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ORIGINAL RESEARCH

Analyzing enablers of artificial intelligence for decarbonization: implications for circular supply chains

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Abstract

This study comprehensively explores the pivotal position that Artificial Intelligence (AI) enables on the advancement of decarbonization efforts, mainly in the context of Circular Supply Chains (CSCs). Employing a two-stage methodology, this study delves into identifying and analyzing the enablers essential for leveraging AI in the pursuit of decarbonization objectives. In the first stage, a literature review and an exploratory factor analysis are performed to discern the key enablers of AI for decarbonization initiatives. This process resulted in the identification of 15 significant enablers and categorization of enablers into environmental, organizational, institutional, and technological categories. Building upon the findings from the first stage, this study progresses to its second stage, wherein the Grey-Ordinal Priority Approach (G-OPA) is applied to analyze the identified enablers. The results indicate that adopting recyclable materials to enhance the efficiency of supply chains, emphasizing local production for recovery practices through advanced technology, and managing product life-cycle through intelligent and additive manufacturing technologies are the top three enablers. The application of the G-OPA enriches the robustness and comprehensiveness of the analysis, enabling an understanding of the complex interplay among the enablers. By clarifying the key enablers, business planners and designers can migrate from traditional linear supply chains to more sustainable CSCs through the careful implementation of enablers for decarbonization.

Keywords Artificial intelligence · Decarbonization · Circular supply chains · Grey-ordinal priority approach

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1 Introduction

The notion of circular economy (CE) has received extensive global consideration as a sustainable alternative to the "take, make, and dispose" approach (Geissdoerfer et al., 2017). The Ellen MacArthur Foundation (EMF) (2015) promoted CE as a regenerative and curative business system that seeks to retain the best quality and usefulness of goods, parts, and supplies in biological and technical cycles. The shift to a CE is accepted by many as providing social, environmental, and economic advantages (Geissdoerfer et al., 2017; Genovese et al., 2017). It enables more efficient utilization and re-utilization of resources, reducing negative environmental impacts while maintaining growth and prosperity on a holistic level (D'Orazio & Pham, 2025; Lewandowski, 2016; Manninen et al., 2018).

In this regard, Circular Supply Chains (CSCs) have emerged as a significant facilitator driving sustainability in academia and practice (Hobson, 2016; Stewart & Niero, 2018). The CSCs model promotes the practice of taking used or discarded materials and repurposing them for sale, and encourages manufacturers and product sellers to do so (Hazen et al., 2016; Kumar et al., 2021). Incorporating circularity into supply chains would enlarge the scope of sustainability by decreasing the requirement for new materials, thus promoting the flow of materials across supply chains (Farooque et al., 2019; Mishra et al., 2024). Even though there has been an increase in circularity efforts to advance the efficiency of supply chains, it has become quite difficult for organizations to reduce the harmful effects, as it is a complex phenomenon. It is found that supply chains are responsible for almost 90% of carbon emissions (Shi et al., 2019; Wang et al., 2024). This places a higher priority on actions to mitigate environmental and social hazards in CSCs.

The issues of decarbonization and CE have gained significant attention and are converging rapidly due to their interconnectedness (Spiller, 2021; Zhang et al., 2022). The global decarbonization market size was anticipated at USD 1.68 trillion in 2022 and is expected to grow at a compound annual rate of 11.6% from 2023 to 2030 (Grand View Research, 2023). Decarbonizing an economy requires more than just relying on renewable energy sources and efficiency improvements; it also necessitates a comprehensive rethinking of the entire economic model, including every aspect of the product lifespan (Zhao et al., 2022; Zhu & Geng, 2013). Advanced software solutions, such as energy management systems and AI-driven algorithms, assist businesses in monitoring, optimizing, and reducing their carbon footprints (Huang & Mao, 2024). By facilitating renewable energy adoption and waste reduction, the information technology industry inspires organizations to attain net-zero goals, contributing considerably to environmental sustainability (Greg and Strengers, 2024). Thus, decarbonization targets must not only focus on reducing direct emissions and implementing compensation measures but also incorporate all aspects of the supply chains (Leonzio & Zondervan, 2020; Mishra et al., 2024). The CE is anticipated to significantly achieve decarbonization goals, as it considers a circular approach to reusing resources, resulting in sustainable benefits (Sadawi et al., 2021). To successfully transition to a CE, organizations must adopt initiatives and procedures that evaluate activities from a circular perspective (Ivanov, 2021). However, implementing these initiatives and processes requires monitoring, prediction, forecasting, and optimization to produce additional responsive and resilient CSCs (Ozkan-Ozen et al., 2020; Riahi et al., 2021). AI-enabled applications have recently appeared as a promising solution for effectively designing and managing CSCs by automating operational activities (Riahi et al., 2021).

The ability of machines to follow human abilities and communication aids has been identified as AI (Jarrahi et al., 2023). AI is used to solve problems more accurately and rapidly with large amounts of diverse data. Trends such as robotics, Machine Learning (ML), big data, and AI have become prevalent in business to achieve sustainable goals (Di Vaio et al., 2020). Such technologies are used as facilitators across various sectors to optimize value by managing operations and distributing information for sustainability (Nayal et al., 2021; Sanders et al., 2019). AI has revolutionized how we generate and utilize information for making decisions and solving difficulties (Mikalef et al., 2018) and how business is conducted (Schneider & Leyer, 2019). It has increased supply chain efficiency and transparency, which is essential for CSCs (Sanders et al., 2019). Studies show that relying on incremental innovations and enhancing existing operations may no longer be adequate, given the current state of knowledge and technology (Nilsson & Göransson, 2021). John et al. (2022) highlighted the positive impact of AI on decarbonization in the steel industry. The advent of AI has enabled novel approaches to business, including the shift from conventional supply chains to CSCs (Ripanti & Tjahjono, 2019). While supply chain innovation necessitates transparency, collaboration, and understanding between the parties involved or partners (Yun & Liu, 2019), these parties can spark transitions toward long-term innovation (Vaisman et al., 2022). Furthermore, big data and digitization have also improved awareness of the supaply chain's social and environmental implications (Wang et al., 2024).

According to recent studies, technological advancements can potentially improve carbon reduction by up to 20% (Inderwildi et al., 2020). The UN's Sustainable Development Goals (SDGs), particularly SDG 13 on Climate Action, underline leveraging technology to manage climate change and minimize emissions. Similarly, the Green Deal objective of the European Union (EU) is to make Europe the first carbon–neutral continent by 2050, supporting the execution of advanced technologies like AI, IoT, and renewable energy systems (European Parliament, 2022). On a national level, NITI Aayog has launched initiatives such as the National Electric Mobility Mission and the Roadmap for Carbon Capture Utilization and Storage, highlighting the role of AI and advanced technologies in converting industries towards sustainability (Mukherjee & Chatterjee, 2022). Smart grids, smart meters, and blockchain are not just trendy buzzwords in the energy industry. A significant study on AI and decarbonization (Rolnick et al., 2022) shows that electricity systems possess a wealth of data and tremendous potential for AI applications. AI can aid in all aspects, including research, deployment, and operation of electrical system technologies. AI can assist in developing new technologies, improving demand and renewable energy forecasts, optimizing grid management, and enhancing system monitoring (Ahmad et al., 2021). Digital technologies have already begun transforming our economy and way of life. By embracing CE principles, this transformation can create value and generate more comprehensive societal benefits. However, effective use of AI demands an in-depth comprehension of the problem. Moreover, the transition to the CE requires cooperation among a network of trusted partners. For example, data generation, collection, and sharing require stakeholder collaboration.

