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Environmentally Sustainable Development: The Role of Supply Chain Digitalization in Firms' Green Productivity

Ruixiang Xue[1] | Tze San Ong[1,2] | Assunta Di Vaio[3]

[1]School of Business and Economics, Universiti Putra Malaysia, Serdang, Malaysia | [2]Department of Business Administration, Daffodil International University, Dhaka, Bangladesh | [3]Department of Law, University of Naples "Parthenope", Naples, Italy

Correspondence: Assunta Di Vaio (susy.divaio@uniparthenope.it)

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ABSTRACT

In the midst of the global push for environmental protection and sustainable development, supply chain digitalization (SCD) has become a key enabler of both operational efficiency and green production. The existent literature, however, has mainly focused on SCD's impact on operational efficiency, neglecting its role in advancing environmental sustainability through green total factor productivity (GTFP). This study addresses this gap by examining how SCD influences GTFP, both directly and indirectly via the mechanism of supply chain resilience (SCR). Data from Chinese A-share firms between 2013 and 2023 was analyzed using a comprehensive double machine learning approach, revealing SCD's significant positive impact on GTFP and the crucial role of SCR in this relationship. Heterogeneity analysis further indicated that SCD's ability to improve GTFP is most pronounced in state-owned firms, heavily polluting industries, and economically developed regions, adding an original dimension to the findings. By establishing the critical role of SCD in promoting environmental sustainability, this study makes valuable contributions to the literature and offers policy insights for countries aiming to accelerate the digitalization and green transformation of their supply chains.

1 | Introduction

The continued expansion of the global economy is intensifying environmental challenges, including rising temperatures, resource depletion, and land degradation, which are becoming increasingly critical (Guo et al. 2024). The State of the Global Climate 2024 report reveals that 2024 is the hottest year ever recorded, underscoring growing global alarm and the urgent need for more decisive environmental action (Ripple et al. 2024). To address this challenge, firms must implement environmentally sustainable production practices that maintain both efficiency and competitiveness. This requirement is particularly critical in the context of China (Jiakui et al. 2023; Javeed et al. 2024). While being the largest developing country in the world and among the most rapidly transitioning economies, China also produces the highest level of carbon emissions globally (Dong and Yang 2024). This reality has positioned environmental sustainability as a top priority for the nation's future development (Raihan and Bari 2024). To this end, China has set a "carbon peak" target, requiring firms, key contributors to carbon emissions, to promote clean production and develop green products. The aim is to improve the environmental performance of these firms, thus ensuring their sustainable development (Zhou et al. 2024).

In this regard, green total factor productivity (hereafter GTFP) has emerged as a comprehensive metric for gauging firms' environmentally sustainable performance (Yang and Liu 2024). GTFP is defined as a firm's capacity to generate economic value while limiting environmental damage (Dai et al. 2025). GTFP extends the evaluation of output efficiency beyond traditional inputs such as labor and technology by incorporating environmental aspects like resource use and pollution levels. As a result, GTFP reflects a firm's overall capacity to operate sustainably and manage its environmental impact in a measurable way (Yu and Zeng 2024). Improving GTFP is essential for reducing the pressure on natural resources and limiting environmental degradation. This aligns with the broader sustainability target and contributes directly to achieving sustainable development goals focused on sustainable industrialization (SDG9), responsible consumption and production (SDG12), and climate action (SDG13) (Hao et al. 2023). Studies on GTFP have identified environmental taxes (Gao et al. 2024), green regulations (Fan et al. 2022) and financial aid (Lu et al. 2024) as key factors of direct and indirect investments in firms' environmental sustainability.

Digital transformation has been increasingly recognized as a key factor of innovation, operational efficiency, and sustainable development outcomes (Sun et al. 2024). Within the supply chain domain, supply chain digitalization (hereafter SCD) emerges as a critical strategy for addressing environmental challenges such as pollution and inefficient resource use (Shen et al. 2025). By improving coordination between upstream and downstream operations and improving the integration of information flows, SCD contributes to more efficient and responsive supply chain management (Chauhan et al. 2022). At the same time, digital technologies embedded in supply chain activities support the transition toward more environmentally sustainable production practices (Xu et al. 2025). In this context, Del Giudice et al. (2022) provide a significant theoretical contribution by framing digital transformation as a structural metamorphosis that reshapes organizational processes, strategies, and planning. Their analysis, grounded in Business Model Innovation and Resilience theories, highlights how the adoption of digital technologies not only improves operational efficiency and long-term profitability but also enables firms to integrate sustainability into core business models. Applied to the supply chain, this perspective reinforces the view that SCD is not merely a technological upgrade, but a strategic lever for achieving environmental and social goals through improved planning, stakeholder engagement, and adaptability to external risks, such as those posed by climate change. Therefore, SCD reflects a broader transformation of supply chains into resilient, sustainable, and innovative-driven ecosystems. Consequently, SCD is critical for firms in achieving sustainable competitive advantage. Indeed, countries across the globe are recognizing its growing importance, as proven by the various policies they have enacted to cultivate SCD (Singh and Maheswaran 2024). China is not exempt from this phenomenon; the Chinese government has been proactively encouraging sustainable SCD since 2017, when it initiated a pilot SCD acceleration program. Notwithstanding this progress, SCD's potential implications for GTFP have been relatively underexplored.

