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Exploring the Spillover Effect of Supply Chain Digitalisation on Pollution Emissions Through Social Network Analysis

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ABSTRACT

The supply chain consists of interconnected businesses and organisations responsible for the flow of goods and services. As firms increasingly adopt digital technologies, the spillover effects of supply chain digitalisation (SCD) on environmental performance remain underexplored. This study examines how the digitalisation of suppliers and customers influences pollution emissions in midstream manufacturing firms. Using data from Chinese A-share-listed firms and social network analysis, we construct a novel indicator to measure SCD. Our findings reveal that digitalisation within the supply chain significantly reduces pollution emissions through three key mechanisms: cost efficiency, improved resource allocation and green technology innovation. The effect is more pronounced in high-pollution industries, regions with stricter environmental regulations and regions with well-developed digital infrastructure. These insights highlight the strategic role of digital transformation in driving corporate sustainability and provide valuable implications for firms and policymakers navigating green business strategies.

JEL Classification: M19, O32, O00

1 | Introduction

The impact of digitalisation on corporate pollution emissions has garnered significant academic attention in recent years. However, most existing studies have primarily focused on the effects of digital transformation within firm boundaries, paying limited attention to the broader implications across supply chain networks (Guo et al. 2023). As firms operate within increasingly interconnected value chains, the digitalisation of upstream and downstream partners may exert substantial spillover effects on midstream firms, particularly in relation to environmental performance (Herkenhoff et al. 2024; Yang and Lin 2020). Despite its relevance, this network-based perspective on digital transformation and pollution reduction remains underexplored.

Supply chain digitalisation (SCD) refers to the comprehensive integration of digital technologies across supply chain functions, including demand forecasting, R&D, production, distribution, retail and after-sales services (Wu et al. 2019; Yu et al. 2024). While the environmental benefits of digitalisation at the firm level have been well documented (Feng et al. 2022; Zhao et al. 2024; Fazio et al. 2025), a growing literature highlights that sustainability practices often diffuse across supply chains, producing externalities for connected firms (Ren et al. 2023; Xu et al. 2023; Xu et al. 2024). For example, suppliers' and customers' digital upgrades may improve midstream firms' environmental performance via knowledge spillovers, efficiency gains, and joint innovation platforms (Lian et al. 2022). In light of these dynamics, this study seeks to answer the following research question (RQ): *Can SCD reduce pollution emissions in midstream firms, and if so, through what mechanisms?*

To address this question, we propose a novel analytical framework to assess the spillover effects of SCD on environmental performance. We draw on the resource-based view (RBV) and dynamic capabilities theory to suggest that firms embedded in more digitally advanced supply chain networks are better positioned to reduce emissions. In addition, we adopt the Environmental Kuznets Curve framework (Grossman and Krueger 1993) to explore the mechanisms through which SCD contributes to environmental improvement. Following this conceptual foundation, we hypothesise the following:

- **H1.** *SCD reduces corporate pollution emissions.*

- **H2a.** *SCD promotes pollution reduction by lowering business operating costs.*

- **H2b.** *SCD promotes pollution reduction by optimising resource allocation.*

- **H2c.** *SCD promotes pollution reduction by incentivising green technological innovation.*

To empirically test these hypotheses, we use data on Chinese A-share listed companies. China's rapid digital transformation and environmental policy evolution provide a relevant context for exploring this question. Specifically, this study undertakes three key tasks empirically. First, we construct a dynamic supply chain network based on supplier–enterprise–customer linkages among Chinese A-share listed companies. A network topology distance indicator is developed to measure the spillover effects of digitalisation within the supply chain. Second, we quantify SCD by aggregating the digital patent counts of each firm's upstream and downstream partners, weighted by their network proximity to midstream firms. This weighted aggregation captures the intensity of digitalisation across the supply chain. Third, using a fixed-effects model and panel data from 2007 to 2022, we empirically assess the impact of SCD on pollution emissions in midstream manufacturing firms, and examine the underlying mechanisms driving this relationship, in response to four hypotheses.

This study makes three key contributions to the literature:

- Theoretical extension of social network theory in supply chain research: We develop a network-distance weighted measure of SCD and demonstrate that digitalisation among suppliers and customers significantly reduces midstream firms' pollution emissions. This cross-fertilisation between green supply chain research and social network analysis responds to the call for extending social network theory into the supply chain domain (Borgatti and Li 2009).
- Innovative application of social network analysis to measure SCD: Departing from previous studies that use binary indicators—such as exposure to supply chain innovation pilot programmes (Chen et al. 2025; Meng and Lin 2025; Wang and Li 2024)—this study develops a continuous, network-based indicator of SCD. This measure reflects the intensity and variation of digitalisation. It captures the interconnected nature of production networks and enables a more fine-grained analysis of digitalisation spillovers.
- Mechanism analysis grounded in the Environmental Kuznets Curve framework: By examining how SCD promotes pollution reduction through economies of scale, improved resource allocation and green technological innovation, this study offers a theoretical foundation for understanding the environmental benefits of digital transformation.

Overall, this research provides valuable implications for both firms and policymakers pursuing green development strategies and digital transformation initiatives.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature and develops the research hypotheses. Section 3 outlines the data, variables and methodology. Section 4 presents the empirical results and analysis. Section 5 discusses the findings and policy implications and concludes the study.

2 | Literature Review and Hypothesis Development

2.1 | Literature Review

2.1.1 | Pollution Emission Challenge

Industrialisation, urbanisation and the heavy reliance on fossil fuels contribute significantly to pollution emissions, exacerbated by weak environmental regulations. Prior studies highlight the environmental and health risks posed by greenhouse gases (GHGs), sulphur dioxide (SO_2), and nitrogen oxides (NO_x), particularly in rapidly industrialising economies such as China and India (Jiang et al. 2014; Yang et al. 2022; World Health Organization 2021; United Nations Environment Programme (UNEP) 2020). Severe air pollution in these regions is primarily attributed to coal combustion (Zhang et al. 2011; Greenstone and Hanna 2014). Additionally, the prioritisation of economic growth often results in lax enforcement of environmental policies, allowing pollution levels to remain persistently high (Kong and Zhu 2022; Wang et al. 2004; Van Rooij et al. 2017).

The transportation and energy sectors further compound pollution issues. Rising vehicle ownership, inefficient public transport systems and continued reliance on coal-fired power plants are major contributors to deteriorating air quality (Guttikunda and Calori 2013; Zhang et al. 2011; Lin and Zhu 2019). Furthermore, the 'pollution haven hypothesis' suggests that firms relocate pollution-intensive industries to countries with weaker environmental regulations, increasing emissions in host nations (Cole et al. 2011; Eskeland and Harrison 2003).

The consequences of pollution are severe, with both health and economic implications. Long-term exposure to fine particulate matter ($PM_{2.5}$) is linked to reduced life expectancy and premature deaths, particularly among vulnerable populations in China and India (Chen et al. 2013; Guttikunda and Calori 2013).

Additionally, industrial water pollution contributes to significant economic losses, with GDP reductions of up to 2% annually in developing economies (Kong and Zhu 2022; Wang et al. 2004; Damania et al. 2019).

Addressing these challenges requires a multifaceted approach, including stronger regulatory enforcement, greater investment in clean technologies and enhanced global cooperation to curb the offshoring of pollution-intensive industries. By implementing stricter environmental policies and fostering innovation in green technologies, firms and policymakers can work towards more sustainable industrial development.

2.1.2 | SCD

SCD refers to the integration and application of digital technologies to streamline transactions and communication among various stakeholders within a company's supply chain (Mukhopadhyay and Kekre 2002; Sanders and Swink 2020). This section reviews the literature from three perspectives: measurement of SCD, its advantages and its challenges.

2.1.2.1 | Measurement of SCD. Empirical studies adopt diverse strategies to measure SCD. Researchers often use binary indicators, such as firm participation in the Supply Chain Innovation and Application pilot programme (Meng and Lin 2025; Wang and Li 2024). Others rely on text-based indices, measuring the frequency of digital-related keywords in annual reports by machine learning methods (Yang et al. 2023). Beyond these approaches, survey-based measures are also common, where firms are evaluated using items that rate their ability to apply digital technologies in supply chain operations (Nasiri et al. 2020; Rashid et al. 2024; Le et al. 2024). Our study extends this line of research by developing a network distance weighted SCD index, which aggregates the digital innovation of both upstream suppliers and downstream customers. Unlike binary policy exposure or firm-level surveys, this index reflects the relational and networked nature of digital spillovers within supply chains.

2.1.2.2 | Advantages of SCD. The importance of SCD has grown markedly, particularly during the COVID-19 pandemic, as firms have sought to strengthen resilience and productivity in an increasingly digital world (Sharma et al. 2020; Ivanov and Dolgui 2021). By leveraging digital tools, firms can reduce costs, optimise resource allocation and enhance information symmetry across networks (Barreto et al. 2017; Gorbach 2017; Loske and Klumpp 2020). These improvements foster agility, accuracy and transparency in supply chain processes, ultimately driving competitive advantage (Baird and Raghu 2015; Opresnik and Taisch 2015). The core components of SCD include big data analytics, sensor-equipped manufacturing systems, robotics, augmented reality, sophisticated tracking and additive manufacturing (Ivanov et al. 2019). Such integration improves real-time decision-making, automates workflows and facilitates collaboration among stakeholders, enhancing communication across supply chain stages and driving innovation in product development and distribution (Shahadat et al. 2024). Moreover, SCD has empowered businesses to address market fluctuations and evolving consumer demands with achieving faster, more flexible, product-focused, efficient and precise performance (Seyedghorban et al. 2020), while reducing reliance on manual labour through automation, thereby improving efficiency and reducing errors (Tjahjono et al. 2017).

