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Gen-AI Is Not an Option for Environment Sustainability-Enabling of Gen-AI for Responsible and Green Supply Chains Using a Grey Network Map (GNM)

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ABSTRACT

Environmental sustainability in supply chains is no longer considered a compliance concern. It has become a strategic capability challenge, as firms seek to use Generative artificial intelligence (Gen-AI) to improve decision quality, resource efficiency and responsible operations. However, despite growing interest in Gen-AI, its adoption for green and responsible supply chains remains limited in developing countries where policy support, digital readiness and organizational preparedness are major issues. Therefore, based on dynamic capabilities theory, the present study examines how firms can build the capabilities required to adopt Gen-AI for environmentally sustainable and responsible supply chain practices. First, this study identifies key adoption enablers through a structured literature review. Then, these enablers are validated using a survey based on a 5-point Likert scale. In the main analytical model, a Grey network map (GNM) based on Grey-Decision-making trial and evaluation laboratory (Grey-DEMATEL) approach is used to examine the causal relationship among the validated enablers and to identify driving and dependent factors under the conditions of uncertainty. The findings of this study reveal that government and policy support, as well as top management support, are the main causal enablers and indicate that strategic leadership can help in the adoption of Gen-AI for green and responsible supply chains. Also, knowledge management, collaborative culture, and a global collaboration network are the main outcome enablers, which are influenced by causal enablers. The findings suggest a few policy actions, such as the design of sector-focused AI adoption guidelines, targeted incentives for green digital infrastructure and national capability-building programmes to support managerial and workforce readiness. The study contributes by offering a validated and structured framework that explains how Gen-AI adoption can be strategically enabled to support green and responsible supply chains.

Abbreviations: AI, artificial intelligence; API, application programming interface; DCV, dynamic capabilities view; DEMATEL, decision-making trial and evaluation laboratory; ERP, enterprise resource planning; ESG, environmental, social and governance; FMCG, fast-moving consumer goods; Gen-AI, generative artificial intelligence; GNM, grey network map; IoT, internet of things; ISM, interpretive structural modelling; PRISMA, Preferred Reporting Items for Systematic Reviews and Meta-Analyses; RO, research objectives; RQ, research questions; SDGs, sustainable development goals; SMEs, small and medium enterprises.

1 | Introduction

AI tools are widely used in operations and supply chain management in areas like predictive maintenance, risk management, demand forecasting, quality control, scheduling and optimization (Fosso Wamba et al. 2024). In literature, Generative artificial intelligence (Gen-AI) has disrupted various industries and is considered a computational technique, which has the potential to generate new and meaningful content, including text, image and audio generation from training data (Feuerriegel et al. 2024). After the introduction of AlphaGo in 2015, AI has made a comeback through Chat Generative Pre trained Transformer (ChatGPT) in 2022 by OpenAI, which has gained popularity over the globe (Fui-Hoon Nah et al. 2023). It uses techniques such as neural networks and deep learning algorithms for original content generation, which is not included in the training data set (Li, Liu, et al. 2024). According to the McKinsey Global survey, there is significant growth in the usage of Gen-AI tools, and most organizations are using them in at least one of their business functions.[1] Also, the existing literature reveals that there has been significant growth in ChatGPT in the last few years, which has the potential to transform business models and areas of operations and supply chain management (Fui-Hoon Nah et al. 2023). The concept of digital supply chain management has become popular in the last few years and is commonly addressed in academic literature (Büyüközkan and Göçer 2018). This is driven by disruptive technologies such as IoT, big data analytics and AI, which provide new opportunities for integration and flexibility in the supply chain (Al-khatib et al. 2024). In literature, supply chain management is an emerging topic, and the rapid development and integration of Gen-AI into supply chains is reshaping the future of supply chain due to technological advancements (Jackson et al. 2024). It offers new opportunities to automate supply chain operations, improve resilience and make decisions. Unlike traditional AI-based models, it helps to generate multiple simulated scenarios and novel solutions to supply chain optimization (Boone et al. 2025). According to McKinsey, it offers opportunities for entire logistics operations, including planning, warehousing, optimization and transportation through advanced AI models, which helps to improve efficiency in logistics operations.[2] In the current scenario, due to factors such as information technology, offshore production, outsourcing and globalization, supply chain practices across the globe are going through a significant transformation. This results in more complexity in supply networks and sustainability issues (Ngo et al. 2024). This complexity presents new challenges for industries related to forecast demand, process optimization and resource efficiency (Wu et al. 2025). These issues have been widely discussed in academic literature by various scholars (Hofmann et al. 2014; Ngo et al. 2024; Rajeev et al. 2017; Seuring et al. 2008; Truant et al. 2024). In such scenarios, the implementation of advanced technologies plays an important role in addressing sustainability issues in operations and supply chain management (Bag et al. 2021; Esmaeilian et al. 2020; Kumar et al. 2021; Luthra and Mangla 2018). However, industries are also adopting circular supply chain models to minimize their ecological footprints. Recent evidence also reveals that supply chain logistics and green transportation play an important role in improving green economics even under the influence of green finance, oil price shocks and geopolitical risks (Kartal and Taşkın 2026). However, such studies do not explain the organizational and policy enablers required to adopt Gen-AI to support green and responsible supply chains.

The existing literature has discussed circular business models to address sustainability issues (Geissdoerfer et al. 2018; Vegter et al. 2020). But the safety issues remain in activities like remanufacturing and recycling in circular supply chains. These issues can be addressed through Gen-AI, which has the potential to revolutionize safety management through predictive analysis and proactive monitoring (Chen et al. 2025). However, combining Gen-AI with the metaverse has the potential to address resiliency issues in the supply chain. Gen-AI can be combined with the metaverse to create a virtual representation of supply chain entities that help to enable adaptive response in the supply chain network (Meafaa et al. 2025). Despite Gen-AI's potential to address sustainability challenges in the supply chain, most industries are not able to use it and realize its benefits (Li, Zhu, et al. 2024). However, existing literature shows a focus on constructing Gen-AI metrics, but there is a lack in developing capabilities to address environmental challenges in the supply chain (Kurrahman et al. 2025). Although the supply chain challenges can be addressed through Gen-AI, a comprehensive theoretical framework for Gen-AI application in supply chains is still limited (Wu et al. 2025). Compatibility, observability and trialability have a positive effect on Gen-AI adoption in the supply chain, but complexity resists its adoption (Gao et al. 2025). The advancements in Gen-AI and the digital supply chain help organizations to achieve their SDGs. With the use of Gen-AI, digital supply chain organizations can improve their ESG performance (Wang and Zhang 2025). This is particularly important for SMEs as these are more vulnerable to disruptions. In such cases, Gen-AI can be used to generate scenarios and analyse large data sets, which help in risk identification. It also improves decision-making through AI insights (Ahmad et al. 2024). But integrating this into the supply chain requires trust, data security, technical, operational and ethical issues (Chen et al. 2025). Similarly, evidence from the United States shows that AI-related patents can shape the relationship between energy consumption patterns and CO_2 emissions, which highlights the environmental relevance of AI-related innovation (Kartal et al. 2026). Nevertheless, these macrolevel findings do not explain how firms can build capabilities and enable conditions that are needed to adopt Gen-AI in green and responsible supply chains. The existing literature also reveals that there is limited focus on the exploration of enablers of adopting Gen-AI in the supply chain to improve its sustainability. The main issues discussed in terms of data, organizational and technological issues (Fosso Wamba et al. 2024). The other challenges are trust in data sources, privacy issues, technology adoption and implementation (Fosso Wamba et al. 2023). These challenges are more important for developing countries where the digital infrastructure is limited and technological readiness is lower. In such a scenario, it is important to identify which enablers need to be addressed at the initial level. This is the initial study, which examines the enablers in Gen-AI adoption in the supply chain in developing countries. To address the above-discussed gaps, this study aims to systematically explore the enablers in Gen-AI adoption within supply chains of developing countries, validate the findings through empirical evidence and prioritize and analyse the interdependencies among these enablers using hybrid methods. Based on these aims, the ROs and RQs are formulated as follows:

RQ1: What are the enablers that help in the adoption of Gen-AI for green and responsible supply chains within developing countries?

RQ2: What is the causal interrelationship among these enablers, and how can they help to reshape future supply chain strategies?

Based on these research questions, the following research objectives have been developed to guide the investigation in a structured and focused manner.

RO1: To identify enablers to adopt Gen-AI for green and responsible supply chains in developing countries.

RO2: To prioritize the identified enablers and analyse their causal interrelationships

To address the above-discussed ROs and RQs, an integrated approach was adopted. In the initial stage, a literature review was conducted on databases like Scopus. This database was considered due to its quality and widespread acceptance in academic literature. The initial list of identified enablers was discussed with an expert panel from industries for their contextual validation. From the theoretical point of view, this paper discusses the emerging discourse on Gen-AI-enabled sustainable operations by developing a validated framework that maps how foundational enablers drive responsible and green supply chain adoption. It extends the application of the Grey DEMATEL approach and offers a structured understanding of interdependencies among the enablers, which is not discussed in the literature. From the managerial perspective, the findings provide a clear road map for firms by identifying where to prioritize their investments, such as leadership commitment and data quality, to accelerate Gen-AI adoption for sustainability outcomes. From the policy perspective, the study highlights the need for targeted regulatory guidance, incentives and national digital readiness programmes to build ethical, transparent and environmentally aligned AI-enabled supply chains.