New technologies, particularly AI, have enabled developed nations to achieve circularity, but developing nations lack the necessary infrastructure and advanced technological setup (de Sousa Jabbour et al., 2018; Galati & Bigliardi, 2019) to harness the power of such technologies. While general AI enablers have been identified for circularity (Moeuf et al., 2018, 2019; Tortorella & Fettermann, 2018), these have not yet been explored from the perspective of emerging economies. Therefore, there is a pressing need to discover potential AI enablers that can lead to CSCs in developing economies, considering environmental, technological, governance, and institutional factors (Pacchini et al., 2019). This study explores potential AI enablers for managing carbon footprint in developing economies, which can facilitate the long-term goal of designing CSCs. As a result, this study takes a novel hybrid empirical decision-making method to address the challenges raised above. The following Research Objectives (ROs) are identified.

RO1: To identify and categorize key AI enablers that support decarbonization within the context of CSCs in developing economies.

RO2: To analyze the relative importance of identified enablers of AI for decarbonization.

The following steps were used to attain the aforementioned ROs. Initially, a thorough and meticulous literature study was performed to identify possible AI enablers for decarbonization. A large-scale survey-based empirical analysis was conducted using Exploratory Factor Analysis (EFA) to validate the enablers identified during the literature research. Finally, G-OPA was used to calculate the weights of each shortlisted enabler to determine their usefulness in achieving circularity. The findings of this study are relevant to both researchers and practitioners. This one-of-a-kind study identifies critical AI enablers for decarbonization and proposes strategies for improving circularity in industrial enterprises in developing nations. Policymakers can benefit from this research by gaining critical recommendations for improving manufacturing policies in developing countries.

2 Literature review

To ensure the relevance of the current study, it is crucial to investigate existing literature before embarking on further research. As a result, a comprehensive literature review was done. The subsequent subsections describe the research on AI adoption in decarbonization. In addition, a separate section discusses the research gaps discovered in the literature.

2.1 Circular supply chains (CSCs)

CSCs represent a shift from traditional linear supply chains towards systems that minimize waste and maximize resource efficiency through reuse, recycling, and remanufacturing (Roy et al., 2022; Guide Jr and Van, 2009). This approach aligns with the goals of decarbonization by reducing greenhouse gas emissions across all aspects of the supply chain. Despite extensive research on Closed-Loop Supply Chains (CLSC), which focuses on reverse logistics for remanufacturing and reuse, there is a substantial gap in understanding how these principles can be extended and incorporated into CSCs to achieve broader decarbonization goals (Canales et al., 2017). The existing studies often overlook the potential for proactive design and forward logistics strategies that enhance sustainability. CSCs and CLSCs differ in their scope and approach to sustainability and decarbonization. While CLSC primarily focuses on reverse logistics, remanufacturing, refurbishing, and reusing returned products to enhance sustainability, CSCs encompass a broader, more integrated approach that includes proactive design, forward and reverse logistics, and continuous resource optimization throughout the product lifecycle (Mishra et al., 2023). Although the principles of CLSC significantly contribute to sustainability, CSCs aim to achieve decarbonization by leveraging advanced technologies such as AI, IoT, and real-time data analytics to optimize resource use and reduce emissions at all stages (Kazancoglu et al., 2022). By incorporating both forward and reverse logistics and emphasizing the entire lifecycle of products, CSCs provide a more comprehensive and dynamic framework for achieving decarbonization goals, making it a unique and essential proposition in the current sustainability landscape (Delpla et al., 2022). Further, the integration of CLSC insights can indeed enhance CSC strategies, but the broader, systemic approach of CSCs ultimately offers more robust solutions for decarbonization.

AI plays an essential part in enabling CSCs by optimizing resource use and improving process efficiencies (De Giovanni, 2022). AI-driven technologies, such as predictive analytics, ML, and IoT sensors, support real-time monitoring and data-driven decision-making, which are fundamental for identifying inefficiencies and decreasing emissions (Ghoreishi et al., 2023). Environmental enablers, such as using sustainable materials and renewable energy sources, combined with organizational commitment and supportive institutional frameworks, are vital for successfully implementing CSCs (Hussain & Malik, 2020). Technological advancements, including blockchain and IoT, provide the infrastructure needed for efficient resource management and tracking, facilitating transparency and traceability in supply chain activities (Esmaeilian et al., 2020).

Despite these advancements, several challenges obstruct the extensive implementation of CSCs for decarbonization. Significant obstacles include high initial investment costs, technological complexity, and organizational opposition to change (Kandasamy et al., 2023). Additionally, the lack of standardized metrics for measuring circularity and carbon reduction poses a challenge. To address these shortcomings, regulators, industry leaders, and researchers must work together to establish comprehensive CSC implementation methods and frameworks. Future research should focus on integrated frameworks that combine CSC principles with AI-driven technologies to enhance decarbonization efforts, providing a more robust understanding of how to effectively implement CSCs.

The literature provides a useful framework that suggests that successful adoption of CSCs requires technological advancements and alignment of organizational culture, policies, and human factors (Ciriello et al., 2024). It also emphasizes the value of stakeholder engagement, top management support, and good communication at all levels of the supply chain. Organizations may construct more resilient and adaptive supply chains that are suited to achieving decarbonization and sustainability goals by considering both social and technical factors.

2.2 Studies related to AI adoption in decarbonization

AI has received greater interest in the past few decades as a viable approach for developing more sustainable processes, notably in CSCs. By improving resource tracking and optimizing operations, AI may serve a crucial role in achieving decarbonization in CSCs (Acerbi et al., 2021). Table 1 reflects a summary of recent literature on AI, decarbonization, and CSCs.

Logistics and transportation optimization is one of the primary areas where AI can support decarbonization efforts. AI algorithms can analyze data from multiple sources, such as Global Positioning System (GPS) tracking, weather data, and road conditions, to determine the most energy-efficient delivery routes to reduce carbon emissions (Song et al., 2022). Additionally, AI can help optimize manufacturing systems by identifying energy efficiency improvements through ML algorithms (Bocken et al., 2016).