2.1.2.3 | Challenges of SCD. Despite these benefits, SCD also presents several challenges. In sectors such as the food supply chain, inefficiencies such as waste and loss can result from weak integration (Jensen et al. 2013), poor collaboration (Dora 2019; Sharma et al. 2022), inadequate communication (Irani and Sharif 2016) and unpredictable consumer behaviour (Aktas et al. 2018; Martindale and Schiebel 2017). More broadly, high implementation costs, infrastructure gaps and organisational resistance may hinder digital transformation. Nonetheless, research suggests that the advantages of SCD outweigh these challenges, particularly in improving supply chain efficiency and reducing information asymmetry among firms. These benefits contribute to enhanced digital transformation and overall supply chain performance (Bigliardi et al. 2022; Yu et al. 2024).

2.1.3 | The Role of SCD in Emission Reduction

Existing studies confirm that digitalisation can reduce pollution and enhance environmental performance, though the underlying mechanisms vary across contexts. A first strand of research highlights technological and productivity mechanisms. Chinese evidence shows that digital transformation cuts emissions via green technology innovation, factor allocation and environmental disclosure (Zhu et al. 2023), while productivity gains also play a role (Zhao et al. 2024). Complementing this view, sector-level evidence from the United States suggests that cloud computing enhances users' energy efficiency (Park et al. 2023). A second strand of work emphasises infrastructure and connectivity as enabling conditions. OECD evidence indicates that broadband networks generate positive environmental effects by enabling cleaner practices and reducing CO_2 emissions (Briglauer et al. 2023). European regional studies similarly show that digital technologies reduce the carbon footprint through the virtualisation of production and consumption (Fazio et al. 2025). A third perspective underscores institutional and governance mechanisms. For example, Huong and Thanh (2022) find that digitalisation enhances environmental performance, with business digitisation and public services improving environmental health, and connectivity and skills strengthening ecosystem vitality.

In recent years, SCD has emerged as a pivotal mechanism for reducing firm pollution and carbon emissions. Unlike a purely intra-firm upgrade, SCD is an inter-organisational transformation that facilitates real-time information exchange, enhances coordination, and promotes collaborative innovation. Because supply chains are inherently networked, SCD generates spillover effects that extend beyond firm boundaries, shaping environmental outcomes across multiple tiers (Ren et al. 2023). A growing body of empirical research highlights the tangible benefits of SCD for emission reduction. Lerman et al. (2022) show that smart supply chains improve green performance by managing external green relationships and establishing internal green activities. Meng and Lin (2025), using the Supply Chain Innovation and Application Pilot programme as a quasi-natural experiment in China, find that implementing SCD leads to a 5.4% reduction in carbon emissions among pilot firms compared to non-pilot firms. Similarly, a study of listed Chinese companies from 2010 to 2021 demonstrates that SCD contributes to emission reductions through three primary pathways: technological innovation, easing financial constraints, and increasing market attention (Shen et al. 2025). SCD also fosters the low-carbon transformation of businesses by enhancing their absorptive, innovative and adaptive capacities (Yang et al. 2025). Through better supply chain coordination and the integration of greener technologies, firms can transition towards more sustainable production models while simultaneously improving cost efficiency and regulatory compliance (Ma et al. 2024).

2.1.4 | Research Gap

A vast body of literature has explored the determinants of corporate pollution emissions, offering valuable insights into pollution reduction strategies. However, most studies conceptualise firms as isolated entities, overlooking the broader network of stakeholders that influence their environmental practices. In reality, corporate pollution emissions are significantly affected by spillover effects from supply chain stakeholders, including suppliers and customers, who play a crucial role in shaping firms' green initiatives through direct trade relationships (Junaid et al. 2022).

With the rapid advancement of technologies such as AI, BDA and IoT, SCD has emerged as a transformative trend. SCD facilitates real-time data exchange, enhanced resource optimisation and greater transparency throughout the supply chain. These capabilities hold the potential to influence corporate pollution emissions by improving operational efficiency, optimising production planning and enabling more sustainable inventory management. Despite extensive research on the drivers of firm-level pollution, there is a notable gap in understanding the causal relationship between SCD and corporate pollution emissions. Investigating the mechanisms through which SCD affects pollution levels is an essential direction for future research.

The most relevant studies to this paper are Meng and Lin (2025) and Chen et al. (2025), which examine the role of SCD in carbon emission reduction. However, this study presents two major limitations. First, they employ the Supply Chain Innovation and Application pilot policy as a proxy for SCD, which introduces potential measurement errors. The primary objective of this policy is to foster cost reduction, supply–demand matching and green development, rather than explicitly promoting digitalisation across supply chains. As such, it fails to capture the full extent of firms' digitalisation efforts. Second, the proxy variable used in these studies is a binary (0–1) indicator, which does not account for the degree or evolution of SCD across firms and over time. This simplification obscures important dynamics, such as a firm increasing its level of digitalisation from 15% in 1 year to 20% in the next. Consequently, this approach oversimplifies the complex and gradual nature of digital transformation and its environmental implications.

To address these limitations, future research must develop a more precise quantification framework for measuring SCD and re-examine its environmental effects using scientifically robust methodologies. By doing so, scholars can gain deeper insights into how digital supply chain transformations contribute to corporate sustainability and pollution reduction.

2.2 | Theoretical Foundation

2.2.1 | Conceptual Framework

This study builds upon the Environmental Kuznets Curve hypothesis (Grossman and Krueger 1993) to develop a mechanism-based analytical framework that examines how SCD influences pollution emissions in manufacturing firms. The Environmental Kuznets Curve framework is particularly useful for analysing how technological advancements, such as digitalisation, can lead to improved environmental outcomes as economies develop and shift towards more sustainable practices (Liu, Li, et al. 2024; Ullah et al. 2024). The Environmental Kuznets Curve theory suggests that economic growth impacts environmental pollution through three primary channels: scale effects, structural effects and technological effects. Given that SCD is a structural transformation driven by technological innovation, it has significant implications for pollution reduction through these three effects.

1. Scale effect ('Cost Effect'): As firms expand operations, SCD enables them to reduce per-unit production costs by improving operational efficiency and minimising resource waste. Through automation and optimised production planning, firms can scale up output while reducing pollution intensity.
2. Structural effect ('Resource Allocation Effect'): SCD facilitates enhanced coordination and resource optimisation across supply chains. It improves inventory management, transportation efficiency and production scheduling, ultimately lowering energy consumption and emissions.
3. Technological effect ('Green Technology Innovation Effect'): SCD accelerates the adoption and diffusion of green technologies by fostering innovation in cleaner production methods, energy-efficient processes and low-carbon logistics. Digital platforms enhance firms' ability to invest in and implement sustainable technologies.

By incorporating these three mechanisms into the conceptual framework, seen in Figure 1, this study provides a micro-level analysis of how SCD contributes to corporate pollution reduction. The subsequent sections build on this framework to empirically test the relationships between SCD, cost efficiency, resource allocation and green innovation.

2.2.2 | Hypotheses

Drawing from the RBV theory, firms can enhance their competitive advantage by effectively leveraging their resources and capabilities. The synergy created by knowledge sharing and digital technologies fosters innovation, allowing firms to develop more efficient and sustainable operations (Haseeb et al. 2019; Rossit et al. 2019). In the context of SCD, digital technologies enhance

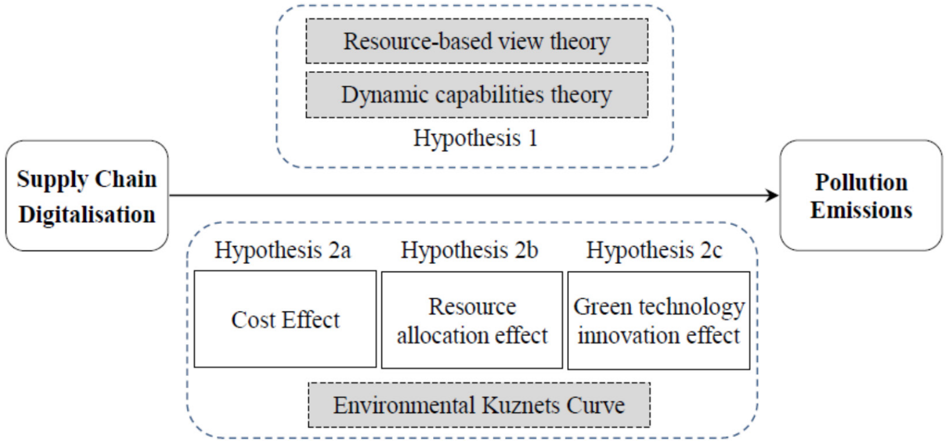

FIGURE 1 | Conceptual framework.

communication, coordination and information exchange among firms, facilitating better access to resources and fostering collaboration in green innovation. This enables firms to implement environmentally friendly practices such as energy-efficient production, optimised logistics and waste reduction, which contribute to lower pollution emissions.

Moreover, dynamic capabilities theory suggests that firms gain a competitive edge by continuously adapting and realigning resources to evolving market conditions (Fainshmidt et al. 2019). Through SCD, firms enhance their agility in response to environmental regulations, optimise operations and integrate sustainability-focused innovations into their supply chains. This digital transformation reduces transaction costs, improves resource management, and enhances environmental performance (Antonelli 2003; Gao et al. 2022). By improving the efficiency of energy use and reducing waste, digital supply chains contribute directly to pollution reduction.

Furthermore, SCD lowers operational costs and enhances the economic efficiency of firms (Abakah et al. 2023). These efficiency gains particularly enable firms to reinvest in green innovation. Digital technologies enable firms to optimise the allocation of resources, integrate innovation activities and enhance their environmental performance through real-time data processing and decision-making (Geng et al. 2023). This facilitates the adoption of sustainable practices, such as reducing emissions during production and transportation processes. Additionally, digital technologies enhance the resilience and adaptability of supply chains, improving their ability to respond to environmental challenges (He et al. 2024). By creating closer relationships with key suppliers and streamlining processes, firms can reduce environmental risks and minimise pollution during production cycles. The integration of digital technologies also enables companies to better monitor and control their environmental impact, allowing them to align with sustainability goals and comply with regulatory requirements (Christopher and Holweg 2011). In summary, SCD plays a crucial role in reducing firm pollution.