Section 2 discusses the literature review and research gaps, Section 3 discusses survey design and data analysis, Section 4 discusses the results and discussions, and Section 5 discusses the conclusion and future research scopes.

2 | Literature Review

The present section discusses the role of Gen-AI and its enablers in the context of green and responsible supply chains.

2.1 | Literature Selection Approach

To address the RQs discussed in the introduction section, it is necessary to identify the enablers of adopting Gen-AI within the context of green and responsible supply chains. This required examining how Gen-AI is influencing sustainable practices, what progress has been documented in the prior studies and the

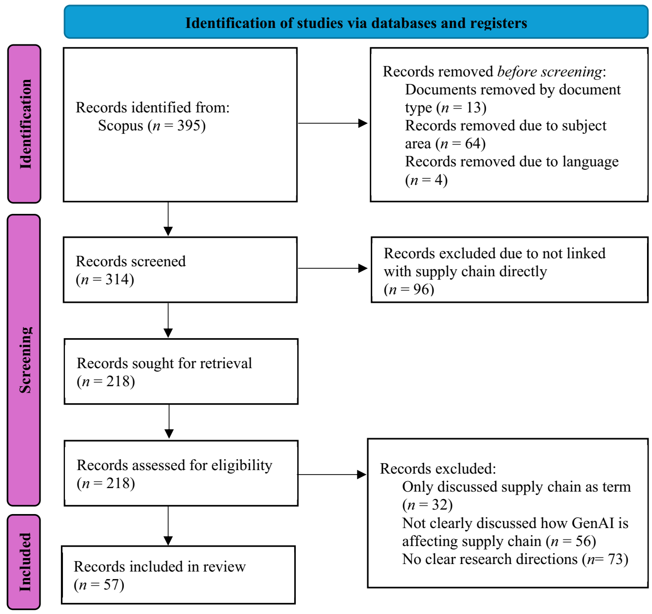

FIGURE 1 | PRISMA diagram for the literature review.

potential research avenues that are still unexplored. Therefore, a structured review of relevant academic and practitioner-oriented publications was conducted. Given the vast volume of existing work on Gen-AI, sustainability and supply chain management, a rigorous selection method was essential to ensure that only suitable contributions were included. For this purpose, the PRISMA framework was considered. The PRISMA approach is widely accepted and recognized for transparent literature review. It is also considered the systematic procedure to identify, screen and select literature that aligns with the predefined objectives. The PRISMA approach includes four phases: (1) identification of potential studies, (2) screening of titles and abstracts, (3) inclusion and exclusion criteria and (4) final selection of studies based on the relevance to Gen-AI and sustainable supply chain themes. The use of PRISMA is important to reduce bias and ensure that selected studies are comprehensive and focused. The detailed step of this procedure is presented in the following subsections, whereas Figure 1 visually represents the PRISMA flow applied in this research.

2.1.1 | Identification of Relevant Literature

The first phase of the review process is focused on the database selection for article collection. In this study, the SCOPUS database was selected as the primary source for literature collection. The decision to select this database relies solely on its extensive coverage of peer-reviewed journals, conference proceedings and subject areas relevant to both artificial intelligence and supply chain management. As compared to other databases such as Web of Science and IEEE Xplore, Scopus provides a broader interdisciplinary scope, which is particularly important given that the intersection of Gen-AI, sustainability and supply chain spans multiple domains, including operations, computer science and environmental studies. To identify the initial pool of relevant studies, a search string was applied to the database. This includes the combination such as *Generative AI OR* 'Large Language Models' with *supply chain*, which helps to cover the wide range of studies that addressed both technological and sustainability dimensions.

2.1.2 | Screening of Papers

Following the initial identification of literature, the second stage is to refine the pool of identified papers that are more relevant to the objectives of the present study. The goal was to ensure that peer-reviewed literature considered in this study addresses both areas, i.e., Gen-AI and supply chain practices in the context of green or responsible supply chains. The search string includes both Gen-AI-specific keywords and supply chain to cover the most relevant studies. Apart from this, additional filters were applied, which include the inclusion of peer-reviewed articles only. This systematic screening step removed a significant number of papers that were either too generic or contextually misaligned or had less connection to the research objectives. This helped us to select more refined literature that is aligned with the research objectives of the present study. Finally, based on all criteria as discussed in Figure 1, a total of 57 articles were included in the study.

2.2 | Introduction to AI and Gen-AI in Supply Chains

Over the years, manufacturing organizations have realized the potential of artificial intelligence in the supply chain, which offers advanced capabilities in automation, prediction and decision-making (Dash et al. 2019). It includes a wide range of computational techniques, including machine learning and natural language processing, that enable organizations to manage their supply chain data with more accuracy (Agarwal and Jayant 2019). Building on these foundations, Gen-AI represents a new paradigm in which algorithms can generate novel outputs such as production schedules, different scenarios and demand forecasts. It extends the application of traditional approaches in AI beyond predictive analytics (Fosso Wamba et al. 2023). Gen-AI has the ability to manage uncertainty and improve resilience in disruptions. In existing literature, it has been highlighted as a tool to reduce operational cost by optimizing logistics while supporting sustainability initiatives such as emission reduction and circular economy practices (Jourabchi Amirkhizi et al. 2025). Recent studies also discussed that Gen-AI is critical for SMEs and enables them to maintain their market competitiveness (Shore et al. 2024). In the past few years, this area has grown significantly with the wide range of disciplines, including operations research, information systems and human resource management, to investigate the implications of Gen-AI for resilience, agility and sustainability in business models (Ajaero and Anjorin 2024; Fosso Wamba et al. 2023; Malhotra and Manzoor 2025). This reflects how Gen-AI is evolving and improving the performance of organizations. Different Gen-AI tools with their applications in Operations management are discussed in the Figure 2.

FIGURE 2 | Different Gen-AI-based tools and their applications in operations management.

2.3 | Applications of AI and Gen-AI in Supply Chains

The rapid advancement of Gen-AI, which is supported by tools like Gemini and ChatGPT, is not limited to supply chains but is also reshaping firms' business models (Teng et al. 2025). Nevertheless, despite rising global debate and interest, there remains a scarcity of empirical studies that examine its impact on supply chain management (Fosso Wamba et al. 2023). At the same time, leading companies such as Volkswagen, Toyota and General Mills have started implementing Gen-AI tools for real-time monitoring, material-transport planning and demand forecasting. These early applications have shown improvements in decision-making and operational efficiency (Dubey et al. 2024).

Gen-AI is increasingly being integrated into operations and supply chain management, as scholars and practitioners recognize its potential to enhance decision-making and streamline processes (Fosso Wamba et al. 2023). The existing studies highlight the challenges in consolidation and validation of diverse data sources but also discuss the AI's ability to improve demand planning through advanced analytics (Shekhar et al. 2023). In logistics optimization, Gen-AI has been applied in route planning, load optimization and last-mile delivery (Boone et al. 2025). Similarly, it has applications in inventory management in which predictive models can balance the stock levels in a dynamic market, which helps to minimize both shortage and excess inventory (Hao et al. 2024; Tanskanen et al. 2015). AI is widely used in production scheduling, in which Gen-AI algorithms can dynamically adjust the schedules in response to disruptions such as supplier delays or machine breakdown (Gangwar et al. 2025; Sai et al. 2025). Beyond the traditional applications of AI, Gen-AI is the emerging domain that is gaining attention due to predictive simulations and scenario analysis (Hao et al. 2024; Jourabchi Amirkhizi et al. 2025). These applications discuss that AI and

FIGURE 3 | Gen-AI applications in supply chain.

Gen-AI not only improve the operational efficiency but also expand the strategic role of the supply chain to achieve resilience and sustainability. Further Gen-AI applications in the supply chain are discussed in the Figure 3.

2.4 | Theoretical Framework: Dynamic Capabilities View

The adoption of Gen-AI for green and responsible supply chains cannot be understood only as a technological decision but also as a strategic and organizational process in which firms must identify opportunities, mobilize resources and reconfigure routines to respond to changing sustainability and supply chain requirements. Therefore, the DCV theory is adopted as the theoretical foundation for this study. DCV explains how firms can develop the ability to sense opportunities, seize them through timely decisions and reconfigure their resources and processes in response to dynamic environments (Gangwar et al. 2025). Recent studies related to sustainability also considered dynamic capabilities as useful for firms' adaptation under sustainability transitions and changing external pressures (Bhadra et al. 2024; Correggi et al. 2024). This is also important for the present study, because Gen-AI adaptation in supply chains is both technologically and organizationally dependent. Recent studies in operations and supply chain management also discussed this. Jackson et al. (2024) developed a capability-based framework to analyse Gen-AI in supply chain and operations management. Gangwar et al. (2025) examined the determinants of Gen-AI and its effect on supply chain management performance through DCV. In the related context, Shore et al. (2024) discussed that Gen-AI can improve resilience in SMEs during crisis conditions, which reinforces the idea that Gen-AI becomes valuable when firms can combine technological inputs with adaptive organizational capabilities.

