	0.59	0.18	0.46	0.47	0.16	0.32	0.54	0.13
B2	0.46	0.56	0.24	0.00	0.00	0.00	0.53	0.45	0.20	0.48	0.52	0.23	0.48	0.48	0.20	0.49	0.49	0.19	0.40	0.58	0.24	0.42	0.52	0.18	0.36	0.59	0.23
B3	0.49	0.52	0.23	0.26	0.63	0.20	0.00	0.00	0.00	0.41	0.51	0.15	0.42	0.57	0.25	0.27	0.63	0.20	0.52	0.48	0.21	0.30	0.59	0.19	0.41	0.53	0.18
B4	0.30	0.64	0.24	0.41	0.48	0.14	0.68	0.34	0.15	0.00	0.00	0.00	0.30	0.62	0.22	0.33	0.60	0.23	0.45	0.45	0.15	0.43	0.55	0.23	0.62	0.33	0.14
B5	0.45	0.51	0.19	0.44	0.55	0.23	0.34	0.55	0.17	0.58	0.48	0.22	0.00	0.00	0.00	0.44	0.55	0.23	0.65	0.34	0.17	0.35	0.58	0.20	0.37	0.55	0.19
B6	0.59	0.45	0.21	0.52	0.52	0.25	0.37	0.55	0.19	0.42	0.52	0.19	0.57	0.40	0.17	0.00	0.00	0.00	0.35	0.56	0.17	0.27	0.58	0.14	0.38	0.55	0.20
B7	0.40	0.60	0.26	0.49	0.45	0.18	0.30	0.62	0.22	0.43	0.52	0.20	0.29	0.62	0.19	0.45	0.52	0.21	0.00	0.00	0.00	0.51	0.55	0.26	0.38	0.55	0.18
B8	0.40	0.50	0.15	0.38	0.56	0.19	0.50	0.49	0.21	0.47	0.49	0.20	0.57	0.40	0.18	0.36	0.57	0.20	0.58	0.39	0.16	0.00	0.00	0.00	0.48	0.48	0.20
B9	0.43	0.53	0.20	0.51	0.55	0.26	0.53	0.45	0.19	0.30	0.56	0.13	0.37	0.57	0.21	0.62	0.33	0.13	0.51	0.49	0.22	0.73	0.29	0.17	0.00	0.00	0.00
B10	0.67	0.40	0.21	0.30	0.62	0.22	0.55	0.51	0.24	0.50	0.52	0.23	0.48	0.48	0.19	0.36	0.58	0.21	0.44	0.51	0.18	0.65	0.34	0.17	0.55	0.48	0.23
B11	0.26	0.62	0.18	0.51	0.48	0.21	0.45	0.57	0.26	0.44	0.55	0.23	0.29	0.60	0.18	0.45	0.58	0.26	0.61	0.40	0.20	0.33	0.62	0.24	0.30	0.58	0.14

Appendix III*:* Spherical Fuzzy Relative Significance Ratings of Barriers

Barrier	DE1			DE4			DE2			DE3			DE5			DE6			DE7			DE8			DE9			Aggregated			Score
B1	0.60	0.40	0.30	0.70	0.30	0.20	0.60	0.40	0.30	0.70	0.30	0.20	0.70	0.30	0.20	0.50	0.50	0.40	0.60	0.40	0.30	0.60	0.40	0.30	0.70	0.30	0.20	0.631	0.385	0.275	3.380
B2	0.30	0.70	0.20	0.60	0.40	0.30	0.30	0.70	0.20	0.60	0.40	0.30	0.60	0.40	0.30	0.20	0.80	0.10	0.60	0.40	0.30	0.60	0.40	0.30	0.60	0.40	0.30	0.462	0.564	0.267	2.240
B3	0.20	0.80	0.10	0.70	0.30	0.20	0.20	0.80	0.10	0.70	0.30	0.20	0.70	0.30	0.20	0.60	0.40	0.30	0.60	0.40	0.30	0.60	0.40	0.30	0.50	0.50	0.40	0.484	0.534	0.257	1.577
B4	0.30	0.70	0.20	0.70	0.30	0.20	0.10	0.90	0.05	0.70	0.30	0.20	0.70	0.30	0.20	0.50	0.50	0.40	0.60	0.40	0.30	0.60	0.40	0.30	0.60	0.40	0.30	0.476	0.575	0.259	2.293
B5	0.10	0.90	0.05	0.70	0.30	0.20	0.10	0.90	0.05	0.70	0.30	0.20	0.70	0.30	0.20	0.60	0.40	0.30	0.60	0.40	0.30	0.50	0.50	0.40	0.40	0.60	0.30	0.396	0.614	0.254	3.310
B6	0.30	0.70	0.20	0.60	0.40	0.30	0.30	0.70	0.20	0.60	0.40	0.30	0.60	0.40	0.30	0.20	0.80	0.10	0.60	0.40	0.30	0.70	0.30	0.20	0.80	0.20	0.10		0.569	0.237	2.196
B7	0.70	0.30	0.20	0.70	0.30	0.20	0.70	0.30	0.20	0.70	0.30	0.20	0.70	0.30	0.20	0.30	0.70	0.20	0.50	0.50	0.40	0.40	0.60	0.30	0.40	0.60	0.30	0.540	0.500	0.259	1.452
B8	0.20	0.80	0.10	0.60	0.40	0.30	0.20	0.80	0.10	0.70	0.30	0.20	0.70	0.30	0.20	0.50	0.50	0.40	0.40	0.60	0.30	0.30	0.70	0.20	0.30	0.70	0.20	0.386	0.595	0.240	3.240
B9	0.20	0.80	0.10	0.60	0.40	0.30	0.10	0.90	0.05	0.60	0.40	0.30	0.60	0.40	0.30	0.60	0.40	0.30	0.40	0.60	0.30	0.70	0.30	0.20	0.70	0.30	0.20	0.435	0.601	0.246	3.008
B10	0.10	0.90	0.05	0.60	0.40	0.30	0.30	0.70	0.20	0.60	0.40	0.30	0.60	0.40	0.30	0.70	0.30	0.20	0.50	0.50	0.40	0.70	0.30	0.20	0.60	0.40	0.30	0.457	0.573	0.270	2.388
B11	0.60	0.40	0.30	0.60	0.40	0.30	0.60	0.40	0.30	0.60	0.40	0.30	0.60	0.40	0.30	0.50	0.50	0.40	0.50	0.50	0.40	0.60	0.40	0.30	0.60	0.40	0.30	0.576	0.404	0.325	2.383