Based on this theoretical foundation, we propose the following hypotheses:

Hypothesis 1. *SCD reduces corporate pollution.*

The following will discuss how SCD drives pollution reduction through the cost effect, resource allocation effect and green technology innovation effect.

SCD enables firms to optimise resource allocation, streamline operations and reduce inefficiencies, leading to significant cost savings. By leveraging digital technologies such as BDA, IoT and advanced manufacturing systems, firms can improve demand forecasting, inventory management and procurement processes (Ivanov et al. 2019; Sanders and Swink 2020). These improvements reduce operational costs, allowing firms to reinvest savings into sustainable practices, such as energy-efficient production and green innovation.

Empirical studies support this relationship. For example, Gao et al. (2022) found that digitalisation improves energy efficiency by reducing energy consumption and waste through technological innovation and resource optimisation, leading to lower operational costs and improved environmental performance. Similarly, He et al. (2024) demonstrated that SCD enhances firms' ability to drive green innovation, optimise resource use and improve environmental performance, aligning operations with sustainability goals. Additionally, Geng et al. (2023) demonstrate that SCD reduces transaction costs and improves resource allocation, enabling firms to adopt cleaner production methods and lower pollution, which in turn reduces operating costs. These findings highlight how pollution reduction serves as a channel for lowering operating costs.

Based on this theoretical and empirical foundation, we propose the following:

Hypothesis 2a. *SCD promotes pollution reduction by lowering business operating costs.*

This hypothesis focuses on how digitalisation improves efficiency, reduces waste, and lowers environmental impact. By reducing pollution, firms can achieve significant cost savings, further driving sustainability and operational efficiency.

SCD enhances the efficiency of resource allocation within firms by improving communication, coordination, and decision-making across the supply chain. Digital technologies, such as

BDA, IoT and advanced manufacturing systems, enable firms to better forecast demand, manage inventory, and streamline procurement processes (Ivanov et al. 2019; Sanders and Swink 2020). This optimisation reduces inefficiencies in resource use, leading to lower energy consumption and waste generation. By leveraging real-time data and analytics, firms can align production schedules with actual demand, minimising overproduction and reducing the environmental footprint of their operations (Gao et al. 2022; He et al. 2024).

Empirical studies have demonstrated that digitalisation improves energy efficiency and resource management, which are critical for reducing pollution emissions. For instance, Gao et al. (2022) found that digitalisation reduces energy consumption and waste through technological innovation and resource optimisation, leading to lower operational costs and improved environmental performance. Similarly, He et al. (2024) showed that SCD enhances firms' ability to drive green innovation and optimise resource use, aligning operations with sustainability goals. Furthermore, Geng et al. (2023) highlighted that digitalisation reduces transaction costs and improves resource allocation, enabling firms to adopt cleaner production methods and lower pollution emissions.

Additionally, the integration of digital technologies fosters closer collaboration among supply chain stakeholders, improving the alignment of resources with market needs and reducing inefficiencies (Colicchia et al. 2019; Liu et al. 2022). This collaborative approach ensures that resources are allocated more effectively, reducing waste and enhancing the overall sustainability of the supply chain. Therefore, the optimisation of resource allocation through SCD serves as a key mechanism for reducing pollution emissions, supporting the hypothesis that digitalisation promotes pollution reduction by optimising the allocation of business resources. We propose the following:

Hypothesis 2b. *SCD promotes pollution reduction by optimising the allocation of business resources.*

Studies indicate that SCD promotes pollution reduction by driving green technology innovation (Li et al. 2025; Luo et al. 2024). Moreover, SCD affects green technology innovation by mitigating financial constraints, improving efficiency, enhancing transparency and optimising resource allocation, digital tools help companies adopt sustainable practices, minimise waste and lower emissions (Luo et al. 2024).

Studies have shown that SCD mitigates financial constraints, including underinvestment and instability (Wei et al. 2015), which frequently obstruct enterprises' innovation efforts, particularly in the realm of green innovation (Andersen 2017). Innovative talent is essential for promoting green innovation. Furthermore, SCD optimises the structure of innovation talent through cost and signalling mechanisms (Luo et al. 2024). For instance, Upadhayay et al. (2024) argue that from a cost perspective, SCD reduces enterprise management expenses, increases investment in R&D and raises the proportion of R&D personnel. Moreover, from a signalling perspective, enterprises that adopt supply chain innovations and pilot applications demonstrate their strong influence and innovation capabilities. This signals to the external market, attracting more innovative talent and enhancing the R&D personnel structure within the company (Chen et al. 2024).

SCD enhances efficiency through automation, intelligent management, and data integration (Seyedghorban et al. 2020). It also optimises processes by extracting insights from data to enhance internal operations (Lu and Weng 2018). Internal digitalisation helps control operating costs across departments, while external digitalisation reduces intercompany communication costs, strengthens partnerships, accurately predicts customer needs and enhances customer loyalty (Zhou et al. 2023).

According to stakeholder theory, external demand drives green innovation (Kawai et al. 2018). Traditional supply chains rely on high production and excess inventory to maintain market share, leading to resource waste due to amplified demand fluctuations (Lu et al. 2024). However, SCD mitigates imbalances by enabling real-time demand tracking, reducing inventory and enhancing supply–demand alignment, thus reducing wastage (Zhang et al. 2024). It also lowers supplier search and switching costs while promoting transparency to prevent speculation (Belitski et al. 2024; Zhang et al. 2022). Additionally, digitalisation shifts consumer behaviour towards online and integrated product consumption, increasing the need for product diversification and innovation (Santoalha et al. 2021). Thus, digital supply chains foster synergy, transparency and innovation, strengthening resource planning and meeting evolving market demands (Culot et al. 2020; Frank et al. 2019). Consequently, we propose the following:

Hypothesis 2c. *SCD promotes pollution reduction by incentivising green technology innovation.*

3 | Research Design

3.1 | Data and Sample Size

This study focuses on A-share listed manufacturing firms in China from 2007 to 2022. Manufacturing firms are selected due to their high pollution intensity, making them a critical sector for evaluating the environmental effect of SCD (Jiang et al. 2014).

The dataset is compiled from three primary sources:

First, the China Stock Market & Accounting Research (CSMAR) Database provides firm financial data and supply chain relationships. CSMAR is widely used in empirical research on Chinese firms, particularly in corporate finance, strategy and environmental management (Liu, Zhang, and Zhang 2024). The supply chain relationship data identify the top five suppliers and top five customers for each listed firm. These suppliers and customers are not necessarily publicly listed companies. In addition, pollution emission data is obtained from the Environmental Research Database module within CSMAR, which complies with corporate environmental performance indicators based on corporate annual reports, sustainability reports and corporate social responsibility disclosures. This source offers firm-year level pollution data that aligns with the time frame and digitalisation trends studied in this research. This dataset covers five major types of pollutants: sulphur dioxide (SO_2), nitrogen oxides (NO_x), chemical oxygen demand (COD), ammonia nitrogen (NH_3-N) and smoke dust. As firms report pollutant quantities using different units (e.g., kilogrammes, tonnes or 10,000 tonnes), we convert all values into tons to ensure comparability. The dataset is collected and standardised by a professional data provider, who uses multiple disclosure channels to minimise missing values. Nevertheless, firm-year observations without any reported emission information—approximately 27.0% of the sample—are excluded from our analysis.

Firm pollution emission data are reported in accordance with the environmental statistics system administered by China's Ministry of Ecology and Environment (MEE). The MEE centrally organises the 'Pollution Source Statistics Reporting System', which is implemented step by step by local environmental authorities. Under this system, key monitored firms are required to submit monthly reports on a firm-by-firm basis, while non-key firms are estimated at the quarterly level. Listed manufacturing firms, due to their large scale, are typically classified as key monitored firms. These key firms are legally obliged to conduct self-monitoring, calculate their emissions accordingly and report the data. Consequently, pollution data are generated under unified reporting standards and definitions, ensuring relatively high consistency across firms. Nevertheless, reporting bias may still exist. For example, firms might underreport emissions to evade regulatory scrutiny, and regional variation in enforcement capacity may introduce systematic discrepancies. We argue that such reporting bias is unlikely to be correlated with the treatment variable SCD in our study for at least two reasons. First, the reporting standards and monitoring requirements are determined and enforced by the MEE and local authorities, and these institutional arrangements are largely independent of whether or not a firm is subject to SCD. Second, our empirical design focuses on within-firm changes over the year via two-way fixed effects, so any time-invariant misreporting tendency of a firm is differenced out. Under these two conditions, reporting bias, if present, would not interfere with the unbiasedness of parameter β_1.

It is worth noting that while earlier studies often relied on China's Annual Firm-Level Industrial Survey (AFIS) and the China Environmental Statistics Database (CESD) to analyse industrial pollution (Jiang et al. 2014; Kong and Zhu 2022), these datasets are only available up to 2014. Given the rapid pace of digital transformation in China over the past decade, such legacy data sources are inadequate for assessing the evolving impact of SCD on environmental performance. Therefore, CSMAR's more recent and comprehensive data provides a more suitable basis for analysis.

Second, the China Research Data Service Platform (CNRDS) provides firm-year level patent data used to assess firms' digital technology innovation capabilities. This includes digital patent applications by upstream suppliers and downstream customers, which are essential for constructing a network-based measure of SCD. The detailed methodology for calculating digital innovation and constructing the SCD indicator is provided in Section 3.2.

Third, macroeconomic data is drawn from the China City Statistical Yearbook and local government work reports, covering variables such as regional GDP, environmental regulation intensity, and other city-level indicators. These are aggregated at the city-year level and used as control variables to account for external influences on firm pollution emissions.