Using DCV as a primary lens also allows the identified enablers (See Section 2.5) in this study to be interpreted as part of a capability-building system rather than as disconnected adoption factors. The enablers such as data availability and quality, knowledge management and global collaboration networks can be understood as supporting the firm's sensing capability because they strengthen information visibility, learning and opportunity recognition. Enablers such as top management support, digital infrastructure readiness, government and policy support are closely associated with the seizing capability as they enable resource commitment, governance and strategic alignment during adoption. Enablers such as human–AI collaboration, employee training and upskilling, resilience and risk management are linked with the reconfiguring capability because they allow firms to transform routines and develop new competencies.

2.5 | Enablers to Gen-AI Adoption in Green and Responsible Supply Chains

For organizations to effectively adopt Gen-AI in supply chain operations, certain enabling factors must be present to ensure that technological integration leads to tangible sustainability outcomes. Based on the literature, enablers to Gen-AI adoption in the responsible and green supply context are presented in Table 1. The table shows the identified enablers, which cover technological, organizational, policy and capability-related dimensions.

2.6 | Research Gap and Study Motivation

The Gen-AI tools are widely recognized due to their transformative potential to revolutionize operations and supply chain management (Fosso Wamba et al. 2023). But its integration

TABLE 1 | Enablers to Gen-AI adoption in a responsible and green supply chain context.

Notation	Enabler name	A brief description	References
E1	Knowledge management	It refers to effective knowledge sharing, and utilization, which strengthen organizational learning from AI adoption	(Gangwar et al. 2025; Zhang, Zuo, and Yang 2025)
E2	Human–AI collaboration	Collaboration between employees and AI tools improves decision-making, efficiency and innovation	(Hao et al. 2024; Fosso Wamba et al. 2025; Zhang, Zuo, and Yang 2025)
E3	Trust and transparency mechanisms	Clear governance and transparent data practices promotes the acceptance of AI systems among stakeholders	(Hao et al. 2024; Romeo and Lacko 2025; Teixeira et al. 2025)
E4	Data availability and quality	It refers to reliable, accurate and accessible data, which are the foundation for training AI models and generating actionable insights	(Gangwar et al. 2025)
E5	Collaborative culture	It refers to the culture of trust and cooperation which promotes information sharing and smooth cross-functional integration of AI	(Romeo and Lacko 2025; Tanskanen et al. 2015; Zhang, Zuo, and Yang 2025)
E6	Employee training and upskilling	Workforce development in firms ensures that employees can collaborate with AI systems and adapt to evolving technological requirements	(Hao et al. 2024; Riad et al. 2024; Romeo and Lacko 2025)
E7	Top management support	It refers to the strategic commitment from senior leadership, which ensures alignment of resources, vision and policies necessary for successful AI adoption	(Akhtar et al. 2024; Chen et al. 2024; Zhang, Zuo, and Yang 2025)
E8	Resilience and risk management	AI enables proactive monitoring and response to disruptions, which enhance supply chain robustness and agility	(Hao et al. 2024; Khan et al. 2025; Romeo and Lacko 2025)
E9	Sustainability alignment	AI adoption supports environmental goals by optimizing resources, reducing waste and aligning with green regulations	(Hao et al. 2024; Romeo and Lacko 2025; Tiwari et al. 2024)
E10	Customer-driven innovation	AI-driven insights enable firms to design products and services that respond to evolving customer needs	(Chakraborty et al. 2024; Hao et al. 2024; Romeo and Lacko 2025)
E11	Digital infrastructure readiness	It refers to strong IT systems, cloud platforms and connectivity, which serves as backbone to integrate and scaling AI applications	(Chakraborty et al. 2024; Hao et al. 2024; Walter et al. 2025)
E12	Dynamic capabilities	It refers to the firm ability to reconfigure resources and adapt processes, which enable effective integration of AI in dynamic environments	(Chen et al. 2024; Romeo and Lacko 2025; Zhang, Zuo, and Yang 2025)
E13	Government and policy support	Regulatory clarity, financial incentives and policy frameworks helps to improve AI adoption across industries	(Chen et al. 2024; Romeo and Lacko 2025; Tiwari et al. 2024)
E14	Global collaboration networks	Digital maturity promotes international alliances and partnerships, which improves competitiveness and innovation	(Hao et al. 2024; Meafa et al. 2025; Zhang, Zuo, and Yang 2025)

into the green supply chain has several challenges. Although Gen-AI holds the potential to improve resiliency, efficiency and sustainability, which are some of the core principles of Industry 5.0 (Rojek et al. 2025), the existing literature in this area remains limited and fragmented due to limited empirical investigations (Romeo and Lacko 2025). The integration of Gen-AI applications into the supply chain requires significant investment for digital infrastructure, continuous upgrades and maintenance (Hao et al. 2024). Also, many organizations are facing difficulties to align Gen-AI based applications with the existing processes due to a lack of upgraded systems, a lack of interoperability, higher costs and unanticipated operational issues (Chen et al. 2024). Other challenges also include the absence of a reliable mechanism for error detection, limited resources and insufficient experience to deploy Gen-AI-driven solutions (Hao et al. 2024; Romeo and Lacko 2025). These challenges restrict the scalability of Gen-AI-based solutions for the supply chain. Many organizations, particularly from developing economies, are still relying on the conventional supply chain practices and show their hesitation to adopt Gen-AI-based tools (Shore et al. 2024). This is due to a lack of awareness about the potential benefits of Gen-AI applications in the supply chain, the absence of a testbed environment and uncertainty over associated risks (Al-khatib et al. 2024). Also, there is a shortage of digitally skilled labour that is capable of managing Gen-AI-enabled systems and ensuring compliance with ethical and environmental regulations (Romeo and Lacko 2025; Walter et al. 2025). As a result, organizational readiness to adopt Gen-AI for a responsible supply chain remains unexplored in the literature. Although several enablers to Gen-AI adoption in supply chain, such as economic viability, regulatory support and organizational readiness, have been conceptually identified, but they real world impact on Gen-AI adoption in supply chain is not well understood (Chakraborty et al. 2024). The existing literature lacks empirical investigations to study how these factors interact to facilitate the adoption in industries (Khan et al. 2025). Recent macrolevel evidence also indicates that AI-related innovation does not automatically translate into environmental sustainability, as policy stringency and broader transition conditions remain critical (Kartal et al. 2025). This also strengthens the need to identify enablers that can support effective Gen-AI adoption in green and responsible supply chains.

3 | Methods

3.1 | Survey Design and Validation of Enablers

To validate the significance of the identified enablers for Gen-AI adoption in green and responsible supply chains, a structured survey-based approach was employed. The survey was conducted to know expert opinions from academia and industry professionals having experience in operations, sustainability and digital transformation. This quantitative assessment is done to provide empirical support to understand how each enabler contributes to the broader goal of green and responsible supply