Table 1 Recent literature specific to AI, decarbonization, and CSCs

References	Objectives	Methodology	Outcomes
Xu et al. (2023)	The study aimed to explore the influence of technologies in low-carbon supply chain management	Systematic literature review	The study integrated technology adoption and low-carbon SCM based on the technology–organization–environment (TOE) framework
Zhao et al. (2022)	The study evaluated the drivers of decarbonization in the plastic industry	Grey DEMATEL approach	The outcomes from the study reflected that joint promotion by stakeholders and market impact substantially affect low-carbon production
Alamoush et al. (2022)	The study presented an incentive scheme for reducing greenhouse gas emissions and promoting decarbonization	Content analysis review	The study proposed a framework for providing incentives to ships at the forefront of implementing decarbonization technologies
Brinken et al. (2022)	The study aimed to estimate the CO_2 reduction potentials for various Logistics 4.0 technologies	Empirical analysis	The study estimated small reduction potentials for technologies and most supply chain steps
John et al. (2022)	The objective was to study the potential of AI-enabling technologies impacting the decarbonization of the energy-intensive steel industry	Case study approach	The study outcome reflected the capabilities to minimize the barriers to sustainability innovation
Mulvaney et al. (2021)	The study highlighted potential materials required to decarbonize electricity and mobility	Review study	The study outcome recommended moving toward a circular economy to decarbonize electricity and mobility
Thiede (2022)	The study highlighted the contribution of cyber-physical production systems to the decarbonization of industry	Empirical analysis	The study reflected the best practice technologies to support energy demand and renewable energy supply
Nunes et al. (2023)	The study identified potential drivers for the decarbonization of energy production	Systematic literature review	The outcome of the study reflected biomass as an option to decarbonize
Skoczkowski et al. (2020)	The study identified the potential of the Technology Innovation System (TIS) towards attaining decarbonization in the steel industry	Systematic literature review	The outcomes of the study reflected the role of actors in supporting the implementation of new production technologies

In product design, AI algorithms can be used to reduce waste and decrease the environmental impact of CSCs by predicting product lifecycles and designing products with recyclable materials, which helps decrease the necessity for raw materials and reduces carbon emissions (Niu et al., 2019). AI can also help circular business models to keep items and resources in use for the longest feasible time through repair, refurbishment, and reuse (Bianchini et al., 2019). AI can eliminate new product requirements and lower carbon emissions by predicting demand for second-hand products and supporting the creation of circular marketplaces (Ghisellini et al., 2016). In conclusion, AI has great potential to considerably contribute to decarbonizing CSCs by optimizing processes, reducing waste, and supporting the development of circular business models.

An inadequate understanding of system design, technology implementation, and application scenarios might result in uneven collaboration among technical professionals and business executives, posing challenges to managers when introducing new technologies (Saberi et al., 2019). Recent research has examined the possibilities of AI applications for decarbonization in various industries and environments. For example, Zhou (2022) thoroughly evaluated AI applications in renewable energy systems and provided a standard process for designing robust renewable energy systems for structures. Liang et al. (2022) modeled a network system using a three-stage Data Envelopment Analysis (DEA) model to examine the production processes of the manufacturing industry. Li et al. (2022) conducted an empirical investigation on the influence of industrial robots on emissions of carbon reduction and discovered that industrial robots have greater emission reduction impacts in developed nations compared to developing nations. Bonilla et al. (2022) presented research on AI for long-term decarbonization in the Spanish energy market, identifying potential impediments to achieving a renewable electrical mix without installed power. Finally, Liao et al. (2022) presented research on a cloud-edge-device collaborative, dependable, and communication-efficient digital twin for managing low-carbon electrical equipment, which optimizes channel and computational resource allocation to reduce communication costs.

In a recent study, Xie et al. (2022) examined the challenges associated with implementing a digitized power grid and underlined the potential of AI algorithms to drive this implementation. Additionally, Sun et al. (2022) investigated the low-carbon effects of AI in the context of the ice and snow industry using a mathematical model based on low-carbon constraints. Damoah et al. (2021) inspected the contribution of AI-enabled medical drones in enhancing the Healthcare Supply Chain (HSC) in Ghana, leading to efficient carbon reduction and noise-free drones for medical product delivery, which can contribute to attaining the SDGs. In a different study, Xi et al. (2021) created a low-carbon gas utilization system by integrating solvent-based carbon capture with methanol production-based carbon utilization and employing the Particle Swarm Optimization (PSO) method to detect low-carbon throughout the scheduling period. Alamoush et al. (2022) proposed an incentive plan for reducing GHG emissions in the maritime industry. Finally, Pulselli et al. (2019) provided an improved carbon accounting approach for analyzing GHG emissions in urban contexts, estimating the carbon footprint of urban neighborhoods, and proposing mitigation strategies to attain carbon neutrality.

An investigation was conducted to anticipate carbon emissions in China's cement sector (Li & Gao, 2018). The study's findings help to shape regulations for decreasing carbon emissions in China's cement sector. Ibn-Mohammed (2017) offered a mixed-method strategy to address the difficulties of climate change mitigation. The study developed a quantitative energy model for building energy retrofit advice. Nabavi-Pelesaraei et al. (2016) adopted an AI approach to perform resource management in the cropping system. The study focused on orange orchid cultivation in Iran.

Although the research on AI for managing decarbonization in CSCs is in its infancy, several studies (Akbari & Hopkins, 2022; Vargas et al., 2018) reported set of enablers influencing the role of AI in achieving circularity. These enablers influence the adoption process in a broader context. In this context, Table 2 elaborates upon the enablers identified from the literature.

3 Research gaps

Despite extensive research on CLSC, particularly its role in remanufacturing, refurbishing, and reusing returned products, a significant gap exists in understanding how these principles can be expanded and incorporated into the broader concept of CSCs to achieve decarboniza-

Table 2 List of enablers of AI for decarbonization

Code	Enablers of AI for decarbonization	Description	References
E1	Framing standardized interfaces for processes associated with decarbonization	This enabler helps formulate benchmarks for the processes related to decarbonization	Zhou et al.2022; Xie et al., 2022
E2	Developing a modular architecture for better compatibility of supply chains	To design an efficient supply chain, it is essential to have modular technological frameworks to improve its functioning	Akbari & Hopkins, 2022; Xie et al., 2022
E3	Emphasizing local production for recovery practices through advanced technology	This enabler focuses on recovery mechanisms through local production, which can be achieved through technological aspects	Hazen et al., 2016; Roberts et al., 2022; Agostinho et al., 2016
E4	Adopting recyclable materials to enhance the efficiency of supply chains	To make supply chains more reliable and dynamic, it is necessary to adopt recyclable inputs that can be later refurbished effectively	Vargas et al., 2018; Liang et al., 2022
E5	Provision of online monitoring for quality assurance and control	Quality assurance and control need to be systematically channeled through technological activities	Schröder et al., 2019; Roberts et al., 2022
E6	Designing ubiquitous network technologies for logistics	Decarbonization can be achieved if global networking technologies can control the logistics network	Zhu et al.2022; Liang et al., 2022
E7	Managing product life-cycle through intelligent and additive manufacturing technologies	Maintaining the circularity in supply chains requires control over the product life cycle in every phase. To manage and maintain that control, additive manufacturing technologies are required	Schröder et al., 2019; Roberts et al., 2022; Chen et al., 2022
E8	Optimizing sourcing and procurement processes through hyperintelligent sorting systems	Hyperintelligent sorting systems are the exemplifications of AI in achieving circularity. Using these systems, sourcing and procurement can be easily optimized	Vargas et al., 2018; Akbari & Hopkins, 2022; Sharma et al., 2022
E9	Provisions for regular value assessments for used and recycled products	Recycled products need to be continually assessed through innovative AI technologies to enhance the efficiency of circular supply chains	Hazen et al., 2016; Akbari & Hopkins, 2022
E10	Developing inventory and maintenance systems based on real-time data sets	Acquiring technologies to manage inventory and maintenance systems through real-time data sets ensures that there is no delay in the whole supply chain process	Vargas et al., 2018; Roberts et al., 2022; Wang et al., 2024
E11	Framing guidelines for continuous technology transfers	Technology transfers enable continuous improvisations and create a path for new opportunities	Schröder et al., 2019; Akbari & Hopkins, 2022; Jauhar et al., 2023
E12	Support of top management and government authorities	Administrative support acts as the catalyst for creating a regulatory framework for CSCs	Vargas et al., 2018; Schröder et al., 2019
E13	Ensuring effective monitoring through e-governance for transparency and accountability	Assurance of accountability and transparency through effective e-governance mechanisms will ensure fair policies throughout the system	Hazen et al., 2016; Zhou et al.2022
E14	Facilitating waste reduction by adapting smart technologies	Waste management is an important prerequisite for implementing circularity and reducing carbon emissions	Schröder et al., 2019; Vargas et al., 2018; Zhou et al.2022; Okorie et al., 2023