By integrating firm-level financial and environmental data with city-level controls, we construct an unbalanced panel dataset. We exclude firms under special treatment status (ST and *ST), which account for 2.2% of the sample, as well as observations with missing firm characteristics (0.7%). The final panel contains 24,476 firm-year observations covering 2770 manufacturing firms from 2007 to 2022.

3.2 | Variables

3.2.1 | Measuring Pollution Emissions

The dependent variable is corporate pollution emissions (P). Consistent with established methodologies in the literature, data on pollution emissions for Chinese listed firms is sourced from the 'Environmental Research Database' module of the CSMAR database. This module provides detailed environmental data, including pollution emissions and resource consumption, which are derived from the annual reports, sustainability reports, and CSR reports of listed firms. The pollutants considered include five pollutants (e.g., sulphur dioxide and nitrogen oxides), water pollutants (e.g., chemical oxygen demand and ammonia nitrogen) and solid pollutants (smoke dust).

To address the challenge of inconsistent dimensions across different pollutants, we follow the methodology by Su and Sheng (2021) to construct a composite pollution emission index, as specified in Equation (1). Specifically, the raw data for each of the five pollution indicators are standardised using the extreme value method. In this approach, $pollu_{imt}$ represents the standardised pollution emission amount for the mth pollutant of firm i in year t, and $\overline{pollu_{mt}}$ denotes the average emission of the mth pollutant across all firms for year t.

$$P_{it} = \frac{1}{5} \sum_{m=1}^{5} pollu_{imt} \times \frac{pollu_{imt}}{\overline{pollu_{mt}}} \tag{1}$$

3.2.2 | Measuring SCD

The core independent variable is SCD (Dig), constructed in three steps.

Step 1: Construct the supply chain network. The first step is to construct the supply chain network by treating the listed firms and their upstream and downstream suppliers and customers as nodes, with trade relationships represented as edges. Data on these relationships is sourced from the CSMAR database, which provides information on suppliers and customers of listed firms. We then establish relationship lists in the format of 'firm code - year - supply chain firm'. Here, the supply chain firms include both suppliers and customers. For example, if firm i in 2022 connects to multiple firms ($j1$, $j2$, $j3$), we construct the observations $i-2022-j1$, $i-2022-j2$ and

$i-2022-j3$. We import these relationships into the social network analysis software UCINET to generate an undirected adjacency matrix $\boldsymbol{G}$ that represents whether a trade relationship exists between any two firms. The rows and columns of the matrix correspond to firms in the supply chain network, with matrix element a_{ij} equal to 1 if a direct trade relationship exists between firms i and j, and 0 otherwise. Network distances are computed using the Dijkstra algorithm, which identifies the minimum number of connections required for these firms to establish a trade relationship. If no connected trade path exists, the network distance is set to zero.

Step 2: Calculate the weight of the supply chain firm. The principle underlying this step is that the further the network distance between firm i and firm j, the smaller the impact of firm j on firm i. The weight is thus defined in Equation (2) as follows:

$$w_{ijt} = \frac{1/dist_{ijt}}{\sum_{j \neq i} 1/dist_{ijt}} \tag{2}$$

where $dist_{ijt}$ is the network distance between supply chain firm j and firm i in year t. The numerator is the reciprocal of the network distance, and the denominator is the sum of the reciprocals of the network distances for all supply chain firms j. A higher weight indicates that supply chain firm j exerts a greater impact on firm i.

Step 3: Calculate the degree of SCD. We obtain the degree by performing a weighted sum of the digital patent applications filed by supply chain firms, using the weights calculated in Step 2. The digital patent applications (*Dig_pat*) of supply chain firm j serve as a proxy for the digitalisation level of these firms, because patents related to digital technologies reflect a company's capacity in adopting and implementing digital solutions. Digital patents typically encompass a wide range of technological advancements, including digital tools, software systems, data analytics and automation processes—key components of digital transformation. By examining the volume of digital patents filed by a company, we can gain insight into its investment in digital technologies and its commitment to digital innovation.

We do not employ the text analysis method here, which is sometimes used to measure digitalisation through the analysis of corporate reports or other textual data (Dauth et al. 2017; Zhu et al. 2022). This approach is limited to listed firms, thus excluding non-listed firms in the supply chain. As a result, it cannot provide a comprehensive or accurate measure of SCD. The final calculation of the SCD degree (*Dig*) is given in Equation (3) as follows:

$$Dig_{it} = \sum_{j \neq i} w_{ijt} \times Dig\_pat_{jt} \tag{3}$$

Step 3 involves quantifying digital technological innovation. In 2021, the National Bureau of Statistics of China released the 'Statistical Classification of the Digital Economy and Its Core Industries (2021)', which provides a scientific and standardised framework for defining the digital economy and its core sectors. This classification is based on the 'National Economic Industry Classification' system, a foundational tool used for categorising economic activities in China, supporting both statistical analysis and policymaking. The most current version follows the GB/T 4754-2017 standard, which came into effect on 1 October 2017.

To construct the digital technology innovation indicator, the following steps are undertaken:

1. Industry code mapping: We first compile the four-digit codes from the National Economic Industry Classification that correspond to the digital economy and its core industries, as outlined in the 2021 classification document.
2. Patent classification matching: These industry codes are then matched with the International Patent Classification and National Economic Industry Classification Reference Table (2018) to establish a correspondence between the 'Digital Economy and Its Core Industries Code' and the 'International Patent Classification (IPC) Number'.
3. Patent Identification and Aggregation: Using the matched IPC codes, we extract relevant patent data from CNRDS. Patents that fall within the defined digital economy categories are identified and aggregated at the firm-year level.

The resulting firm-level measure of digital technology innovation is denoted as *Dig_pat*. This indicator captures the extent of digital innovation activity within each firm over time. The identification and matching process is illustrated in Figure 2.

To enhance clarity for those less familiar with network analysis, we provide a graphic illustration of how the SCD is constructed. Figure 3 presents a simplified example: Firm A has two customers—Firm 1 and Firm 2—and one supplier, Firm 3. Furthermore, Firm 3 itself has two suppliers—Firm 4 and Firm 5. The digital patent applications filed by these firms are as follows: Firm 4 has filed four digital patents, Firm 1 has filed one, while Firms 2, 3 and 5 have filed none.

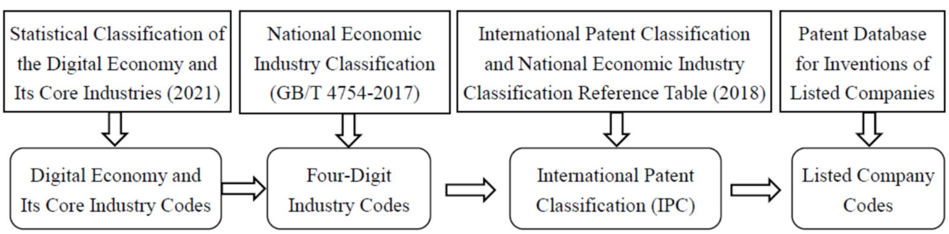

FIGURE 2 | Methodology for constructing the digital technology innovation indicator.

The specific context for this example is presented in Table 1. Firm A and Firm 1 require only one connection to establish a trade relationship, so their network distance is 1. In contrast, Firm A and Firm 4 need two connections (through Firm 3), resulting in a network distance of 2. Other cases follow the same logic. The weights in this example are then straightforwardly derived from Equation (2). To calculate the overall SCD score (*Dig*) for this example, we use the following formula: $Dig = 1/(1+1+1+1/2+1/2)*1+(1/2)/(1+1+1+1/2+1/2)*4+0+0+0 = 0.75$.

3.2.3 | Control Variables

To ensure the robustness of our empirical analysis, we incorporate a comprehensive set of control variables at both the form and city levels, following prior studies (Qi et al. 2023; Xie et al. 2023; Hu et al. 2024).

Firm-level control variables: firm size (Size): measured as the natural logarithm of total assets; labor force (lnL): represented by the natural logarithm of the number of employees; leverage ratio (Lev): defined as the ratio of total liabilities to total assets; cash flow (Cash): measured as the ratio of net cash flow from operating activities to total assets; operating years (lnAge). The natural logarithm of the number of years a firm has been in operation controls for experience and corporate maturity; return on equity (ROE): calculated as net profits divided by shareholders' equity; and ownership structure (Top1): defined as the shareholding proportion of the largest shareholder (%).

City-level control variables: Economic Development (lngdp): Measured as the logarithm of regional GDP, and environmental regulation (Regulation): quantified as the proportion (%) of environmental regulation-related keywords to the total word frequency in government work reports (Xie and Huang 2023).

These control variables help isolate the impact of SCD on firm pollution emissions, ensuring that our findings are not confounded by firm characteristics or regional economic conditions.

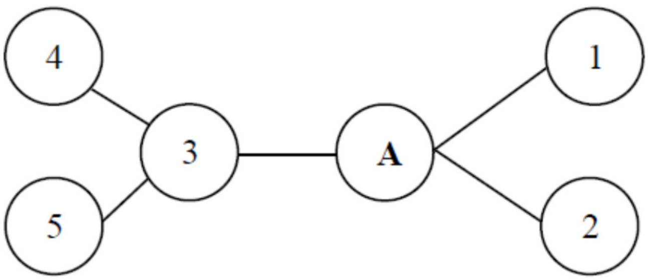

FIGURE 3 | A simple example of the methodology for measuring supply chain digitalisation.

3.3 | Model Settings

To analyse the impact of SCD on corporate pollution emissions and test Hypothesis 1, we specify the following baseline regression model, Model (4):

$$lnP_{it} = \alpha + \beta_1 Dig_{it} + \beta_2 X_{it} + \lambda_i + \delta_t + \varepsilon_{it} \tag{4}$$

In Equation (4), lnP_{it} represents the logarithm of pollution emissions of firm i in year t, and Dig_{it} denotes the SCD level of firm i in year t. X_{it} is a vector of control variables, including firm size, labour force, debt-to-equity ratio, cash flow, operating years, ROE and the economic development level and environmental regulation intensity of the city where the firm is located. Firm fixed effects (λ_i) control for time-invariant firm-specific characteristics, while year fixed effects (δ_t) account for national-level shocks that may affect firm pollution emissions. ε_{it} is the error term. The primary coefficient β_1 captures the causal effect of SCD on corporate pollution emissions. A negative and significant β_1 would indicate that increased SCD is associated with lower pollution emissions.