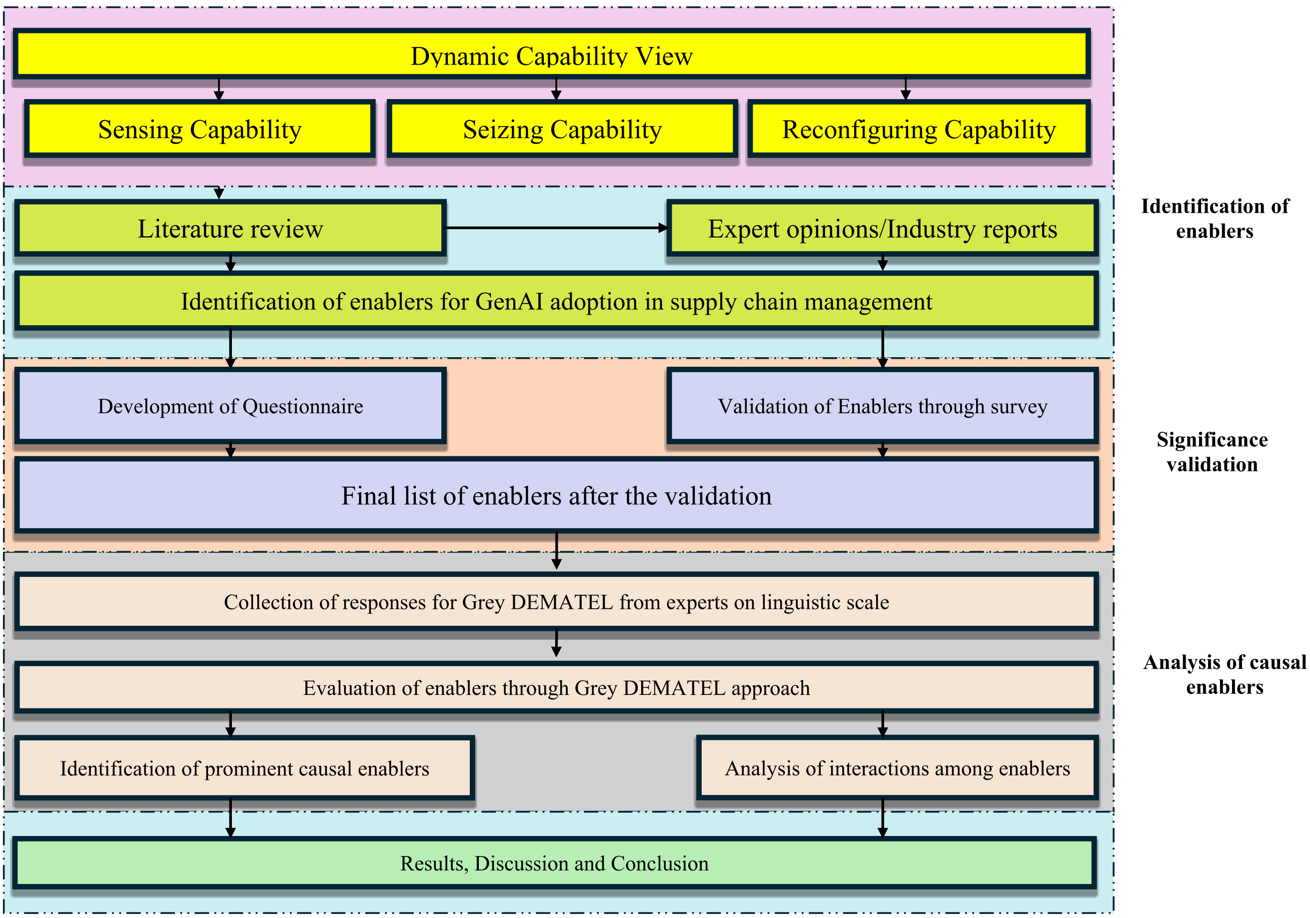

FIGURE 4 | Framework for the study.

chains through Gen-AI adoption. The framework for the study is shown in Figure 4.

3.2 | Survey Instrument and Measurement Scale

In the initial stage, a questionnaire was designed based on insights from the literature review. The questionnaire includes two sections. The first section was related to the demographic information, including respondent background, organizational type, sector and years of experience. The second section was focused on the assessment of the importance of the key enablers discussed in Section 2. To quantify experts' perceptions, a 5-point Likert scale was adopted (1, *Not important*; 2, *Slightly important*; 3, *Moderately important*; 4, *Important*; and 5, *Very important*). All the respondents were asked to rate the importance of each enabler based on their understanding of Gen-AI's role in sustainable supply chains. This approach allowed a consistent measurement of subjective opinions.

3.3 | Sampling and Data Collection

For the present study, data were collected from professionals working in manufacturing, logistics, retail and technology-based organizations. The survey was administered online using an online form that circulated through professional networks, LinkedIn and industry associations. In response, a total of 152 valid responses were received. In which 68% of respondents were male, and 31.6% were female. The respondents were from different industry sectors such as manufacturing (38.2%), logistics and transportation (20.4%), retail/FMCG (17.1%), IT and consulting (13.2%) and healthcare and energy (11.1%). The detailed demographic details are shown in Table 2. The table shows the distribution of respondents across the different demographic variables.

3.4 | Data Analysis and Validation

Descriptive statistics were used to evaluate the mean importance score of each enabler. The mean score was considered a direct indicator to investigate significance, whereas the standard deviation was used to identify the level of agreement among respondents. The results revealed that all the identified enablers from the literature are relevant in the context of developing economies and can be considered for further analysis. The mean scores and standard deviation of each enabler are shown in Table 3.

TABLE 2 | Demographic details.

Demographic variable	Category	Frequency (n)	Percentage (%)
Gender	Male	104	68.4
	Female	48	31.6
Educational qualification	Graduate	42	27.6
	Postgraduate	84	55.3
	Doctorate	26	17.1
Work experience (years)	Less than 5	28	18.4
	6–10	47	30.9
	11–15	39	25.7
	Above 15	38	25
Industry sector	Manufacturing	58	38.2
	Logistics and transportation	31	20.4
	Retail/FMCG	26	17.1
	IT and consulting	20	13.2
	Others (energy, healthcare, etc.)	17	11.1
Job role/designation	Supply chain/operations manager	47	30.9
	Procurement/planning executive	33	21.7
	Senior executive/head of department	29	19.1
	Analyst/engineer	28	18.4
	Consultant/researcher	15	9.9
Organization size	Small (< 250 employees)	34	22.4
	Medium (250–1000 employees)	66	43.4
	Large (> 1000 employees)	52	34.2

TABLE 3 | Relevance of enablers based on survey results.

Enabler name	Mean score	Standard deviation	Relevance
Knowledge management	3.66	1.11	Yes
Human–AI collaboration	3.39	1.12	Yes
Trust and transparency mechanisms	3.49	1.17	Yes
Data availability and quality	3.45	1.14	Yes
Collaborative culture	3.53	1.10	Yes
Employee training and upskilling	3.64	1.10	Yes
Top management support	3.53	1.13	Yes
Resilience and risk management	3.36	1.06	Yes
Sustainability alignment	3.44	1.07	Yes
Customer-driven innovation	3.36	1.08	Yes
Digital infrastructure readiness	3.51	1.10	Yes
Dynamic capabilities	3.38	1.08	Yes
Government and policy support	3.49	1.11	Yes
Global collaboration networks	3.37	1.16	Yes

3.5 | Grey DEMATEL Approach

In the present study, a grey possibility degree-based DEMATEL approach was adopted to rank and identify causal interrelationships between enablers. This method is particularly well-suited to address group decision-making problems under an uncertain environment, where subjective judgements and incomplete information often hinder the reliability of conventional decision-making methods.

Step 1: In this step, the initial relationship matrix (R) is developed. Let n be the experts evaluating the direct influence of each enabler E_x on every other enabler E_y. This is done using a linguistic scale represented in Table 4. It explains how qualitative expert judgements were transformed into grey numerical values. This helps to provide a basis for modelling uncertainty in expert evaluations and supports the application of the Grey DEMATEL approach.

TABLE 4 | Linguistic assessment and grey scale for the study.

Linguistic terms	Crisp values	Grey numbers
No influence	0	[0,0.1]
Very less influence	1	[0.1,0.3]
Less influence	2	[0.2,0.5]
Medium influence	3	[0.4,0.7]
High influence	4	[0.6,0.9]
Very high influence	5	[0.9,1.0]

Step 2: Calculate the corresponding Grey matrices.

In this step crisp ratings from Step 1 are converted into bounded Grey numbers to explicitly model the vagueness of human judgement. G_{xy}^{l} represents the Grey number (defined by upper bound and lower bound) for the influence of E_x on E_y by expert l.

$$G_{xy}^{l} = \left(\underline{\otimes} G_{xy}^{l}, \overline{\otimes} G_{xy}^{l} \right) \tag{1}$$

Step 3: Determine the average Grey matrix.

For the opinions of all experts, the average of Grey matrices is calculated by averaging the lower and upper bounds separately across all experts. This results in the final aggregated Grey matrix $\widetilde{G}_{xy.}$

$$\otimes \widetilde{G}_{xy} = \left(\sum_{1} \frac{\underline{\otimes} \mathrm{G}_{\mathrm{xy}}^{\mathrm{l}}}{n}, \sum_{1} \frac{\overline{\otimes} \mathbf{G}_{\mathbf{xy}}^{\mathbf{l}}}{n} \right) \tag{2}$$

Step 4: Transform the average Grey matrix into Crisp relationship matrix (B).

The aggregated Grey numbers in $\widetilde{G}_{xy}$ must be converted back into definite single values. This is done by using modified-converting fuzzy data into crisp scores approach.

Step 5: Normalized direct relationship matrix (N)

The matrix (B) is normalized to ensure that the mathematical operation in the next step converges. The normalization factor (L) is calculated based on the maximum row sum in (B).

$$L = \frac{1}{\max_{1 \le x \le e} \sum_{y=1}^{e} B_{xy}} \tag{3}$$

The normalized direct relationship matrix (N) is then

$$\mathrm{N} = \mathrm{L} * \mathrm{B} \tag{4}$$

Step 6: Determine the total relationship matrix.

The total relationship matrix (T) captures all direct and indirect influences between every pair of enablers and reflects how a change in one factor propagates through the entire system.

$$\mathrm{T} = \mathrm{N}(\mathrm{I} - \mathrm{N})^{-1} \tag{5}$$

Here, (I) represents the identity matrix.

Step 7: Obtain causal parameters.

The total relationship matrix calculated using Equation (5) is used to derive two key vectors R and C, which define the causal role of each enabler.

R (Row summation—Effects given): The sum of rows in the total relationship matrix. This is the total influence given by the enabler to all others and indicates its driving power.

$$R = \left[\sum_{y=1}^{e} a_{xy}\right] \tag{6}$$

C (Column summation—effects received): The sum of the columns in the total relationship matrix. This is the total influence received by the enabler from all others and indicates its dependence.

$$C = \left[\sum_{x=1}^{e} a_{xy}\right] \tag{7}$$

Step 8: Causal diagram.

The final step in Grey DEMATEL is to plot the results on the diagram using the vector pairs. This visual map classifies enablers into different roles:

1.1. Prominence (R + C): This is on the horizontal axis and represents the overall centrality or importance of the enabler within the system.