Table 2 (continued)

Code	Enablers of AI for decarbonization	Description	References
E15	Creating awareness towards AI-enabled methods for circularity at the consumer level	It is important to create awareness of such technologies to achieve circularity on a holistic level	Akbari & Hopkins, 2022; Liang et al., 2022; Chowdhury et al., 2022

tion. While CLSC has successfully demonstrated the benefits of reverse logistics and waste reduction, it predominantly focuses on the end-of-life stage of the product lifecycle, often neglecting the potential for proactive design and forward logistics strategies that can further enhance sustainability and carbon reduction.

Existing studies on CLSC primarily address the operational aspects of reverse logistics, with a limited exploration of the systemic and holistic approaches needed for comprehensive decarbonization. The current literature does not thoroughly examine how AI and advanced technologies can be leveraged to optimize both forward and reverse logistics within CSCs. Furthermore, while CLSC has been extensively studied in the context of sustainability, its specific implications for decarbonization within the framework of a CE have not been fully explored. There is a need to investigate on how the principles of CLSC can be expanded to encompass the entire lifecycle of products to advance a more comprehensive approach to reducing carbon emissions.

The current body of literature provides limited insights into the influence of the adoption of AI-enabled decarbonization practices. There is a need to explore how top management support, government policies, and consumer awareness can drive the execution of sustainable practices across the supply chain. Addressing such research gaps requires an interdisciplinary approach that combines insights from supply chain management, sustainability science, and technology innovation. By exploring the synergies between CLSC and CSCs and integrating advanced technologies, further research can provide a more robust framework for achieving decarbonization and promoting CE. This study intends to help close such gaps by identifying AI enablers for decarbonization and creating a comprehensive framework for CSCs.

4 Research methodology

The priorities of enablers are determined using a two-stage integrated methodology. EFA is used in the first stage to categorize and eliminate less important enablers. The second stage employs the G-OPA to derive the local and global weights of enablers. Figure 1 depicts the framework outlining the integrated methodology, and the description of the methodology is provided in the following sub-sections.

4.1 Data collection

This study used an integrated methodology that includes EFA and G-OPA. A questionnaire survey was performed for EFA in order to structure and categorize the enablers of AI. Several samples relevant to the research topic were selected for this study. The question items

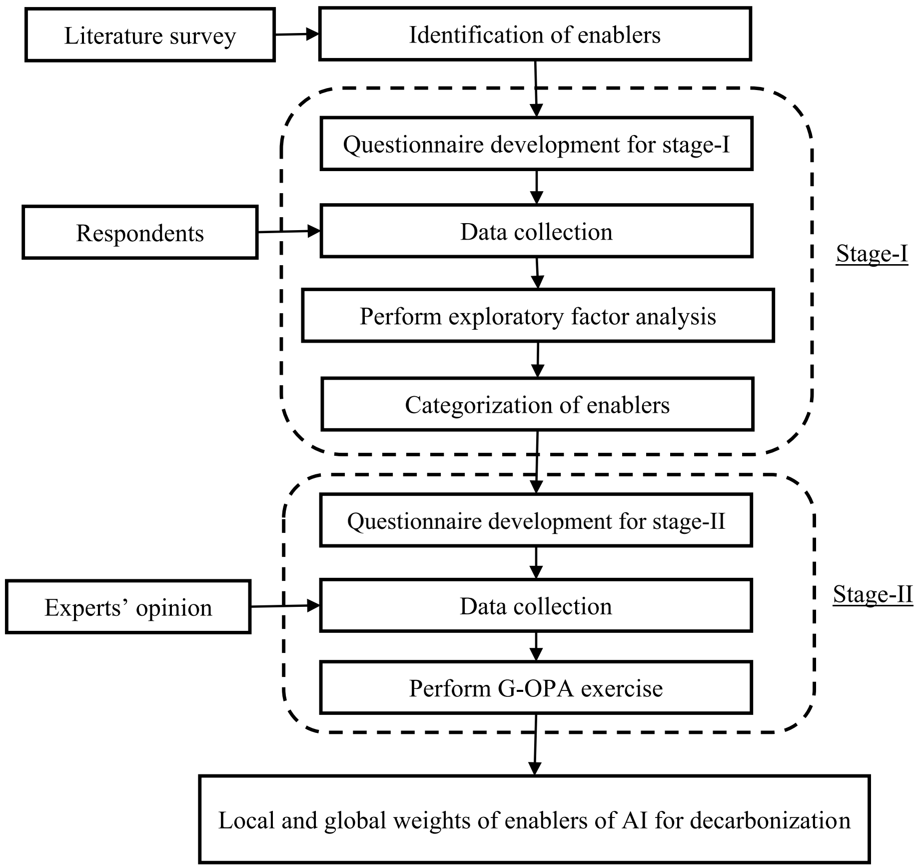

Fig. 1 Methodological framework used in this study

were developed using the literature study and piloted by a group of researchers, IT industry practitioners, and logistics and supply chain professionals. After completion, it was distributed in July 2022 for data collection using an online survey. We employed purposive sampling techniques to choose samples for data collection. Respondents for this exercise include working professionals in supply chains, technology innovation, AI, and sustainability. The participants were informed that the research being conducted was academic and that their information would be totally confidential. Additionally, respondents were asked to rank the importance of enablers on a scale of 1 to 5.

Purposive sampling was utilized in conjunction with the snowballing technique for the G-OPA exercise. Given the importance of expertise, seven experts in the relevant field have been invited to participate in this activity. Prior studies have also suggested that seven experts are sufficient for applying G-OPA (Mahmoudi & Javed, 2022; Pamucar et al., 2022; Shardeo & Sarkar, 2024). Afterward, priority was determined based on their research experience and academic qualifications. Table 3 lists the details of the experts and their fields of expertise. An online questionnaire was issued to the experts, who were asked to rank the enablers on a grey scale based on their importance.