To further examine the mechanisms through which SCD influences emissions and test Hypotheses 2a–2c, we employ the following model, given in Equation (5):

$$M_{it} = \alpha + \beta_3 Dig_{it} + \beta_2 X_{it} + \lambda_i + \delta_t + \varepsilon_{it} \tag{5}$$

where M_{it} represents the mediating variables, including cost effect, resource allocation effect and green technological innovation effect. The specific measurement methods for these variables are provided in Section 4.3. Other variables are defined as in Model (4).

A statistically significant β_3 in the expected direction would confirm the mediating role of these mechanisms in explaining the relationship between SCD and pollution emissions; Hypotheses 2a–2c are supported. By incorporating fixed effects and controlling for potential confounders, our model aims to minimise omitted variable bias and improve the robustness of causal inference.

TABLE 1 | Steps for calculating the supply chain digitalisation (SCD).

Combinations	Number of firm *j*'s *Dig_pat*	Dist	Weight (w_{ijt})	Weighted sum
A–F1	1	1	1/(1 + 1 + 1 + 1/2 + 1/2)	0.75
A–F2	0	1	1/(1 + 1 + 1 + 1/2 + 1/2)	
A–F3	0	1	1/(1 + 1 + 1 + 1/2 + 1/2)	
A–F4	4	2	(1/2)/(1 + 1 + 1 + 1/2 + 1/2)	
A–F5	0	2	(1/2)/(1 + 1 + 1 + 1/2 + 1/2)	

4 | Results and Analysis

4.1 | Descriptive Statistics

Table 2 presents the descriptive statistics of the main variables in the analysis. The average pollution emission (*lnP*) is 1.912, with a relatively low standard deviation of 0.321, indicating moderate variability in emissions across the sample. In contrast, the mean for SCD (*Dig*) score is 0.726, but a standard deviation of 0.993 indicates significant variation among firms. A minimum value of 0 indicates that some firms have not digitised their supply chains at all, while a maximum value of 6.181 highlights firms with highly digitised supply chains.

4.2 | Empirical Results

Table 3 presents the correlation matrix for the variables, focusing on the relationship between pollution emissions (*lnP*) and SCD (*Dig*). The correlation coefficient between *lnP* and *Dig* is −0.014, which is statistically significant. This negative correlation suggests that higher levels of SCD are associated with lower pollution emissions.

However, it is important to note that correlation does not imply causation. The observed negative correlation may be influenced by confounding factors or other underlying variables affecting both pollution emissions and digitalisation. To obtain more reliable results and draw causal inferences, Table 4 presents the estimated results from Equation (4), assessing the impact of SCD on firm pollution emissions. The inclusion of firm and year fixed effects helps account for unobserved heterogeneity across firms and over time.

The results indicate that, without control variables, the estimated coefficient for SCD (*Dig*) is negative and statistically significant at the 1% level, suggesting that SCD is associated with lower pollution emissions. This relationship remains consistent even after incorporating control variables, reinforcing the argument that the negative association is not merely due to omitted confounding factors. Specifically, a one-standard-deviation increase in SCD (0.993) corresponds to a 0.7% reduction in pollution emissions, highlighting the spillover effect of digitalisation within midstream supply chains. In summary, the findings from Table 4 indicate a significant negative relationship between SCD and firm-level pollution emissions, providing strong support for Hypothesis 1.

We further compare the direct effect of firm digitalisation with the spillover effect of SCD to provide a clearer sense of magnitude. Firm-level digitalisation is measured by the logarithm of the number of annual digital patent applications (*lndig_pat*), with a standard deviation of 1.311. According to the regression results in Column (3) of Table 4, a one-standard-deviation increase in SCD (0.993) corresponds to a 1.1% reduction in pollution emissions, whereas a one-standard-deviation increase in *lndig_pat* (1.311) corresponds to a 6.4% reduction. In other words, the spillover effect of digitalisation transmitted through supply chains is approximately one-sixth of the direct effect. This finding is theoretically reasonable. Digitalisation generates its strongest impact when firms directly adopt and integrate digital technologies into their internal operations, as this enables them to reorganise production processes, implement green technologies, and exert full control over emission-reduction practices. In contrast, spillover effects operate indirectly: They rely on the transmission of knowledge, practices, and incentives across organisational boundaries. This process is subject to frictions such as heterogeneous absorptive capacities, incomplete information sharing and weakening influence as network distance increases. As a result, only a fraction of the benefits realised by one firm can be transmitted to its supply chain partners.

To visualise the magnitude and shape of the above association, Figure 4 plots the predicted emissions curve (*lnP*) over SCD (*Dig*), with 95% confidence intervals. The curve declines monotonically as *Dig* increases, indicating that higher SCD is associated with lower predicted emissions. Moving from $Dig = 0$ to $Dig = 1$, *lnP* falls from 1.918 to 1.911, implying a reduction of about 0.7%. Further increases are economically meaningful: raising *Dig* from 1 to 3 (4) is associated with

TABLE 2 | Descriptive statistics.

Variables	Observations	Mean	Std. dev	Min	Median	Max
lnP	24,476	1.912	0.321	0.858	1.987	2.477
Dig	24,476	0.726	0.993	0	0.007	6.181
Size	24,476	22.01	1.180	19.74	21.858	25.598
lnL	24,476	7.723	1.139	5.088	7.647	10.853
Lev	24,476	0.411	0.194	0.057	0.406	0.888
Cashflow	24,476	0.050	0.068	−0.150	0.048	0.248
lnAge	24,476	1.804	1.021	0	2.079	3.555
ROE	24,476	0.054	0.147	−0.819	0.066	0.355
Top1	24,476	33.559	14.082	8.760	31.495	71.24
lngdp	24,476	10.507	0.832	7.919	10.607	11.768
Regulation	24,476	0.583	0.384	0.259	0.535	2.588

TABLE 3 | Correlation matrix.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) *lnP*	1.000										
(2) *Dig*	−0.014**	1.000									
(3) Size	0.196***	0.186***	1.000								
(4) lnL	−0.011*	0.212***	0.805***	1.000							
(5) Lev	−0.124***	0.075***	0.394***	0.396*	1.000						
(6) Cashflow	0.046***	0.007	0.110***	0.160***	−0.166***	1.000					
(7) lnAge	−0.213***	−0.028***	0.122***	0.148***	0.170***	−0.013**	1.000				
(8) ROE	−0.005	0.055***	0.119***	0.116***	−0.238***	0.339***	−0.040***	1.000			
(9) Top1	−0.115***	0.001	0.111***	0.163***	0.008	0.091***	−0.022***	0.116***	1.000		
(10) lngdp	0.536***	0.093***	0.043***	−0.038***	−0.141***	0.065***	−0.223***	0.046***	−0.097***	1.000	
(11) Regulation	0.086***	−0.098***	0.084***	0.027***	0.053***	−0.019***	0.067***	−0.047***	0.006	−0.429***	1.000

Note:
***Significant at the 1% level;
**Significant at the 5% level;
*Significant at the 10% level.

additional declines of roughly 1.4% (2.0%). Relative to the baseline $Dig = 0$, advancing *Dig* to the upper bound of the observed range yields a cumulative decrease close to 4%. The confidence interval remains narrow across most of the support and widens slightly only at the upper tail, which suggests that the estimates are precise for the bulk of the sample and that the results are not driven by a small number of outliers. These patterns accord with the estimated semi-elasticity of about −0.7% per unit of *Dig*.

4.3 | Addressing Endogeneity

The model controls for a range of factors influencing firm pollution emissions. However, some potential omitted variables remain, such as the green awareness and social responsibility of supply chain firms, which are both related to SCD and may affect pollution reduction. The presence of these omitted variables could introduce endogeneity issues.

Additionally, a reverse causal relationship exists between firm pollution emissions and SCD. While digitalisation may reduce emissions, firms with lower pollution levels may also be more likely to invest in digital technologies. These firms often have better access to green financing, which can support technological investments, and they may view digitalisation as a means to further optimise operations, reduce waste, and enhance efficiency. This bidirectional causality creates a potential source of endogeneity that could bias estimation results.

To address these endogeneity concerns, this study constructs an instrumental variable for SCD and employs a two-stage least squares (2SLS) estimation, controlling for bidirectional fixed effects. The instrumental variable is a dummy indicating whether a firm is designated as a 'supply chain innovation and application pilot firm' (SCIAP) in the current year and beyond (1 if yes). To promote industrial integration and innovation, the Chinese government introduced policies supporting supply chain security and development. In 2017, the State Council issued an opinion to enhance supply chain capabilities, followed by a 2018 circular identifying 266 pilot enterprises tasked with innovating and applying modern supply chain technologies, optimising industrial collaboration and establishing new standards (Luo et al. 2024). The SCIAP policy is evidently linked to SCD, thereby satisfying the relevance condition. Furthermore, the exogeneity condition is also plausibly satisfied. The SCIAP policy was introduced to foster supply chain collaboration, resilience and digital modernisation. Importantly, it does not include components related to environmental regulation, such as green subsidies, emission caps and pollution penalties. As such, it is unlikely to influence firm-level pollution emissions through any channel other than its intended effect on supply chain. Furthermore, SCIAP designations are determined at the supply chain level (e.g., smart manufacturing chains in auto, electronics and biomedicine), rather than based on the environmental characteristics of individual firms. This targeted, non-environmental scope reinforces the plausibility of SCIAP satisfying the exclusion restriction as an instrumental variable for SCD.