1.2. Relation (R − C): This is on the vertical axis and determines the causal category of the enabler.

1.2.1. Positive (R − C): This represents that the enabler is from the cause group

1.2.2. Negative (R − C): This represents that the enabler is from the effect group.

To plot the final diagram, a threshold value is calculated to filter out negligible relationships and only plot the significant causal links.

3.6 | An Exemplary Application

In recent years, India has emerged as one of the fastest growing economies, with its manufacturing and service sectors increasingly adopting advanced digital technologies. Due to the digitalization efforts by Indian organizations and more focus on Industry 4.0-based technologies, the Gen-AI solution has created new opportunities for organizations to improve their sustainability, resiliency and efficiency in the supply chain. Therefore, Indian industries need to understand how Gen-AI can be integrated within the supply chain processes to improve competitiveness and achieve sustainability goals.

To investigate this, the present study investigates a case from the FMCG sector, which is growing rapidly and leveraging digital technologies for demand forecasting, logistics planning and customer engagement. The selected sector is a growing sector in India and covers regional warehouses and outlets. This sector is committed to digital transformation, emphasizing the integration of AI-driven analytics and generative design solutions to improve operational performance and sustainability outcomes. Through the purposive sampling approach, we contacted 26 experts from this sector. Out of these experts, nine experts agreed to participate in the study, which consists of supply chain managers and digital transformation leaders with more than 10 years of experience in this area. At the initial level, the list of 14 enablers, which was derived from literature, was presented to the experts. Further, the experts were asked to validate the list of enablers and add missing enablers if necessary or remove those that are not relevant. After discussions, they agreed that all 14 enablers are relevant and considered for the analysis.

Following this, the experts evaluated the direct influence of one enabler over another using a linguistic scale mapped to grey numbers. From these evaluations, the individual grey direct-relation matrices were constructed. By applying Equation (2), the average direct-relation matrix (Z) was obtained. This was then normalized using Equations (3) to form the normalized direct-relation matrix (N). Subsequently, the total relation matrix (T) was derived using Equation (5). The summation of rows and columns provided the causal parameters (Ri and Ci) as per Equations (6) and (7). From these, the prominence (Pi) and net effect (Ei) values were obtained. Enablers with positive Ei were classified as causal enablers (drivers), whereas negative Ei values were classified as effect enablers (outcomes). The cause and effect diagram was constructed for both lower and upper values, which represent the directional relationships among enablers. The results were further discussed with the expert panel to validate their practical relevance. The findings provide both academic and managerial insights to prioritize critical areas for investment and capability building. Further, Table 5 shows the Grey relationship matrix for Gen-AI enablers by Expert 1. It reflects how Expert 1 assessed the direct influence of each enabler on others using the grey linguistic scale. It gives an initial view of expert judgement at the individual level before aggregation. Table 6 shows the Grey relationship matrix for Gen-AI enablers by Expert 9. Table 7 shows the normalized initial direct relation matrix. It shows the standardized influence values among the enablers after normalization. These values form the basis for computing the total relation matrix and identifying the overall causal structure among enablers. Table 8 shows the net effect and prominence based on Ri and Ci values. It shows the overall importance of each enabler through prominence values and classifies them into cause and effect groups through net effect values. Positive net effect values indicate causal enablers, whereas negative values indicate effect enablers. This helps to identify which enablers act as key drivers in Gen-AI adoption for green and responsible supply chains. The cause and effect enablers are shown in Figure 5. Further, Figure 6 shows the interaction among the enablers.

4 | Results and Discussion

4.1 | DEMATEL Results Findings and Discussion

The findings of the present study provide significant insights into the structural relationship among the enablers for the adoption of Gen-AI for responsible and green supply chains. Using

TABLE 5 | Grey relationship matrix for Gen-AI enablers by Expert 1.

	E1		E2		E3		E4		E5		E6		E7	
E1	**0.0,0.1**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**
E2	0.1,0.3	0.0,0.1	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3
E3	0.1,0.3	0.1,0.3	0.0,0.1	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3
E4	0.1,0.3	0.1,0.3	0.1,0.3	0.0,0.1	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3
E5	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.0,0.1	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3
E6	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.0,0.1	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3
E7	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.0,0.1	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.6,0.9
E8	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.4,0.7	0.0,0.1	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.6,0.9
E9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.4,0.7	0.4,0.7	0.0,0.1	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.6,0.9
E10	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.4,0.7	0.4,0.7	0.4,0.7	0.0,0.1	0.4,0.7	0.4,0.7	0.4,0.7	0.6,0.9
E11	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.0,0.1	0.4,0.7	0.4,0.7	0.6,0.9
E12	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.0,0.1	0.4,0.7	0.6,0.9
E13	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.0,0.1	0.6,0.9
E14	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.0,0.1

	E8		E9		E10		E11		E12		E13		E14	
E1	**0.0,0.1**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**
E2	0.1,0.3	0.0,0.1	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3
E3	0.1,0.3	0.1,0.3	0.0,0.1	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3
E4	0.1,0.3	0.1,0.3	0.1,0.3	0.0,0.1	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3
E5	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.0,0.1	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3
E6	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.0,0.1	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3
E7	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.0,0.1	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.6,0.9
E8	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.4,0.7	0.0,0.1	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.6,0.9
E9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.4,0.7	0.4,0.7	0.0,0.1	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.6,0.9
E10	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.4,0.7	0.4,0.7	0.4,0.7	0.0,0.1	0.4,0.7	0.4,0.7	0.4,0.7	0.6,0.9

(Continues)

TABLE 5 | (Continued)

	E8		E9		E10		E11		E12		E13		E14	
E1	**0.0,0.1**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**	**0.1,0.3**
E11	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.0,0.1	0.4,0.7	0.4,0.7	0.6,0.9
E12	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.0,0.1	0.4,0.7	0.6,0.9
E13	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.0,0.1	0.6,0.9
E14	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.1,0.3	0.0,0.1

TABLE 6 | Grey relationship matrix for Gen-AI enablers by Expert 9.

	E1		E2		E3		E4		E5		E6		E7	
E1	**0.0,0.1**	**0.1,0.3**	**0.2,0.5**	**0.1,0.3**	**0.1,0.3**	**0.2,0.5**	**0.4,0.7**	**0.0,0.1**	**0.1,0.3**	**0.2,0.5**	**0.1,0.3**	**0.1,0.3**	**0.2,0.5**	**0.4,0.7**
E2	0.1,0.3	0.0,0.1	0.1,0.3	0.2,0.5	0.1,0.3	0.2,0.5	0.4,0.7	0.1,0.3	0.0,0.1	0.1,0.3	0.2,0.5	0.1,0.3	0.2,0.5	0.4,0.7
E3	0.2,0.5	0.1,0.3	0.0,0.1	0.1,0.3	0.2,0.5	0.1,0.3	0.4,0.7	0.2,0.5	0.1,0.3	0.0,0.1	0.1,0.3	0.2,0.5	0.1,0.3	0.4,0.7
E4	0.1,0.3	0.2,0.5	0.1,0.3	0.0,0.1	0.1,0.3	0.2,0.5	0.4,0.7	0.1,0.3	0.2,0.5	0.1,0.3	0.0,0.1	0.1,0.3	0.2,0.5	0.4,0.7
E5	0.1,0.3	0.1,0.3	0.2,0.5	0.1,0.3	0.0,0.1	0.1,0.3	0.4,0.7	0.1,0.3	0.1,0.3	0.2,0.5	0.1,0.3	0.0,0.1	0.1,0.3	0.4,0.7
E6	0.2,0.5	0.2,0.5	0.1,0.3	0.2,0.5	0.1,0.3	0.0,0.1	0.4,0.7	0.2,0.5	0.2,0.5	0.1,0.3	0.2,0.5	0.1,0.3	0.0,0.1	0.4,0.7
E7	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.0,0.1	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.0,0.1
E8	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9
E9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.9,1.0	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.9,1.0
E10	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9
E11	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.9,1.0	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.9,1.0

(Continues)

TABLE 6 | (Continued)

	E1		E2		E3		E4		E5		E6		E7	
E1	**0.0,0.1**	**0.1,0.3**	**0.2,0.5**	**0.1,0.3**	**0.1,0.3**	**0.2,0.5**	**0.4,0.7**	**0.0,0.1**	**0.1,0.3**	**0.2,0.5**	**0.1,0.3**	**0.1,0.3**	**0.2,0.5**	**0.4,0.7**
E12	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9
E13	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.9,1.0	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.6,0.9	0.9,1.0
E14	0.2,0.5	0.2,0.5	0.2,0.5	0.2,0.5	0.2,0.5	0.2,0.5	0.4,0.7	0.2,0.5	0.2,0.5	0.2,0.5	0.2,0.5	0.2,0.5	0.2,0.5	0.4,0.7