Table 3 Experts' details used for the G-OPA exercise

Expert	Designation	Years of experience	Field of expertise
Expert 1	Technologist	8	Information technology
Expert 2	Assistant manager	11	Information technology
Expert 3	Deputy manager	18	Circular supply chains
Expert 4	Professor	22	Supply chain and logistics
Expert 5	Associate vice president	24	Information technology
Expert 6	Senior researcher	7	Circular supply chains
Expert 7	General manager	19	Goods transportation

4.2 Categorization of enablers of AI for decarbonization

Fifteen enablers have been extracted from the literature review, as revealed in Table 2. However, the enablers need to be further categorized to understand the commonalities explained among the variables. EFA has been adopted to do this. EFA is a multivariate technique widely used by researchers to extract common factors across items, thereby reducing a larger set of variables to a smaller number of underlying dimensions (Chao & Lin, 2017). In the present study, it is preferred over comparable methods because it can reduce more variables into meaningful sets of constructs while retaining crucial information. Specifically, this study defines the categories and underlying enablers of AI for decarbonization. The suitability of the analysis can be checked prior to using it through the Bartlett Test of Sphericity and the Kaiser–Meyer–Olkin (KMO) value. The KMO value must be greater than 0.6 to meet the sample size requirement, and the significance level for Bartlett's Test of Sphericity must be $p < 0.01$ (Yadav et al., 2020). Also, Cronbach's alpha is frequently used to evaluate the data's reliability and was used in this study. The Varimax method is preferred in the selection of the rotation method due to its ability to strengthen the loadings (Singh et al., 2021). It has also been argued that it assumes no correlation between the dimensions. If correlation is a possibility, the Oblimin rotation method is typically favored to produce accurate results (Reio & Shuck, 2015).

4.3 Prioritization of enablers of AI for decarbonization

Once the enablers have been categorized, they must be further prioritized using priority weights. In this study, OPA has been utilized to obtain the priority weights of the enablers. The OPA is a new Multi-Attribute Decision Making (MADM) method developed by Ataei et al. (2020). It is widely used in business research. However, the decision-making process becomes more complex daily due to associated complexities. It is critical to evaluate the uncertainties involved with them while making decisions. Grey theory is employed to handle ambiguities related to experts' opinions. The rationale behind preferring G-OPA over other similar methodologies is as follows.

Table 4 Sets, indexes, parameters, and variables

Sets	
A	Set of experts ∀ $a \in A$
B	Set of enablers ∀ $b \in B$
Indexes	
a	Index of experts *(1, …, m)*
b	Index of enablers *(1, …, n)*
Variables	
$\otimes Z$	Grey objective function
$\otimes W^{r}_{ab}$	Grey weight of b^{th} enabler by a^{th} expert at r^{th} rank
Parameters	
$\otimes a$	Grey rank of the expert *a*
$\otimes b$	Grey rank of the enabler *b*

Table 5 Grey scale used in this study

Grey number		Interpretation
Lower	Upper	
0.5	1.5	Most important
1.5	2.5	Moderately high important
2.5	3.5	Moderately important
3.5	4.5	Moderately less important
4.5	5.5	Least important

- It does not require linguistic variables and pairwise comparisons like other methods, such as Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), or Best Worst Method (BWM) (Mahmoudi et al., 2021).
- It requires a lesser number of questions to be asked, which increases its efficiency.
- It is simple to use and has fewer complexities.

Since its inception, it has been applied in sustainable technologies selection (Islam, 2021), supplier selection (Mahmoudi et al., 2021), and Electric Vehicle (EV) adoption (Candra, 2022). Despite having several advantages, it has not often been adopted to prioritize criteria and sub-criteria together (categories and enablers in our case). Thus, this study employs G-OPA to prioritize the enablers and their categories of AI technology for decarbonization. The sets, indexes, and variables associated with the G-OPA model are presented in Table 4.

The steps of G-OPA are explained as follows (Mahmoudi et al., 2021).

Step 1: Determination of enablers: The experts determine the potential enablers related to the study.

Step 2: Identification and ranking of the experts: Identify the research domain experts and rank them. Generally, expertise or academic background is considered when prioritizing them.

Step 3: Prioritization of the enablers: In this step, the enablers are ranked by the experts. Based on the crisp rank received from the experts, it is further converted into grey ranks using the scale (Chakraborty et al., 2023) as presented in Table 5.

Step 4: Obtaining the weight of enablers: The final G-OPA model is solved to obtain the final weights of enablers. The linear model for G-OPA is expressed in Eq. (1).

$$
\begin{aligned}
& \text{Max} \otimes Z \\
& \text{Subject to,} \\
& \otimes Z \leq \otimes a \left(\otimes b \left(\otimes W_{ab}^{r} - \otimes W_{ab}^{r+1}\right)\right) \forall a, b\text{and } r \\
& \otimes Z \leq \otimes a \left(\otimes b \left(\otimes W_{ab}^{n}\right)\right) \forall a\text{and } b \\
& \sum_{a=1}^{m} \sum_{b=1}^{n} \otimes W_{ab} = [0.8, 1.2] \\
& \otimes W_{ab} \geq 0 \forall a\text{and } b
\end{aligned} \tag{1}
$$

where $\otimes Z$ is unrestricted in sign.

After solving Eq. 1, we need to obtain the grey weights of the experts and enablers. The grey weights of the enablers can be obtained using Eq. (2).

$$
\otimes W_b = \sum_{a=1}^{m} \sum_{b=1}^{n} \otimes W_{ab} \forall b \tag{2}
$$

To obtain the weights of experts, Eq. (3) is used.

$$
\otimes W_a = \sum_{a=1}^{m} \sum_{b=1}^{n} \otimes W_{ab} \forall a \tag{3}
$$

Step 5: Obtaining final crisp weights: In this step, the grey weights are converted into crisp weights using a kernel. The kernel is expressed in Eq. (4).

$$
\otimes W = \frac{1}{2}(\underline{W} + \overline{W}) \tag{4}
$$

5 Result analysis

The study used an integrated methodology incorporating both EFA and G-OPA. This section details the outcomes of the various stages. Section 4.1. reflects the results obtained from the EFA exercise. The application of G-OPA and its results are described in Sect. 4.2.

5.1 Categorization of enablers

As mentioned in the previous section, this study used EFA to categorize the identified enablers. There are several parameters on which sample size requirements for EFA are determined, including participant-to-indicator ratio, communalities, loadings, the number of factors, and the number of variables (Howard, 2023; McNeish, 2017). We used the participant-to-indicator ratio as an approach to determine the sample size requirement since it is most commonly practiced in the literature. According to this, the literature suggested around 10 or more participants per indicator as an acceptable suggested value (Cattell, 2012; Anthoine et al., 2014). As a result, 118 responses were obtained out of 150, with a response

Table 6 Demographic details of the respondents

Socio-demographic characteristics	n(%)
Gender	
Male	84 (71.19%)
Female	34 (28.81%)
Age	
18–30	21 (17.80%)
31–40	32 (27.12%)
41–50	41 (34.75%)
51–60	24 (20.33%)
Education qualification	
Graduate	66 (55.93%)
Post-graduate	43 (36.44%)
Doctorate	9 (7.63%)

Table 7 Descriptive summary of data for exploratory factor analysis

Measures/ Enablers	E1	E2	E3	E4	E5	E6	E7	E8
N	118	118	118	118	118	118	118	118
Mean	3.73	3.25	3.78	3.96	3.61	3.82	3.75	3.69
Median	4	4	4	4	4	4	4	4
Standard Deviation	0.88	1.27	1.14	1.08	1.00	0.98	0.89	0.89
Minimum	2	1	1	1	1	1	2	1
Maximum	5	5	5	5	5	5	5	5
Skewness	−0.26	−0.44	−0.99	−0.78	−1.05	−0.45	−0.21	−0.31
Kurtosis	−0.59	−0.87	0.23	−0.18	0.86	−0.54	−0.71	−0.23