Table 5 presents the 2SLS estimation results on the impact of SCD on corporate pollution emissions. In the first-stage

TABLE 4 | Impacts of supply chain digitalisation on firm pollution emissions.

	lnP		
Variables	**(1)**	**(2)**	**(3)**
Dig	−0.008***	−0.007***	−0.011***
	(−7.14)	(−7.08)	(−7.89)
lndig_pat			−0.049***
			(−4.43)
Constant	1.918***	1.779***	1.788***
	(2453.85)	(21.49)	(21.52)
Observations	24,476	24,476	24,476
Adjusted R^2	0.912	0.912	0.912
Controls	No	Yes	Yes
Firm and year FE	Yes	Yes	Yes

Note: The standard errors are clustered at the firm level. The numbers are regression coefficients, with *T* statistics in parentheses.
***Significant at the 1% level;
**Significant at the 5% level;
*Significant at the 10% level.

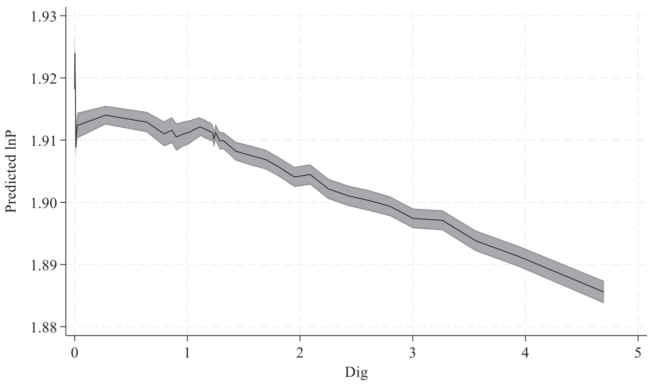

FIGURE 4 | Predicted emission curve with 95% confidence intervals. *Note:* The black solid line shows point predictions; the grey shaded area denotes the 95% confidence intervals.

regression, the coefficient of the SCIAP policy on SCD is significantly positive. The weak instrument test confirms the instrument's strength, as the first-stage *F* statistic exceeds 10, meeting the relevance condition. The second-stage estimation, shown in Column (2), indicates that SCD continues to have a significant negative impact on pollution emissions in manufacturing firms, with results remaining robust.

4.4 | Mechanisms

4.4.1 | Cost Effect

To empirically assess the impact of SCD on firms' operational costs, we follow the measurement approach used by Zhai et al. (2022) and use two cost-related variables: Cost1, defined as the ratio of operating costs to total operating revenue, and Cost2, defined as the ratio of operating costs to total assets.

TABLE 5 | Instrumental variable estimation results.

	Dig	*lnP*
Variables	**(1) First-stage**	**(2) Second-stage**
Dig		−0.065*
		(−1.77)
SCIAP	0.052***	
	(3.30)	
Constant	−1.079*	0.925***
	(−1.93)	(8.67)
Observations	24,476	24,476
Adjusted R^2	0.562	0.879
Kleibergen-Paap rk Wald *F* statistic		11.147
Controls	Yes	Yes
Firm and year FE	Yes	Yes

Note: The standard errors are clustered at the firm level. The numbers are regression coefficients, with *T* statistics in parentheses.
***Significant at the 1% level;
**Significant at the 5% level;
*Significant at the 10% level.

The empirical results in Table 6 show a negative association between SCD (*Dig*) and both cost measures, indicating that digitalisation of suppliers and customers helps reduce operational costs. This cost reduction reflects improved operational efficiency, which means firms can produce the same output with fewer inputs—such as energy, raw materials and transportation—thereby generating less pollution. These findings support Hypothesis 2a, which posits that SCD lowers costs and, in turn, contributes to pollution reduction.

4.4.2 | Factor Allocation Effect

A firm's efficiency in factor allocation is reflected in the proportion and utilisation efficiency of various inputs in the production process. This study examines resource allocation effects from two perspectives: factor misallocation and total factor productivity (TFP). Factor misallocation refers to deviations from the optimal allocation of resources.

Following Hsieh and Klenow (2009) methodology, this study measures factor misallocation using a production function approach. The process involves the following steps: First, assuming constant returns to scale, we estimate a Cobb–Douglas production function to determine the output elasticities of capital and labour, denoted as α' and β', respectively. Output (Y) is measured by total operating revenue, labour (L) by the number of employees and capital (K) by the total value of fixed assets.

Next, the prices of capital and labour are defined as r and w, where r represents the capital price or interest rate faced by the firm, approximated by the benchmark loan interest rate, and w is the average wage, calculated as total employee compensation divided by the number of employees. The degree of resource

TABLE 6 | The impact of supply chain digitalisation on operational costs.

	Cost1	Cost2
Variables	**(1)**	**(2)**
Dig	−0.017**	−0.005*
	(−2.39)	(−1.89)
Constant	−3.205	3.463***
	(−0.63)	(5.80)
Observations	24,476	24,476
Adjusted R^2	0.134	0.689
Controls	Yes	Yes
Firm and year FE	Yes	Yes

Note: The standard errors are clustered at the firm level. The numbers are regression coefficients, with *T* statistics in parentheses.
***Significant at the 1% level;
**Significant at the 5% level;
*Significant at the 10% level.

TABLE 7 | The Impact of supply chain digitalisation on resource allocation efficiency.

	Mis_K	Mis_L	TFP
Variables	**(1)**	**(2)**	**(3)**
Dig	−0.236*	0.009	0.020***
	(−1.95)	(1.17)	(2.88)
Constant	42.479*	10.469***	−1.882***
	(1.93)	(10.91)	(−3.13)
Observations	24,476	24,476	24,350
Adjusted R^2	0.569	0.416	0.696
Controls	Yes	Yes	Yes
Firm and year FE	Yes	Yes	Yes

Note: The standard errors are clustered at the firm level. The numbers are regression coefficients, with *T* statistics in parentheses.
***Significant at the 1% level;
**Significant at the 5% level;
*Significant at the 10% level.

misallocation is then assessed by the deviation between the marginal output of these factors and their respective prices. The misallocation of capital (*Mis_K*) and labour (*Mis_L*) is formalised in Equation (6).

$$Mis\_K = \left|\alpha' Y / rK - 1\right|, Mis\_L = \left|\beta' Y / wL - 1\right| \tag{6}$$

The firm's TFP is measured using the Linear Programming (LP) method, where a higher TFP value indicates greater efficiency in factor integration (Van Beveren 2012).

Table 7 presents the effects of SCD on resource allocation efficiency. Column (1) shows that SCD (*Dig*) has a significant negative impact on capital misallocation (Mis_K), indicating improved capital allocation efficiency. Digitalisation enhances communication and coordination between firms, suppliers and customers, leading to more accurate demand forecasting, optimised inventory management and improved procurement processes. This alignment of resources with market needs reduces inefficiencies and capital misallocation.

In contrast, Column (2) reveals that the effect of SCD on labour misallocation (Mis_L) is minimal, as the coefficient is close to zero and not statistically significant. This suggests that labour allocation is influenced by broader factors, such as market demand fluctuations, labour market flexibility and skill matching, which may have a more direct impact than digitalisation.

Column (3) indicates that SCD has a significantly positive effect on TFP, suggesting that it helps firms optimise resource allocation and enhance productivity. Improved resource allocation efficiency can also contribute to lower pollution emissions, as firms with streamlined production processes generate less waste and have a reduced environmental impact.

In summary, SCD reduces capital misallocation, enhances TFP, and, through the 'resource allocation effect,' helps lower pollution levels in firms. These findings support Hypothesis 2b.

4.4.3 | Green Technological Innovation Effect

Following Li et al. (2024), we classify patents as green or non-green based on the International Patent Green List issued by the World Intellectual Property Organization (WIPO). We then measure firm-level green innovation output by calculating the number of green patents (GP), including green invention patents (GIP) and green utility model patents (GUMP).

Table 8 presents the results on the impact of SCD on firm-level green technological innovation. The findings indicate that a more digitalised supply chain network significantly increases the number of green patent applications, encompassing both green invention and green utility model patents. Similarly, SCD significantly boosts the number of granted green patents. Green technological innovations in production processes help reduce pollutant generation, while innovations in pollution treatment enhance treatment capacity. Together, these factors contribute to lowering pollution emissions. In conclusion, these results support Hypothesis 2c.

4.5 | Heterogeneity Effects

4.5.1 | Industry Classification and Pollution Reduction

Firms in high-pollution industries typically face stricter regulations on pollution control, providing them with stronger incentives to adopt pollution-reduction measures to mitigate compliance risks and costs. SCD helps these firms enhance efficiency and reduce emissions. High-pollution sectors, such as coal and chemicals, are characterised by complex production processes, heavy resource consumption, and substantial pollutant discharge. Through digitalisation, firms in these industries can optimise operations and strengthen pollution control mechanisms.

This study hypothesises that the emissions-reducing effect of SCD is more pronounced for firms in high-pollution industries. To

TABLE 8 | The impact of supply chain digitalisation on green technological innovation.

Number of	GP applications	GIP applications	GUMP applications	GP granted	GIP granted	GUMP granted
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Dig	0.324***	0.199***	0.126***	0.406***	0.092***	0.314***
	(6.37)	(5.85)	(5.12)	(5.30)	(3.14)	(5.38)
Constant	−7.336	−4.167	−3.169	−37.726***	−8.236**	−29.490***
	(−1.64)	(−1.36)	(−1.62)	(−4.41)	(−2.39)	(−4.88)
Observations	24,476	24,476	24,476	24,476	24,476	24,476
Adjusted R^2	0.663	0.630	0.581	0.655	0.579	0.597
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm and year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: The standard errors are clustered at the firm level. The numbers are regression coefficients, with *T* statistics in parentheses.
***Significant at the 1% level;
**Significant at the 5% level;
*Significant at the 10% level.

identify these industries, we follow the China Securities Regulatory Commission's revised *Industry Classification Guidelines for Listed Companies* and the Ministry of Environmental Protection's *Environmental Protection Inspection Industry Classification Management Catalog*, which list 16 high-pollution industries (He et al. 2023). For empirical testing, we conduct group regressions based on industry classification. Figure 5 shows that in the high-pollution industries group, the estimated coefficient is −0.014, meaning that a one-unit increase in SCD corresponds to a 1.4% reduction in emissions. By contrast, the coefficient in non-high-pollution industries is −0.006. This finding underscores the role of digitalisation in helping heavily polluting firms comply with regulatory requirements and mitigate their environmental impact.