	E8		E9		E10		E11		E12		E13		E14	
E1	**0.4,0.7**	**0.4,0.7**	**0.4,0.7**	**0.4,0.7**	**0.4,0.7**	**0.4,0.7**	**0.1,0.3**	**0.4,0.7**	**0.4,0.7**	**0.4,0.7**	**0.4,0.7**	**0.4,0.7**	**0.4,0.7**	**0.1,0.3**
E2	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.2,0.5	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.2,0.5
E3	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.2,0.5	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.2,0.5
E4	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.2,0.5	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.2,0.5
E5	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.2,0.5	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.2,0.5
E6	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.2,0.5	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.2,0.5
E7	0.6,0.9	0.9,1.0	0.6,0.9	0.9,1.0	0.6,0.9	0.9,1.0	0.6,0.9	0.6,0.9	0.9,1.0	0.6,0.9	0.9,1.0	0.6,0.9	0.9,1.0	0.6,0.9
E8	0.0,0.1	0.6,0.9	0.9,1.0	0.6,0.9	0.9,1.0	0.6,0.9	0.6,0.9	0.0,0.1	0.6,0.9	0.9,1.0	0.6,0.9	0.9,1.0	0.6,0.9	0.6,0.9
E9	0.6,0.9	0.0,0.1	0.6,0.9	0.9,1.0	0.6,0.9	0.9,1.0	0.6,0.9	0.6,0.9	0.0,0.1	0.6,0.9	0.9,1.0	0.6,0.9	0.9,1.0	0.6,0.9
E10	0.9,1.0	0.6,0.9	0.0,0.1	0.6,0.9	0.9,1.0	0.6,0.9	0.6,0.9	0.9,1.0	0.6,0.9	0.0,0.1	0.6,0.9	0.9,1.0	0.6,0.9	0.6,0.9
E11	0.6,0.9	0.9,1.0	0.6,0.9	0.0,0.1	0.6,0.9	0.9,1.0	0.6,0.9	0.6,0.9	0.9,1.0	0.6,0.9	0.0,0.1	0.6,0.9	0.9,1.0	0.6,0.9
E12	0.9,1.0	0.6,0.9	0.9,1.0	0.6,0.9	0.0,0.1	0.6,0.9	0.6,0.9	0.9,1.0	0.6,0.9	0.9,1.0	0.6,0.9	0.0,0.1	0.6,0.9	0.6,0.9
E13	0.6,0.9	0.9,1.0	0.6,0.9	0.9,1.0	0.6,0.9	0.0,0.1	0.6,0.9	0.6,0.9	0.9,1.0	0.6,0.9	0.9,1.0	0.6,0.9	0.0,0.1	0.6,0.9
E14	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.0,0.1	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.4,0.7	0.0,0.1

TABLE 7 | Normalized initial direct relation matrix.

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13	E14
E1	0.00	0.01	0.03	0.01	0.02	0.02	0.05	0.06	0.05	0.05	0.05	0.05	0.05	0.02
E2	0.02	0.00	0.01	0.03	0.01	0.02	0.05	0.05	0.06	0.05	0.05	0.05	0.06	0.03
E3	0.03	0.01	0.00	0.01	0.03	0.01	0.06	0.05	0.05	0.05	0.05	0.06	0.05	0.03
E4	0.01	0.03	0.01	0.00	0.01	0.03	0.05	0.05	0.05	0.05	0.06	0.05	0.05	0.03
E5	0.02	0.01	0.03	0.01	0.00	0.01	0.06	0.05	0.05	0.05	0.05	0.06	0.05	0.03
E6	0.02	0.02	0.01	0.03	0.01	0.00	0.06	0.06	0.05	0.05	0.05	0.06	0.05	0.03
E7	0.08	0.09	0.08	0.09	0.08	0.09	0.00	0.06	0.07	0.06	0.07	0.06	0.08	0.08
E8	0.09	0.08	0.09	0.08	0.09	0.08	0.06	0.00	0.06	0.07	0.06	0.07	0.07	0.07
E9	0.08	0.09	0.08	0.09	0.08	0.09	0.07	0.06	0.00	0.06	0.07	0.06	0.07	0.08
E10	0.09	0.08	0.09	0.08	0.08	0.08	0.06	0.07	0.06	0.00	0.07	0.07	0.07	0.07
E11	0.08	0.09	0.08	0.09	0.08	0.09	0.07	0.06	0.07	0.07	0.00	0.06	0.08	0.08
E12	0.09	0.08	0.09	0.08	0.09	0.08	0.06	0.07	0.06	0.07	0.06	0.00	0.07	0.07
E13	0.08	0.09	0.08	0.09	0.08	0.09	0.07	0.07	0.07	0.07	0.08	0.07	0.00	0.08
E14	0.02	0.03	0.02	0.03	0.03	0.03	0.05	0.04	0.05	0.04	0.04	0.05	0.05	0.00

TABLE 8 | Net effect and prominence.

Enabler	Enabler name	Pi	Ei	Pi + Ei	Pi − Ei	Category	Rank
E1	Knowledge management	1.95	2.60	4.55	−0.65	Effect	13
E2	Human–AI collaboration	2.01	2.66	4.67	−0.66	Effect	10
E3	Trust and transparency mechanisms	2.01	2.62	4.63	−0.61	Effect	11
E4	Data availability and quality	2.04	2.67	4.71	−0.64	Effect	9
E5	Collaborative culture	1.98	2.60	4.58	−0.62	Effect	12
E6	Employee training and upskilling	2.06	2.69	4.75	−0.62	Effect	8
E7	Top management support	3.50	2.84	6.34	0.66	Cause	2
E8	Resilience and risk management	3.43	2.79	6.23	0.64	Cause	6
E9	Sustainability alignment	3.45	2.82	6.27	0.63	Cause	4
E10	Customer-driven innovation	3.43	2.79	6.22	0.64	Cause	7
E11	Digital infrastructure readiness	3.50	2.83	6.33	0.67	Cause	3
E12	Dynamic capabilities	3.44	2.82	6.26	0.62	Cause	5
E13	Government and policy support	3.61	2.92	6.54	0.69	Cause	1
E14	Global collaboration networks	1.89	2.63	4.52	−0.74	Effect	14

the Grey DEMATEL approach, the enablers were categorized into causal (driver) and effect (outcome) groups. The classification not only helps to understand the relative importance of different enablers but also highlights how systematic change can be initiated by strengthening the key drivers.

Government and policy support (Rank 1) is the most influential causal enabler, which indicates that institutional frameworks set the overall direction for Gen-AI adoption in green and responsible supply chains. There is a need for clear guidelines on data governance, carbon reporting and ethical AI usage. Firms can implement Gen-AI-based optimization in logistics, sourcing and risk management. Gen-AI-based projects face challenges such as ethical concerns, scalability issues and data integration complexity, which need supportive rules and frameworks (Shekhar et al. 2023). This aligns with the idea that policy acts as a boundary condition that shapes organizational preparedness and the design of robust AI governance structures in the supply chain. Firms should actively monitor national and sectoral AI guidelines and align internal

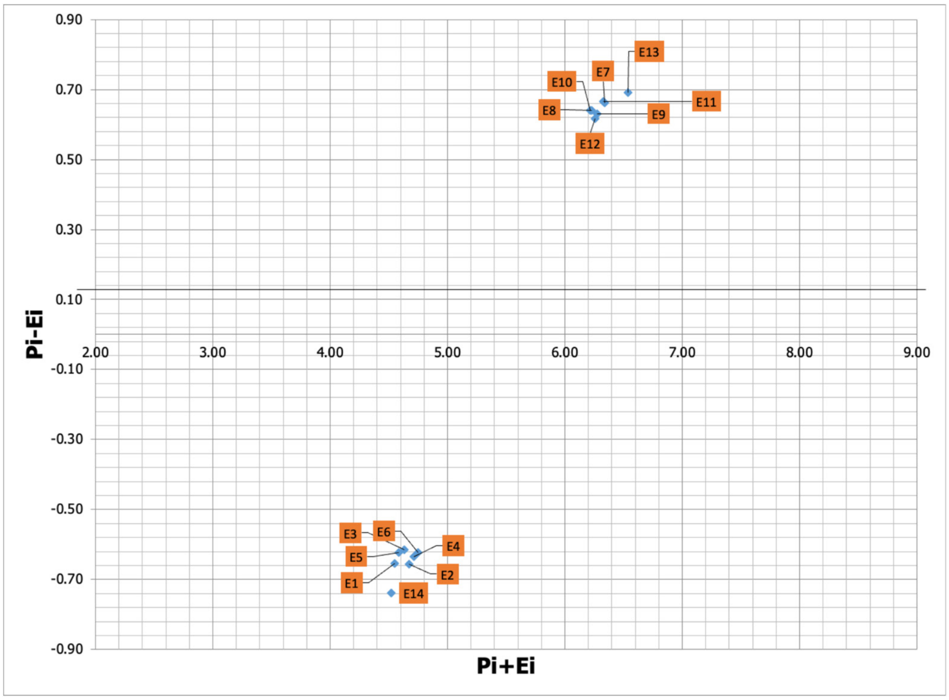

FIGURE 5 | Cause and effect enablers of Gen-AI-enabled supply chains.