Measures/ Enablers	E9	E10	E11	E12	E13	E14	E15
N	118	118	118	118	118	118	118
Mean	3.76	3.22	3.11	3.74	3.11	3.46	3.25
Median	4	3	3	4	3	3	3
Standard Deviation	0.86	0.86	1.23	0.98	1.04	0.73	0.99
Minimum	1	1	1	1	1	2	1
Maximum	5	5	5	5	5	5	5
Skewness	−1.14	0.03	−0.26	−0.88	0.32	0.47	0.01
Kurtosis	2.09	0.23	−0.92	0.60	−0.68	−0.14	−0.15

Table 8 Assumptions checks

Bartlett's test of sphericity			KMO measure of sampling adequacy
χ^2	df	P	
824	105	<.001	0.750

rate of 78.66%. Table 6 shows the demographics of the respondents, while Table 7 shows a descriptive summary of the collected data.

In this study, the EFA has been conducted using Jamovi software (The Jamovi Project, 2022). The gathered responses were analyzed after using EFA with Oblimin rotation. The correlation among the categories, which is also confirmed by the Bartlett Test of Sphericity presented in Table 8, justifies the use of Oblimin rotation. In addition, the KMO value of 0.750 is more than the recommended value of 0.6 (Yadav et al., 2020).

We have used Cronbach's α as a measure to check internal reliability. The recommended value for modest reliability is above 0.7, but a few studies also suggested a Cronbach's α value above 0.6 as acceptable (Nunnally, 1978; Churchill, 1979). Accordingly, Cronbach's α in this study is 0.698, which is closer to 0.7 and greater than 0.6, confirming the reliability of the results. Because the Eigen vectors of the first four factors were greater than 1, a total of four categories have been identified, accounting for 60.8% of the total variance that met the criteria suggested by Hair et al. (2014). Also, it is suggested that the factor loadings above 0.6 and 0.7 are acceptable for exploratory and confirmatory studies, respectively (Hair et al., 2014). Considering this, the variables with factor loadings less than 0.6 have been eliminated from the analysis. It resulted in categories with their underlying enablers.

Uniqueness defines how well a variable is defined by its elements. As suggested by Costello and Osborne (2005), the elements having uniqueness values below 0.6 are preferable. The values met the criteria as all values of uniqueness are less than 0.6. Furthermore, we again consulted with the experts to name the identified categories, considering the characteristics of the underlying enablers. For instance, the environmental category has all the underlying enablers that commonly address environmental concerns in the context of CSCs. Enablers under this category include: adopting recyclable materials to enhance the efficiency of supply chains, provisions for regular value assessments for used and recycled products, and facilitating waste reduction by adapting smart technologies. Similarly, the categories were named as: institutional, technological, organizational, and environmental categories. The categories and underlying enablers with factor loadings are presented in Table 9.

Table 10 presents the summary statistics of the identified categories. The values of SS loadings, also known as Eigenvalues of factors, highlight the total variance explained by each factor. Generally, the factors having SS loadings greater than 1 are retained (Hair et al., 2014). To understand relative explanatory power, the percentage of total variance is calculated. In our case, institutional, technological, organizational, and environmental categories accounted for 18.5%, 17.0%, 14.1%, and 11.2% of the total variance, respectively. Another

Table 9 Factor loadings

Enabler	Categories				Uniqueness
	Institutional	Technological	Organizational	Environmental	
E2	0.934				0.113
E11	0.912				0.176
E12	0.733				0.466
E13	0.710				0.484
E6		0.846			0.282
E8		0.829			0.332
E7		0.791			0.362
E1		0.709			0.423
E5			0.848		0.284
E3			0.678		0.513
E10			0.665		0.563
E15			0.660		0.548
E4				0.843	0.297
E9				0.714	0.468
E14				0.639	0.563

Table 10 Summary statistics of categories

Categories	SS loadings	% of variance	Cumulative %
Institutional	2.77	18.5	18.5
Technological	2.56	17.0	35.5
Organizational	2.12	14.1	49.7
Environmental	1.68	11.2	60.8

Table 11 Experts' opinion regarding the prioritization of categories using the grey number

Expert	Environmental		Institutional		Organizational		Technological	
	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
Expert 1	2.5	3.5	3.5	4.5	0.5	1.5	1.5	2.5
Expert 2	1.5	2.5	0.5	1.5	3.5	4.5	2.5	3.5
Expert 3	2.5	3.5	0.5	1.5	1.5	2.5	3.5	4.5
Expert 4	0.5	1.5	3.5	4.5	2.5	3.5	1.5	2.5
Expert 5	1.5	2.5	2.5	3.5	3.5	4.5	0.5	1.5
Expert 6	0.5	1.5	2.5	3.5	3.5	4.5	1.5	2.5
Expert 7	1.5	2.5	3.5	4.5	0.5	1.5	2.5	3.5

way to retain the number of factors is the cumulative percentage of total variance explained. According to Hair et al. (2014), a cumulative variance of 60% or more is adequate in social sciences research. As shown in Table 10, the four categories explain 60% of the total variance that meets the criteria of retention.

5.2 Ranking of enablers based on influence

The results from the previous section have been carried forward to determine the global weights of the enablers. Following the steps of G-OPA, as discussed in Sect. 2.2, a total of 15 enablers have been determined and categorized under four categories, as reflected in Table 9. Next, the experts were asked to prioritize the categories using a grey scale presented in Table 5. The same process was also followed to prioritize enablers under each category. Afterward, the collected data were converted as per G-OPA specifications using the scale presented in Table 5. For instance, if an expert ranks any enabler/category as "Moderately high important", the corresponding grey number is "1.5, 2.5". The conversion of the linguistic scale into corresponding grey numbers for a category is presented in Table 11. Similarly, all responses were converted and the collective responses of experts on the prioritization of categories using grey numbers. Also, the experts' opinions regarding enablers under the environmental category using grey numbers are presented in Table 12. Similarly, data collected on the prioritization of enablers under the institutional, organizational, and technological categories have been converted into grey numbers. Furthermore, the collected data was formulated as a linear programming model, as shown in Eq. (1). The model was run on LINGO software using a linear solver to obtain the weights. Thereafter, the attained weights were integrated to obtain weights of categories and enablers using Eq. (2).

The final crisp weights of categories and corresponding enablers have been calculated using Eq. (4) and are presented in Table 13. The global weights of enablers shown in Table 13 have been calculated by multiplying the category's weights and the local weights of corresponding enablers. The higher weights reflect the higher priority of the enablers.