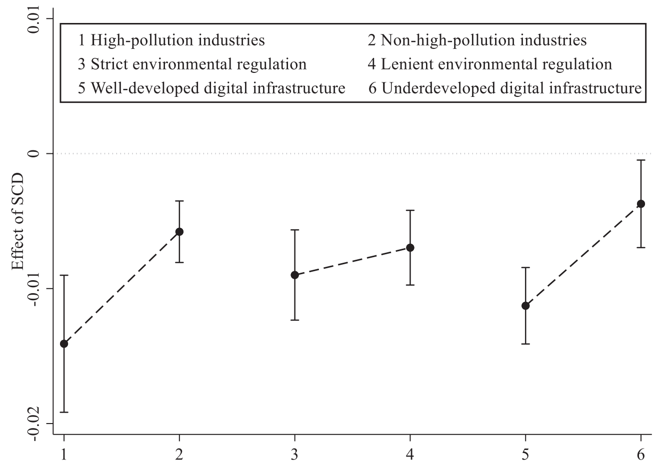

FIGURE 5 | Heterogeneous effects of supply chain digitalisation. *Note:* The solid dots denote estimated coefficients, the vertical lines denote 95% confidence intervals and the horizontal axis indicates the six groups.

4.5.2 | Environmental Regulation Intensity and Pollution Reduction

In regions with stringent environmental regulations, firms face strong pressure not only to comply with environmental laws but also to actively reduce emissions to avoid fines and other economic costs. In this context, SCD serves as a critical tool, enabling firms to better manage resource flows, optimise production processes and reduce pollution emissions more precisely and efficiently. The intensity of environmental regulations amplifies the effectiveness of digitalisation in achieving these goals. Stricter regulations push firms to leverage digital technologies more effectively for monitoring, controlling and reducing emissions, thereby strengthening the emissions-reducing effect of SCD.

Following Bao and Liu (2022) and Xie and Huang (2023), this study uses Python for word segmentation of government work reports, measuring the frequency of environmental regulation-related keywords as a proportion of the total word frequency. This metric serves as an indicator of regional environmental regulation intensity. We then divide the sample into two groups based on the median value of environmental regulation intensity. Figure 5 shows that in regions with stricter environmental regulations, the coefficient is −0.009, compared to −0.007 in less stringent regions. While the difference is modest, the results suggest that stronger regulatory environments enhance the effectiveness of digitalisation in reducing emissions. This finding implies that regulatory pressure and digital transformation are complementary forces, with stringent regulations pushing firms to make fuller use of digital tools for monitoring, control and compliance, thereby amplifying their environmental benefits.

4.5.3 | Digital Infrastructure and Pollution Reduction

One important source of heterogeneity arises from the level of digital infrastructure in the cities where firms are located. Implementing SCD entails substantial upfront and coordination costs, including data collection, transmission, interoperability, and skilled technical support. These costs, and the benefits of cross-firm data exchange, are highly dependent on the quality of local digital infrastructure. In contexts where broadband networks, mobile connectivity, and digital service ecosystems are underdeveloped, the marginal costs of adoption are higher, and the spillover benefits of digitalisation are weaker.

To examine this heterogeneity, we construct a city-level digital infrastructure index following Zhang et al. (2023), based on four components: broadband internet base, mobile internet base, telecommunications base and the scale of the information and software industry. We standardise the four indicators and then apply principal component analysis (PCA) to construct a composite digital infrastructure index. Based on the median value of this index, cities are classified into well-developed and underdeveloped groups. Firms located in cities with an index above the median are classified as operating in well-developed digital infrastructure environments, while those below the median fall into underdeveloped environments. The regression results reported in Figure 5 show that the coefficient of SCD is −0.011 for firms in well-developed cities, compared with −0.004 in underdeveloped ones. This nearly threefold difference indicates that digital infrastructure substantially amplifies the pollution-reduction effect of SCD. In well-developed infrastructure environments, digitalisation enables more seamless data exchange and coordination across supply chain partners, thereby strengthening the diffusion of green practices and technologies. Conversely, weak infrastructure constrains information flows and interoperability, reducing the effectiveness of digitalisation in improving environmental outcomes.

4.6 | Robustness Checks

4.6.1 | Alternative Measurement of the Dependent Variable

China's energy consumption structure is predominantly coal-based, with SO_2 emerging as a major pollutant (Yang et al. 2022). In this section, we measure SO_2 emission intensity using the ratio of SO_2 emissions to total operating revenue and use this as the dependent variable in the regression analysis.

Since 1979, China has implemented an emissions fee system as a form of environmental taxation. As the primary source of pollution, firms' discharge fees are determined by the principles of 'the polluter pays', 'the developer protects' and 'who pollutes, who governs'. These fees can be viewed as the environmental cost of pollution, reflecting the economic costs of environmental externalities in production activities. Following Wang et al. (2024), we remeasure firms' pollution emission intensity by the ratio of their discharge fees to operating revenue (Discharge) and rerun the regression analysis. The results for these two alternative specifications are shown in the first two columns of Table 9, confirming the robustness of our findings.

4.6.2 | Alternative Measurement of the Independent Variable

In Equation (3), the level of digital innovation in supply chain firms (j) is initially measured by the number of digital patents filed. To assess the robustness of our results and ensure they are not sensitive to the measurement of the explanatory variable, we employ two alternative measurement approaches.

First, given the potential lag in the impact of SCD, we use the average number of digital patents filed by supply chain firm j in the current year, the previous year, and the two preceding years as a proxy for firm j's level of digitalisation. The estimation results using this alternative measure are presented in Column (3) of Table 9.

Second, we also measure the digitalisation level of firm j by the number of digital patents granted to the firm in the current year, and we recalculate the core explanatory variable using this measure. The results with this revised measurement are also shown in Column (4) of Table 9. The findings indicate that the conclusions of this study remain qualitatively unaffected by changes in the measurement of SCD.

Third, we validate the original patent-based digitalisation index Dig_pat in Equation (3) by constructing an alternative text-based digitalisation index and deriving a corresponding SCD measure. Specifically, the text-based digitalisation index is calculated using the frequency of digital-related keywords extracted from the Management Discussion and Analysis (MD&A) sections of annual reports for publicly listed firms (Shang et al. 2023). Using this text-based digitalisation proxy, we apply the same network-distance weighted aggregation method as in our baseline specification to construct the ***Text-based SCD*** variable, which captures the average digitalisation level of a firm's suppliers and customers, adjusted for network proximity. We then conduct a robustness test by replacing the patent-based SCD variable with the ***Text-based SCD*** variable in our regression. Due to the availability of annual report data, this regression is restricted to firms whose supply chain partners include at least one listed company. Column (5) of Table 9 shows that the ***Text-based SCD*** is negatively and significantly associated with pollution emissions at the 5% level, consistent with our main findings. In addition, we find a correlation coefficient of 0.413 ($p=0.000$) between the patent-based and text-based SCD measures, confirming a positive relationship between the two proxies. This supports the validity of the patent-based SCD measure as a reliable proxy for SCD.

4.6.3 | Adjusting the Sample Period

The outbreak of COVID-19 at the end of 2019 led to widespread production disruptions, closures and reduced output in many manufacturing firms, causing significant supply chain interruptions that severely weakened the spillover effects of supply chain networks on firms. To mitigate the potential interference of the pandemic on causal inference, we exclude the sample from 2020 onwards. The results shown in Column (6) of Table 9 indicate that the estimated coefficient for the *Dig* remains significantly negative.

5 | Discussions and Implications

This study integrates corporate digital transformation with supply chain management to examine how the digitalisation of upstream and downstream enterprises fosters pollution reduction

TABLE 9 | Robustness checks.

	ln (SO_2_intensity)	ln (Charge)	*lnP*	*lnP*	*lnP*	*lnP*
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dig	−0.011***	−0.056***	−0.007***	−0.008***		−0.011***
	(−6.34)	(−5.02)	(−7.07)	(−6.39)		(−7.96)
Text-based SCD					−0.011**	
					(−2.19)	
Constant	1.084***	3.852***	1.779***	1.777***	1.813***	1.737***
	(7.54)	(3.95)	(21.49)	(21.48)	(18.71)	(15.03)
Observations	24,476	24,476	24,476	24,476	4537	17,297
Adjusted R^2	0.784	0.090	0.912	0.912	0.927	0.896
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm and year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: The standard errors are clustered at the firm level. The numbers are regression coefficients, with *T* statistics in parentheses.
*** significant at the 1% level;
** significant at the 5% level;
* significant at the 10% level.

in midstream firms. Our results indicate that SCD significantly contributes to pollution reduction in midstream firms. This suggests that digital transformation not only enhances a firm's own environmental performance but also generates positive spillover effects throughout the supply chain. These network effects facilitate pollution reduction across interconnected enterprises, underscoring the importance of collaborative digital transformation efforts rather than isolated initiatives (Lerman et al. 2022).

We also find that a one-standard-deviation increase in SCD is associated with a 0.7% to 1.1% reduction in pollution emissions. Given that the distribution of SCD is skewed (with the median close to zero and a wide upper tail), many firms have considerable room for multi-standard-deviation improvements. A two-standard-deviation increase—readily attainable when firms connect with additional digitised suppliers and customers—would imply roughly a 2% reduction in emissions. When aggregated across a large number of firms, even seemingly modest firm-level elasticities translate into meaningful sectoral-level gains. For example, if the top quartile of emitters were to achieve a one-standard-deviation SCD improvement, the implied aggregate reduction would be economically non-trivial.