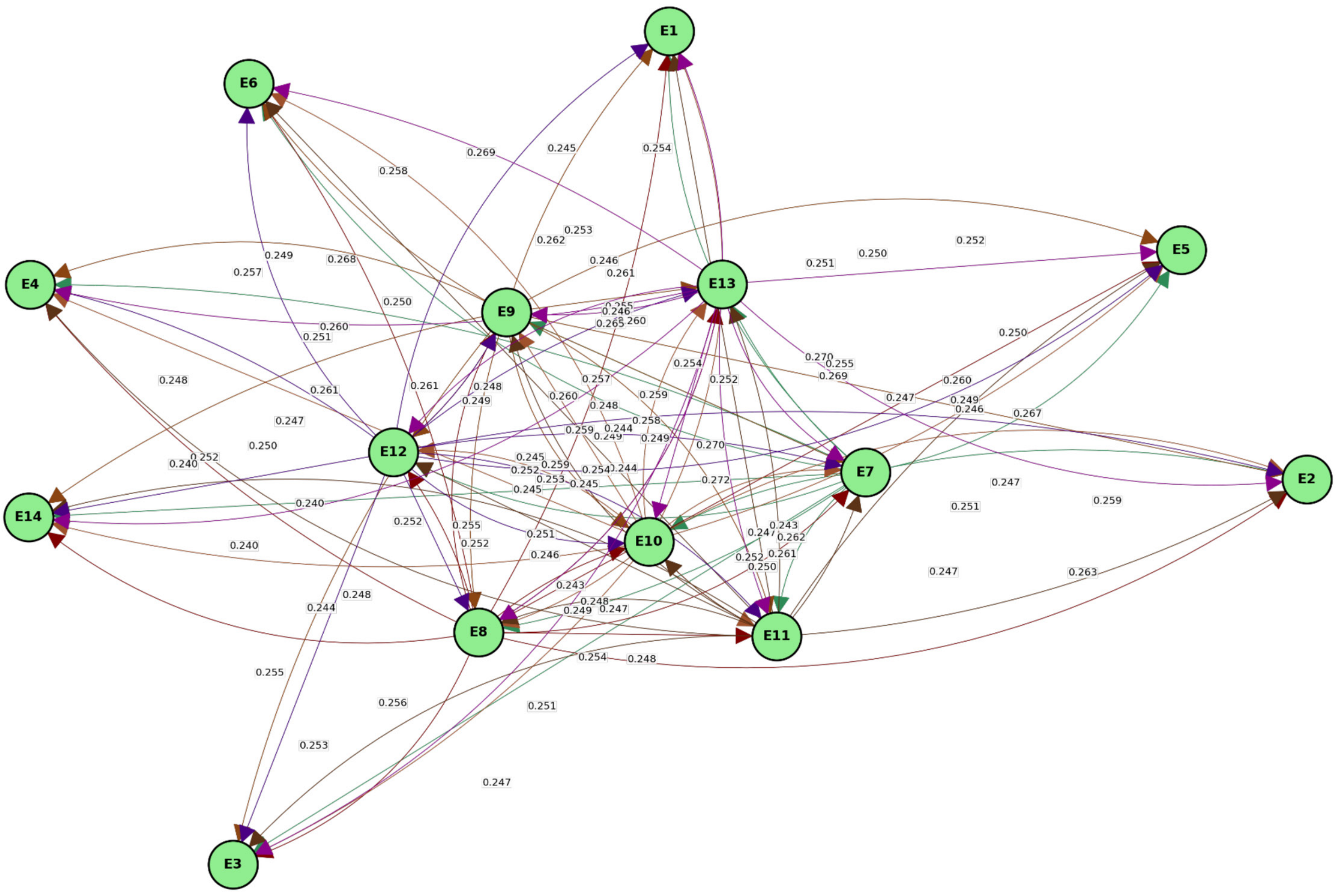

FIGURE 6 | Interaction among the enablers.

AI policies, sustainability targets and reporting practices with these requirements (Liu et al. 2025). They can also use government schemes, tax incentives and pilot programmes to improve their Gen-AI infrastructure and skills.

Top management support (Rank 2) helps to promote Gen-AI initiatives within the organization. When top management sets up a Gen-AI vision and realizes the importance of sustainability, they help overcome organizational inertia and build confidence in AI-driven change. The literature discussion on organizational preparedness and skills gaps also highlights that strategic guidance is needed to move beyond pilot projects and integrate Gen-AI into processes such as forecasting and risk management (Hughes et al. 2026). Digital infrastructure readiness (Rank 3) is also an important causal enabler. Gen-AI cannot support responsible and green supply chains without reliable data platforms, its integration with ERP, IoT systems and secure cloud-based architectures. Therefore Gao et al. (2025) also highlight that combining Gen-AI with blockchain capabilities enhances information transparency, data verification and secure decision-making along the supply chain. These insights support our results, also that infrastructure is important and directly shapes data availability and quality, as well as trust and transparency mechanisms.

Firms should prioritize investments in shared data lakes, API-based integration and secure edge/cloud infrastructure before scaling Gen-AI pilots. They can also use blockchain or similar architecture to ensure data integrity for emissions, resource use and social compliance data. Sustainability alignment (Rank 4) is another important causal enabler. The findings suggest that when sustainability goals are integrated with Gen-AI vision from the beginning, organizations are more likely to select applications that improve resource efficiency, reduce waste and support green logistics. Gao et al. (2025) show that Gen-AI adoption in blockchain-enabled environments can accelerate progress towards SDG9 by enhancing industrial growth and diversification in a more efficient way. Saheb et al. (2022) highlight how AI is increasingly used to support sustainability transitions in energy systems, reinforcing the idea that AI strategies can be aligned with environmental objectives.

In this study, sustainability alignment influences how other enablers, such as top management support and dynamic capabilities, are directed towards green and responsible outcomes. Therefore, firms should frame Gen-AI projects with explicit environmental KPIs, e.g., emissions reduction and waste minimization. These need to integrate with ESG and net zero road maps. Sustainability officers should be involved in Gen-AI portfolio decisions from the start rather than only at the reporting stage. Dynamic capabilities (Rank 5) are also a causal enabler. Shekhar et al. (2023) discuss how Gen-AI predictive and adaptive decision-making can support real-time decisions in disruptions and dynamic market environments. Badakhshan and Ball (2023) also highlights that AI-enabled models can help firms to sense changes, simulate alternatives and reconfigure operations during shocks. These contributions align with our finding that dynamic capabilities help to transform digital infrastructure and sustainability goals into flexible responses, which help to improve resilience and customer-driven innovation. To achieve this, firms can develop Gen-AI use cases that directly support sensing (early warning dashboards), seizing (rapid scenario evaluation) and transforming (reconfiguring suppliers or modes) in their supply chains. They can also institutionalize 'learning from disruptions' using AI-supported postevent analyses. Resilience and risk management (Rank 6) is also a causal enabler. Ivanov (2020) shows how digital simulation tools are essential to anticipate disruption propagation and design resilient supply chains. This also supports our interpretation that organizations with a strong orientation are more likely to use Gen-AI to identify vulnerabilities, stress-test and justify investments in infrastructure and collaboration. Therefore, companies should integrate Gen-AI models into their risk dashboards to forecast disruption scenarios and their environmental impact. Customer-driven innovation (Rank 7) is the last enabler in the causal group. Chakraborty et al. (2024) show that Gen-AI chatbots can transform customer experience by providing personalized recommendations and interactive support, which helps to achieve trust and reuse intentions. In our study, a focus on customer-driven innovation encourages firms to build human–AI collaboration interfaces, design transparent communication about sustainability performance and share knowledge across the network to meet evolving customer expectations for green and ethical products.

Employee training and upskilling (Rank 8) is an effect enabler. Shekhar et al. (2023) discussed that skill gaps are a key barrier to Gen-AI implementation in supply chains, implying that structured training only follows when organizations invest in Gen-AI projects. Firms can therefore use the findings of this study to design targeted training programmes once strategic direction, infrastructure and risk priorities are set, rather than treating training as a stand-alone initiative. Data availability and quality (Rank 9) is also an enabler. Meriton et al. (2021) discussed that big data creates value only when it is accessible, reliable and connected to decision processes. Further, Gao et al. (2025) show that blockchain capabilities provide transparent, secure and high-quality data that Gen-AI can use for forecasting and optimization. Firms can therefore treat data quality improvements as a visible outcome of earlier investments in infrastructure and governance. Human–AI collaboration (Rank 10) is also an effect enabler. Chakraborty et al. (2024) demonstrate that perceptions of interaction quality, credibility and anthropomorphism of Gen-AI chatbots are central to building trust in AI-assisted shopping experiences. Trust and transparency mechanisms (Rank 11) is also an effect enabler.

Gao et al. (2025) show that Gen-AI adoption enhances blockchain capabilities and improves supply chain efficiency and transparency. Chakraborty et al. (2024) also highlight that trust in an AI system is a critical outcome of good design and communication. Our findings suggest that once these upstream conditions are met, trust and transparency can be systematically built into green and responsible supply chains. Collaborative culture (Rank 12) and Knowledge management (Rank 13) are effect enablers. Richey et al. (2023) also discussed that AI in supply chain involves organizational routines, processes and collaboration among stakeholders. Meriton et al. (2021) work on big data-enabled supply chain management shows that knowledge creation and sharing mechanisms are needed to transform data and analytics into continuous value. As firms strengthen their leadership, infrastructure, resilience and training, they are better equipped to develop a collaborative culture and formal knowledge management practices.