Table 12 Experts' opinion regarding enablers of the environmental category using the grey number

Expert	E4		E9		E14	
	Lower	Upper	Lower	Upper	Lower	Upper
Expert 1	0.5	1.5	1.5	2.5	2.5	3.5
Expert 2	1.5	2.5	0.5	1.5	2.5	3.5
Expert 3	0.5	1.5	1.5	2.5	2.5	3.5
Expert 4	0.5	1.5	2.5	3.5	1.5	2.5
Expert 5	1.5	2.5	0.5	1.5	2.5	3.5
Expert 6	0.5	1.5	2.5	3.5	1.5	2.5
Expert 7	0.5	1.5	1.5	2.5	2.5	3.5

6 Discussions

Transitioning from linear to CSCs might pose real obstacles for organizations. To solve these problems, organizations must identify key enablers that can assist corporate business planners and designers navigate the transition process. In this regard, the current study explores and assesses the enablers of AI for decarbonization to design CSCs. This study identified 15 enablers through an extensive literature review and further classified them into four categories: environmental, institutional, organizational, and technological categories by adopting the EFA. Furthermore, the G-OPA approach was adopted to prioritize the identified enablers to assess the implementation levels. The findings from this study reveal that the enablers under the environmental category are the most crucial in adopting AI-enabled CSCs for decarbonization. Prior research has shown that AI may be used to sort plastic and improve knowledge of recycled plastics utilizing multi-sensor data fusion AI-based algorithms (Chidepatil et al., 2020). The technological aspect was also shown to be a crucial enabler for the decarbonization of supply chains using AI. Using AI algorithms brings various advantages, including real-time data analysis to alleviate traffic congestion, optimizing energy consumption for cooling services, and more. AI advancement has resulted in strong analysis algorithms that help with prediction, optimization, and pattern identification. Also, AI aids CSC methods in operational processes by combining operational data with failure and maintenance records for decision assistance (Kristoffersen et al., 2021). In this way, this study contributes to Responsible Consumption and Production (SDG 12) and Climate Action (SDG 13) of the UN's SDGs.

The findings from the study highlight the critical interplay between technological advancements and organizational dynamics in achieving decarbonization through CSCs. The identification of 15 enablers, including key factors such as adopting recyclable materials to enhance the efficiency of supply chains, emphasizing local production for recovery practices through advanced technology, and managing product life-cycle through intelligent and additive manufacturing technologies, underscores the importance of both technical solutions and social factors. The study emphasizes that the successful execution of CSCs requires the integration of advanced AI-driven technologies and the alignment of organizational culture, policies, and human factors (Vlachos, 2023). This study's findings suggest that while environmental and technological enablers are crucial, the human and institutional components, such as top management support and stakeholder engagement, are equally important to drive the transition from linear to CSCs. Furthermore, the prioritization of enablers using the G-OPA approach reveals the necessity for a balanced approach

Table 13 Enablers and their local and global weights

Category with weight	Enablers of AI for decarbonization	Local weight	Global weight	Rank
Environmental (0.405)	Adopting recyclable materials to enhance the efficiency of supply chains (E4)	0.584	0.237	1
	Provisions for regular value assessments for used and recycled products (E9)	0.210	0.085	5
	Facilitating waste reduction by adapting smart technologies (E14)	0.206	0.083	6
Institutional (0.121)	Developing modular architecture for better compatibility of supply chains (E2)	0.141	0.017	14
	Framing guidelines for continuous technology transfers (E11)	0.133	0.016	15
	Support of top management and government authorities (E12)	0.451	0.054	8
	Ensuring effective monitoring through e-governance for transparency and accountability (E13)	0.275	0.033	11
Organizational (0.215)	Emphasizing local production for recovery practices through advanced technology (E3)	0.495	0.106	2
	Provision of online monitoring for quality assurance and control (E5)	0.311	0.067	7
	Developing inventory and maintenance systems based on real-time data sets (E10)	0.086	0.018	13
	Creating awareness towards AI-enabled methods for circularity at consumer levels (E15)	0.110	0.024	12
Technological (0.259)	Framing standardized interfaces for processes associated with decarbonization (E1)	0.141	0.037	10
	Designing ubiquitous network technologies for logistics (E6)	0.170	0.044	9
	Managing product life-cycle through intelligent and additive manufacturing technologies (E7)	0.349	0.090	3
	Optimizing sourcing and procurement processes through hyper-intelligent sorting systems (E8)	0.339	0.088	4

that considers both technical efficiencies and social adaptability. The significant role of AI in facilitating real-time data analysis, optimizing energy use, and supporting decision-making processes aligns with the technical aspects. Simultaneously, the need for collaboration, partnerships, and consumer awareness highlights the social dimension. These findings suggest that organizations must adopt a holistic strategy that integrates advanced technologies with robust organizational practices and stakeholder collaboration to achieve sustainable and decarbonized supply chains. The study presents an exhaustive model for comprehending and dealing with the complexity of implementation, highlighting the importance of both technological and social factors in driving successful and sustainable decarbonization initiatives.

Among the 15 enablers extracted from the literature and discussion with experts, three top enablers were identified. The first-ranked enabler was adopting recyclable materials to enhance the efficiency of supply chains (E4). This is because adopting recyclable materials can enhance the circularity in the supply chain. By using materials that can be recycled and reused, the supply chain can reduce its reliance on virgin materials, reduce waste, and improve resource efficiency. This, in turn, contributes to reducing carbon emissions and achieving decarbonization goals. The second-ranked enabler was emphasizing local production for recovery practices through advanced technology (E3). The supply chain can reduce transportation-related emissions and enhance supply chain resilience by producing goods locally (Ugarte et al., 2016). Adopting advanced technology, such as 3D printing and robotics, can further enhance the efficiency of local production and reduce energy consumption (Kanyilmaz et al., 2022). The third-ranked enabler is managing product life-cycle through intelligent and additive manufacturing technologies (E7). Collaboration and partnerships are crucial in controlling the product life cycle using intelligent and additive manufacturing technologies (Ming et al., 2008). Collaboration can assist in sharing data and insights to increase supply chain efficiency and enhance the effectiveness of decarbonization activities (Kumar et al., 2024). Partnerships can also help in sharing resources and expertise to adopt and implement intelligent and additive manufacturing technologies (Li et al., 2017). In existing times, several organizations focus on the 4Rs (Reduce, Reuse, Recycle & Recover) of sustainability (Leong et al., 2023). However, few of them assess to used and recycled products, which is important for sustainability. Recycled products help to address environmental issues; however, it can be difficult to manage such products due to reliability and life cycle (Zhang et al., 2020). AI-based technologies are promising to facilitate the assessment of such products, as they will further help to keep track of the products and their potential processing. The enabler, Provisions for regular value assessments for used and recycled products (E9), stood at the fifth rank in terms of its influence on adopting AI-enabled technologies. Afterward, the waste generated by organizations can also be traced and monitored using smart technologies for better handling. Also, AI-based technologies can be integrated with organizations to improve processes. The importance of these activities is evident from this study, where Facilitating waste reduction by adapting smart technologies (E14) and Provision of online monitoring for quality assurance and control (E5) stood at the sixth and seventh positions, respectively. However, the literature highlights that awareness of AI-enabled methods for circularity at both consumer and practitioner levels is important for its smooth adoption process (Vishwakarma et al., 2024). This is because consumers play an important part in determining the business tactics firms use. Sensitizing them towards environmental aspects using emergent AI-enabled technologies might force organizations to boost adoption processes. In this study, the awareness of AI-enabled methods for circularity at consumer levels has been rated relatively low. The reason might include the perspective of the internal processes of an organization.