From a policy perspective, these findings suggest that environmental regulations should extend beyond individual firms and foster the digital and green integration of entire supply chain networks. By applying social network analysis, we highlight how collaboration among supply chain partners enables firms to achieve synergies between digitalisation and environmental sustainability. In line with previous research (e.g., Yang et al. 2025; Shen et al. 2025; Meng and Lin 2025), which identified the role of SCD in corporate carbon emission reduction, our findings provide a novel perspective on the pivotal role of SCD in advancing sustainable development within firms.

A key innovation of this study lies in the application of social network methods to corporate digitalisation research, allowing for the quantification of SCD indicators. This approach truly conceptualises the supply chain as a social network, considering the spillover effects of SCD that influence the pollution emission behaviours of both upstream and downstream firms, rather than simply measuring SCD based on whether a firm is directly impacted by policy shocks, as is commonly done in existing literature. Furthermore, drawing on the Environmental Kuznets Curve theory, we conduct an in-depth analysis of the mechanisms through which SCD influences pollution reduction. We identify three key pathways: (1) cost reduction, (2) improved resource allocation efficiency and (3) green technological innovation. These mechanisms highlight how digitalisation enhances operational efficiency, optimises factor utilisation, and fosters the development of environmentally friendly technologies, ultimately reducing emissions. This aligns with existing literature that emphasises the role of digital collaboration in reducing costs, improving resource efficiency, and fostering green innovation (Goldfarb and Tucker 2019; Ding and Chen 2024; Luo et al. 2024).

Additionally, our heterogeneity analysis shows that the pollution-reducing effect of SCD is stronger in high-pollution industries, regions with stringent environmental regulations, and regions with well-developed digital infrastructure. This indicates that the largest effects are concentrated precisely in contexts most relevant to policymakers. In short, SCD is most effective when directed towards sectors and regions that contribute disproportionately to pollution.

In conclusion, this study emphasises that SCD is a powerful driver of pollution reduction, with implications for firms, policymakers and environmental regulators. Encouraging digital collaboration across supply chain networks can create a multiplier effect, enhancing sustainability efforts and fostering a greener industrial ecosystem.

5.1 | Theoretical Implications

This research makes two key contributions to the existing literature: First, we address the call for broader investigations into pollution emissions beyond a single supply chain. Scholars such as Ellram and Tate (2025) have emphasised the need for studies that extend beyond focal firms to consider their entire supply chain ecosystems. To bridge this gap, we leverage supplier-firm-customer matching data and digital patent data from China to examine the impact of SCD on pollution emissions in manufacturing firms. By incorporating a multi-tier supply chain perspective, our study expands the understanding of how digital transformation influences environmental outcomes across interconnected enterprises.

Second, we contribute novel insights by applying social network analysis (Han et al. 2020) to quantify SCD indicators. Our findings reveal that the digitalisation behaviour of a single firm extends beyond its boundaries, influencing both upstream and downstream partners through supply chain network effects. This spillover effect represents a significant advancement in understanding the role of SCD in pollution reduction. Previous studies have primarily analysed firms as isolated entities, overlooking their interdependencies within supply chains (Meng and Lin 2025). By demonstrating that digitalisation fosters positive spillover effects on the pollution reduction efforts of supply chain partners, this research underscores the importance of collaborative digital strategies in achieving environmental sustainability.

By shifting the focus from individual firms to entire supply chain networks, this study advances theoretical discussions on SCD, environmental sustainability, and inter-organisational collaboration. These findings provide a strong foundation for future research and policy development aimed at fostering digitally integrated and environmentally sustainable supply chains.

5.2 | Managerial Implications

This research highlights the critical role of SCD in optimising resource allocation, streamlining operations and reducing inefficiencies. By leveraging digital technologies, firms can enhance demand forecasting, inventory management and procurement processes, leading to cost reductions and improved environmental performance. These efficiencies free up financial resources that can be reinvested into sustainable initiatives, such as energy-efficient production and green innovation. This aligns with empirical findings that underscore pollution reduction as a cost-saving strategy (He et al. 2024; Geng et al. 2023; Gao et al. 2022). Therefore, managers should prioritise digital transformation initiatives to improve decision-making, enhance operational efficiency and drive both financial and environmental benefits.

Additionally, this study demonstrates that the digitalisation practices of focal firms generate positive spillover effects across upstream and downstream partners, amplifying pollution reduction efforts throughout the supply chain. This underscores the importance of collaborative digital strategies in achieving synergies between digitalisation and sustainability. Managers should actively engage supply chain stakeholders, foster closer integration and share digital transformation efforts to maximise environmental benefits. By adopting a coordinated approach, firms can optimise resource use, minimise waste and enhance overall supply chain sustainability (He et al. 2024).

Ultimately, firms that embrace supply chain-wide digitalisation efforts will not only strengthen their competitive advantage but also contribute to broader environmental and regulatory goals. These insights emphasise the need for strategic alignment between digital transformation and sustainability objectives, ensuring that firms achieve both operational excellence and long-term environmental responsibility.

5.3 | Policy Implications

Existing literature highlights the significant role of stakeholders, suppliers, and customers in shaping a firm's green practices, as they maintain direct trade relationships that influence environmental decisions (Junaid et al. 2022; Ma et al. 2024; Meng and Lin 2025). This research provides valuable practical insights into how SCD fosters pollution reduction, offering actionable strategies for practitioners.

To implement these findings, firms should collaborate with supply chain partners to assess current operations with the goal of reducing pollution emissions. This assessment should focus on identifying areas where digital technologies can enhance communication, coordination, and transparency among supply chain stakeholders. By integrating real-time data-sharing platforms and collaborative decision-making tools, firms can improve supply chain integration, optimise resource use and enhance efficiency, leading to lower emissions and improved sustainability performance.

Moreover, firms should establish a digital ecosystem that facilitates continuous monitoring and predictive analytics, enabling proactive measures to identify and mitigate pollution sources. Through strategic digital investments and closer collaboration with supply chain partners, organisations can drive green innovation, comply with environmental regulations and achieve long-term sustainability goals.

6 | Conclusion

This study demonstrates that SCD can reduce pollution emissions in midstream firms, indicating the presence of green spillover effects. This reduction operates through three main mechanisms: operational cost savings, improved efficiency in resource allocation and increased green technology innovation. Additionally, the effects of SCD are especially pronounced in high-pollution industries, regions with stricter environmental regulations and regions with well-developed digital infrastructure.

Theoretically, this study extends existing research by shifting the analytical focus from isolated firm-level digitalisation to supply chain-level digital integration, thereby capturing the broader spillover effects across interconnected business networks. Methodologically, our study improves upon earlier approaches by constructing a continuous, network-based SCD indicator that avoids the oversimplification of binary proxies. This contributes to a more nuanced understanding of how digitalisation spreads and influences sustainability outcomes across supply chains.

From a practical perspective, the findings offer important implications for both firms and policymakers. Firms should consider SCD not only as a driver of operational efficiency but also as a strategic lever for achieving sustainability objectives. Policymakers, in turn, should develop supportive digital infrastructure and targeted regulatory frameworks that promote supply chain-wide digital transformation, particularly in pollution-intensive sectors.

Despite its contributions, this study has several limitations. First, while the digital patent-based measure of SCD effectively captures technological innovation, it may not fully reflect the practical adoption and implementation of digital tools across all supply chain processes. Second, the study primarily focuses on manufacturing firms listed on Chinese A-share markets, which may limit the generalisability of findings to non-listed or service-oriented firms. Future research can address these two limitations in several ways. Subsequent studies may incorporate survey data or qualitative case studies to better capture the actual use and depth of digital technology adoption in supply chains. Expanding the analysis to other sectors or countries could test the generalisability of the observed effects across different institutional contexts.

In a nutshell, this study provides robust evidence that digitalising supply chains is a viable and effective strategy for reducing corporate pollution emissions. As global environmental challenges intensify, integrating digital technologies across the supply chain will be essential to achieving more sustainable and resilient industrial development.

This study has several limitations that also suggest promising avenues for future research. First, our sample is restricted to listed manufacturing firms. While large listed firms are indeed the primary contributors to industrial pollution, this focus inevitably overlooks the pollution behaviours of small and medium-sized enterprises (SMEs). Future research should incorporate SMEs data to provide a more comprehensive picture of pollution reduction across firm sizes. Second, in measuring SCD, we use digital technology patents as a proxy to capture the digitalisation level of supply chain partners, which allows us to include both listed and non-listed firms. Although this indicator has clear advantages in terms of availability and operational feasibility, digital transformation is inherently multidimensional. Relying solely on patents may omit non-technological aspects of digitalisation, such as organisational restructuring, managerial practices or digital culture. Future studies could combine patent data with textual analysis of corporate disclosures, survey-based indices, or third-party digital readiness assessments to construct a richer and more holistic measure of SCD, particularly for non-listed firms. Third, supply chain structures and institutional environments differ across countries, leading to variations in the intensity and scope of SCD spillover effects. For instance, firms in countries with more collaborative supply chain governance may experience stronger spillovers than those in fragmented or weakly regulated networks. Future research should examine SCD–environment linkages in different institutional contexts to enhance the global relevance of our findings.

Author Contributions

Zengdong Cao: conceptualisation, data curation, formal analysis, methodology, software, visualisation, writing – original draft preparation, writing – review and editing. **Nichola Latoya Williams:** conceptualisation, supervision, investigation, writing – original draft preparation, writing – review and editing. **Ibrahim Labaran Ali:** resources, writing – original draft preparation, writing – review and editing. **Ololade Periola:** investigation, writing – original draft preparation, writing – review and editing. **Yasanur Kayikci:** conceptualisation, supervision, project administration, writing – original draft preparation, writing – review and editing.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data will be made available on request.

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