Global collaboration network (Rank 14) is also an effect enabler. It became feasible when firms have already achieved internal readiness, reliable data, trusted AI systems and strong collaborative routines. Gao et al. (2025) focus on supply chain using blockchain and Gen-AI and illustrate how these technologies operate in cross-firm and often cross-border networks. Our results, therefore, suggest that organizational and technological maturity is required for global collaboration. Once the causal enablers are strengthened, firms should invest in structured Gen-AI and role-specific training programmes to build human–AI collaboration skills.

4.2 | Theoretical Implications of the Study

The present study contributes to the theoretical understanding of Gen-AI adoption in the supply chain by discussing a structured causal effect perspective through the Grey DEMATEL approach. Prior studies in this area discussed these enablers but did not reveal how these enablers influence each other. With the help of the Grey DEMATEL approach, this study shows that adoption is not a linear or stand-alone process but a dynamic system that is shaped by interdependencies across organizational frameworks, where the resources and external conditions drive the Gen-AI adoption.

A key theoretical contribution of the present study is the identification of trust and transparency as the causal enabler. Prior studies discuss trust as a consequence of digital adoption, yet the results here indicate that it functions as the prerequisite for AI integration. This research also contributes to the debate on digital transformation by linking AI and Gen-AI adoption to broader supply chain theories. It shows that adoption cannot be fully explained by technological potential alone; instead, it requires the integration of institutional support, organizational adaptability and collaborative practices.

4.3 | Managerial and Policy Implications

The present study findings highlight that responsible integration of Gen-AI in the green and responsible supply chains requires a holistic policy framework that links accountability, innovation and sustainability. India's technology trajectory shows that Gen-AI can enhance productivity by over 40% in key sectors such as IT, manufacturing and logistics, but the challenge lies in ensuring this growth aligns with environmental and social priorities.[3] Therefore, it is suggested that policymakers must move beyond digital adoption to develop policies that incentivize sustainable AI use. In some developing countries like India, initiatives like IndiaAI Mission and the partnership between the Ministry of Skill Development and Entrepreneurship and Meta to establish Centers of Excellence in AI and virtual reality in premium institutes signal a commitment towards inclusive AI ecosystems.[4] Extending such programmes to the manufacturing and logistics sector will help boost Gen-AI-enabled sustainability projects. The government should also develop regulatory sandboxes to test new Gen-AI-based solutions. Given the risk of bias, opacity, and overautomation, policymakers from developing economies must ensure the ethical deployment of Gen-AI by establishing Responsible AI guidelines within the existing data protection framework. Based on the consulting industry's recommendations, integrating AI-specific sustainability metrics into ESG reporting and public procurement norms will be helpful to align corporate incentives with national sustainability goals.

4.4 | Actionable Insights and Research Propositions

The results of the study not only clarify which enablers drive Gen-AI adoption for responsible and green supply chains but also show where managers should act first. Based on the earlier theoretical, managerial and policy implications, this subsection discusses some research propositions based on findings. The focus is on how organizations can convert top management commitment, digital infrastructure, dynamic capabilities, collaborative culture and employee skills into Gen-AI initiatives. Each proposition, therefore, links a specific enabler to expected improvements in green and responsible supply chain performance. These propositions can guide future empirical studies and, at the same time, offer practitioners a structured checklist to design a Gen-AI road map.

Proposition 1. *Institutionalized top management commitment towards Gen-AI and sustainability positively influences Gen-AI adoption for responsible and green supply chains.*

When Gen-AI is integrated into a strategic road map, senior leaders set clear sustainability-related AI goals, allocate budgets and monitor progress through KPIs (Dua 2025). Such visible commitment also supports the development of AI governance boards that oversee ethical use, transparency and accountability in supply chain decisions. These actions reduce internal resistance and ensure that Gen-AI for green objectives is a long-term priority rather than a short-term experiment.

Proposition 2. *Digital infrastructure readiness positively influences the effectiveness of Gen-AI applications to enable real-time and sustainable supply chain operations.*

Robust infrastructure in the form of IoT-enabled devices, ERP integration and cloud platform allows seamless data flows across procurement, production, logistics and reverse logistics (Ivanov et al. 2022). This supports the real-time monitoring and predictive analytics, which are essential for emission-aware routing, energy-efficient production planning and proactive risk management.

Proposition 3. *Strong data governance and high data quality positively influence the reliability and organizational acceptance of Gen-AI based supply chain decisions.*

Data quality and standardization are important components because Gen-AI models depend on consistent, trustworthy inputs to generate useful insights. Developing clear rules on data ownership, validation and interoperability across departments improves the credibility of AI-supported recommendations (Sargiotis 2024). When managers trust the underlying data, they are more willing to use Gen-AI outputs in decisions related to sourcing, inventory and environmental performance.

Proposition 4. *Collaboration with government agencies positively moderates the relationship between Gen-AI adoption and supply chain performance, such that the relationship is stronger when collaboration is high.*

Working closely with government bodies enables firms to access incentives, R&D funding and policy guidance for responsible AI usage (Madhavan et al. 2020). Mechanisms such as carbon credits and targeted schemes can lower the financial barriers to adopting Gen-AI solutions for emission reduction, waste minimization and circular practices. Such collaboration aligns organizational initiatives with national sustainability priorities and reduces regulatory uncertainty.

Proposition 5. *Dynamic capabilities developed through an AI Center of Excellence and structured pilot-scale projects positively influence the achievement of sustainability benefits.*

Establishing an AI centre for excellence and pilot projects helps to create learning loops through which firms can experiment, evaluate, and scale Gen-AI solutions. These practices help to strengthen agility and reconfigure processes over time.

Proposition 6. *A collaborative culture among internal and external partners positively influences the impact of Gen-AI innovation and trust in responsible supply chain initiatives.*

The collaborative culture promotes joint problem-solving and knowledge sharing, which helps in innovation (Kucharska 2017). When partners share data, expectations and constraints, Gen-AI tools can be used to codesign low-carbon solutions and resilient logistics configurations. This collaborative environment also builds trust, which is important when AI-supported decisions can affect multiple stakeholders.

Proposition 7. *Systematic employee training and participation in global collaboration networks jointly enhance human–AI value cocreation and green innovation in supply chains.*

Targeted programmes on data literacy and prompt engineering will be helpful for employees to understand and shape Gen-AI outputs rather than passively accept them. As organizations mature digitally, connecting to global networks will allow them to exchange Gen-AI solutions, benchmark green practices and learn from diverse contexts. In this context, skilled employees and international collaboration play an important role in scaling the Gen-AI solution and improving supply chain resilience. The proposed propositions highlight that Gen-AI will support responsible and green supply chains only when it is integrated in a broader organizational and institutional context. Only technology adoption is not sufficient as its maturity depends on leadership commitment, supportive policies and continuous upskilling. For researchers, these propositions offer a clear path for case studies across different sectors and regions.

5 | Conclusion

The present study provides a comprehensive analysis of enablers that influence Gen-AI adoption for responsible and green supply chains. The study uses a Grey DEMATEL-based approach to identify structural relationships among enablers and classify them into causal and effect categories. It offers critical insights into how organizations can strategically leverage Gen-AI to achieve operational efficiency, resiliency and sustainability goals. The findings of the present study highlight that government and policy support, top management support and digital infrastructure readiness are the most significant causal enablers. Leadership commitment ensures the long-term investment, governance alignment and institutionalization of sustainability-driven digital strategies. Robust technological infrastructure within the organization and high-quality data flows act as the backbone for the effective deployment of AI-driven tools that support green initiatives, optimize processes and reduce waste. The role of government and policy support is also important as regulatory clarity and ethical AI guidelines promote confidence and compliance across industries.

Dynamic capabilities and collaborative culture improve organizational adaptability, which enables firms to reconfigure resources and build a trust-based network. Employee training and upskilling are found to be outcome enablers that evolve as organizations mature digitally. These outcomes rely heavily on the presence of strong leadership and a data-driven culture. The present study also highlights the importance of trust and transparency mechanisms, knowledge management and human AI collaboration as indicators of organizational maturity. From the managerial perspective, the present study offers actionable insights. Organizations can start their journey by integrating AI adoption within their strategic vision, which is supported by clear governance frameworks and performance metrics. There is a need to prioritize workforce readiness through targeted reskilling programmes that will be helpful to prepare employees for human AI collaboration.

5.1 | Limitations and Future Search

Despite its contribution, there are few limitations in this study. First, the analysis was based on a limited number of experts, which can be addressed in future. Second, the Grey DEMATEL approach, although it is effective in capturing interrelationships, relies on expert judgement, which may introduce subjectivity. Future studies could expand the scope by incorporating multimethod approaches such as fuzzy AHP–ISM hybrid models, SEM or system dynamics simulations to validate and strengthen causal relationships.

Author Contributions

All authors contributed significantly to the work.

Endnotes

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