Compared to traditional supply chains, CSCs focus on incorporating social and environmental aspects to expand the economic element of the Triple Bottom Line, whereas traditional supply chains emphasize financial and economic business performance. Meeting the environmental and technological requirements of CSCs is necessary, as is satisfying economic standards and consumer demands to maintain competitiveness (Seuring & Müller, 2008). The existing literature comprehensively explains the management of CSCs across various dimensions (Di Vaio et al., 2020; Nilsson & Göransson, 2021). Moreover, previous research has studied the relevance of AI in constructing models for CSCs that incorporate several circular elements, such as waste minimization (Klumpp & Zijm, 2019), supply chain collaboration (Son et al., 2021), and consumer awareness (El Amrani et al., 2021).

The use of AI as a ground-breaking analytical tool for enhancing supply chain performance is well-recognized in the literature (Grover et al., 2022). Technology plays a crucial part in the construction of worldwide flexible CSCs (Gunasekaran et al., 2016; Vegter et al., 2020). Managers at all levels need to reconsider their approach to managing, viewing, designing, deploying, redesigning, and measuring performance and environmental sustainability across the entire CSCs to ensure circularity (Sanders et al., 2019). Digital applications have influenced almost every industry and all supply chains (Klumpp & Zijm, 2019), and advanced technologies such as big data, AI, and robotics are increasingly used to achieve circularity (Sanders et al., 2019). Consumers also demand easy access to product data to validate circularity, which puts pressure on suppliers to follow circular practices at both the local and global levels (Nikolakis et al., 2018; Parmentola et al., 2022). The establishment of CSCs poses additional challenges, such as inadequate coordination, limited information sharing, unpredictability, planning of material flow, transportation, and supplier selection, which impact the performance of the network and decarbonization efforts (Ali et al., 2022). Organizations need to address these challenges to establish efficient CSCs.

7 Implications of the study

The adoption of AI in the decarbonization of CSCs entails several crucial managerial implications that must be considered. The use of AI can significantly aid CSCs in achieving decarbonization objectives. One of the foremost managerial implications of incorporating AI in CSCs is the need for effective data management. Managers must collect, process, and administer data from various sources, including suppliers, customers, and the supply chain itself. The data collected must be precise, up-to-date, and relevant if AI is to generate meaningful insights. Consequently, managers must invest in sturdy data management systems that can manage large data volumes, process them rapidly, and deliver accurate insights (Chidepatil et al., 2020).

Another important implication is the need for coordination. AI implementation requires synchronization between different stakeholders, including suppliers, customers, technology providers, and regulatory bodies (Ångström et al., 2023). Managers need to identify and engage with the right partners to develop an effective AI-driven decarbonization strategy. Coordination will also help in sharing data and insights, thus enhancing the decarbonization efforts (Son et al., 2021). Investment in AI technology is also crucial for the success of CSCs. For instance, AI-powered predictive maintenance tools can help optimize resource use and minimize carbon emissions (Nikolakis et al., 2018). Furthermore, waste management can be improved by using AI-powered tools to identify and reduce waste, thus increasing sustainability and circularity in the supply chain. Furthermore, incorporating AI-based technology can boost the efficiency of supply chain processes and help manage decarbonization initiatives (Chowdhury et al., 2021).

The current study can be used in practice to encourage the transformation of applicable business models into CSCs. The latest study's considerable contribution of findings is valuable for manufacturing businesses seeking to achieve sustainability by implementing circular practices in their supply chains. This study's findings on AI enablers for decarbonization can encourage business model innovation to progress toward circular practices in various manufacturing enterprises (Mubarik et al., 2025; Yang et al., 2018). The implications of the study assist in securing the fulfillment of SDG 12 related to responsible production and consumption (Roy et al., 2022). The proposed findings from the study result in social, economic, and environmental advantages that concentrate on waste reduction, transparency, and improved operations in supply chains.

Transitioning to CSCs requires a comprehensive approach that integrates forward and reverse logistics, optimizing resource use throughout the product lifecycle. Managers should leverage advanced technologies like AI, IoT, and blockchain to enhance real-time monitoring, data analytics, and decision-making. Additionally, fostering a strong organizational commitment to sustainability is essential. Managers must align corporate strategies with sustainability goals, engage employees at all levels, and ensure top management support to drive the adoption of circular practices and improve overall effectiveness in decarbonization efforts.

Based on the study's findings, the Government should focus on investing in digital infrastructure and incentivizing the development and implementation of AI-enabled technologies, such as energy management systems and predictive analytics, to optimize resource use and reduce emissions. Policymakers should also introduce regulations mandating circular practices, including the use of recyclable materials, lifecycle emission tracking, and waste reduction strategies. Engaging with policymakers and stakeholders is vital for creating an enabling environment for CSCs. Managers should advocate for supportive policies, collaborate with industry partners, and establish standards for sustainable practices. Continuous innovation and adaptation are necessary to stay informed about emerging technologies and best practices. These actions, aligned with multilateral frameworks like the Paris Agreement, can significantly enhance global decarbonization efforts while promoting sustainable economic growth (Gota et al., 2019). By addressing these managerial implications, organizations can successfully transition to CSCs, optimize resource use, and significantly lessen carbon emissions, contributing to environmental sustainability.

8 Conclusions, limitations, and future research directions

This study investigates how AI technology can be integrated with CSC practices to achieve decarbonization. This study assessed the enablers of AI for decarbonization in CSCs by analyzing the literature and prioritizing influential enablers using G-OPA. The results demonstrate that environmental and technological categories are the most influential for AI-enabled CSCs, with adopting recyclable materials to enhance the efficiency of supply chains being the most influential for decarbonization. However, challenges in terms of a lack of data, standardization, and understanding of AI's benefits and risks need to be addressed.

Organizations must grasp how AI might assist their operations while also acknowledging its limitations. While the present study provided insights into enablers of AI for decarbonization, it has some limitations. First, within a particular industrial and regional context, the factors that facilitate AI-enabled decarbonization in CSCs were determined and ranked using a literature-driven and expert-oriented methodology. As a result, the findings may not fully capture industry-specific or country-specific differences, especially in sectors with unique supply chain structures or regulatory frameworks. Furthermore, a thorough analysis of the socio-cultural factors affecting AI adoption and circular practices, such as workforce preparedness, policy awareness, and consumer behavior, was lacking. The dynamic and rapidly evolving nature of AI technologies also poses a challenge, as the relevance and applicability of some enablers may shift over time due to technological advancements or policy changes.

Longitudinal and cross-industry studies should be considered for future research to validate and improve the enablers in various settings. By combining qualitative and quantitative techniques such as case studies, structural equation modeling, and system dynamics, it will be possible to better understand the interdependencies and causal relationships among enablers. Furthermore, a more comprehensive perspective might be obtained by broadening the focus to encompass behavioral and socio-cultural factors, such as stakeholder perceptions, workforce digital literacy, and consumer willingness. Future inquiries may also explore the relationship between AI governance, ethical concerns, and data privacy in the context of CSCs. Lastly, how collaboration with policymakers and international organizations helps decode the technical findings into actionable policy guidelines, ensuring the broader scalability and impact of AI-driven CSCs for global decarbonization, can be explored.

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Declarations

Conflict of interest The authors have no conflict of interest to disclose.

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