Existing literature has proven that SCD exerts significant effects on economic performance (Wang et al. 2025), social performance (El Baz and Ruel 2024), supply chain performance (Nguyen et al. 2023), product innovation (Wang and Zhang 2025), operational efficiency (Wang and Li 2024), green innovation (Singh and Maheswaran 2024) and supply chain risks (Zouari et al. 2021). Zhao et al. (2023) demonstrated the positive impact of SCD on firms' supply chain resilience (SCR), which refers to firms' ability to withstand and recover from negative circumstances (Ge and Bao 2024). Facing uncertain business environments, health crises, and geopolitical instabilities, the resilience of a supply chain is imperative. SCR can be realized through improvements in supplier collaboration, adaptability, and optimal real-time analytics (Belhadi et al. 2024). Evidence further suggests significant differences in SCR across firms' ownership types, industries, and regions; for instance, high-tech manufacturers, smaller or state-owned firms (SOFs), and firms in areas with strong digital infrastructure generally exhibit higher resilience (Mishra and Singh 2023; Qi et al. 2024). In this regard, Di Vaio et al. (2021) suggests a valuable theoretical lens, framing resilience not only as a reactive capacity but as a dynamic governance mechanism. Their perspective, initially developed in the context of water governance, emphasizes the ability of systems, both institutional and infrastructural, to adapt, self-organize, and maintain continuity under pressure from climate, socio-economic, or health-related disruptions. When applied to supply chains, this conceptualization underscores how resilient corporate governance can enhance SCR by enabling coordinated responses, fostering stakeholder engagement, and ensuring sustainability even in complex and volatile environments. Hence, resilience theory provides an integrated framework to interpret how digital capabilities and collaborative governance practices can support firms in navigating crises and achieving long-term continuity. Overall, scholars concur that SCD boosts both performance and resilience. Correspondingly, advances in digital technology are known to directly raise GTFP by encouraging innovation and optimizing production processes (Lyu et al. 2024). Most existing work, however, has investigated SCD's influence on individual outcomes (e.g., production or resource efficiency) without linking its economic and environmental effects on sustainable development. By focusing on GTFP, this study addresses this gap, simultaneously considering the economic and ecological dimensions of production efficiency to provide a comprehensive picture of SCD's implications. We further examine whether SCR mediates the SCD–GTFP relationship, which remains underexplored. In addition, heterogeneity analyses are conducted to assess how the effects of SCD on GTFP vary across ownership structures, industry characteristics, and regional contexts. To achieve these objectives, this study employs a double machine learning (DML) methodology grounded in the resource-based view (RBV), dynamic capabilities theory (DCT) and resilience theory. Our robust theoretical framework thoroughly explains how digitalization can reconfigure conventional supply chains into adaptive, sustainable, and environmentally friendly systems.

This study provides four original contributions. Foremost among these, it develops and validates an integrated SCD–GTFP model, equipping firms with new knowledge on using digital tools to pursue sustainable growth. In doing so, we move beyond prior studies' sole emphasis on digitalization's efficiency gains rather than its concurrent environmental impact. Second, this study operationalizes and assesses SCR as an underlying mechanism, addressing the limited attention it has received as a mediator. The SCD-SCR-GTFP pathway highlights the role of resilience in sustainable development, revealing digitalization to be a key driver of SCR. Third, by examining the heterogeneous effects of SCD on GTFP across different types of firms, this study provides strong support for the formulation of more precise pro-digitalization policies. Finally, by extending the application of the DML method, we overcome the limitations of traditional difference-in-difference models in handling dimensionality issues, yielding greater accuracy and robustness.

The rest of this study is organized as follows: Section 2 explains the theoretical framework and hypotheses; Section 3 details the methodology; Section 4 reports the empirical results; Section 5 presents the discussion; and Section 6 provides the conclusion.

2 | Theoretical Framework and Hypotheses

2.1 | Theoretical Framework

This study is grounded in the RBV, DCT, and resilience theory. The RBV states that a firm's sustained competitive advantage stems from its resources that are rare, inimitable, and non-substitutable (Barney 1991; Wernerfelt 1984). With the growing global attention to environmental protection, firms are increasingly acquiring novel resources, particularly those enabled by digital technologies, to achieve synergistic improvements in both environmental responsibility and firm performance, enhancing their competitive advantage (Chong et al. 2024). In this context, SCD is a critical digital resource that integrates various technologies, technical platforms, data assets, information processing capabilities, real-time communication interfaces, advanced analytics tools, and mechanisms across a supply chain's procurement, production, logistics, and service activities (Wang and Prajogo 2024). This integration facilitates cross-firm information sharing, breaks down information silos, and supports intelligent decision-making (Zhao et al. 2023; Tiwari et al. 2024). Collectively, the elements of SCD provide a robust foundation for firms to develop sustainable competitive advantages. The regulatory environment further heightens the rarity and strategic importance of digital resources in the supply chain. In China, SCD pilot programs delivered through tax incentives and financial aid help firms reduce the cost barriers of digitalization and effectively utilize their existing digital resources for sustainability (Yang et al. 2025b). Tax incentives lower firms' initial investment cost in digital technologies and financial subsidies reduce technology adoption risks, altogether making it easier to embrace environmentally friendly technologies. These digital technologies, brought about by policy, facilitate firms' access to extra production information and perception of market changes, thereby integrating internal production resources and reducing pollution. This reflects DCT.

Although the RBV clarifies how firms acquire valuable resources, it does not fully explain how firms adapt when uncertainties emerge (Eisenhardt and Martin 2000). The DCT, an expansion from the RBV, fills this gap by identifying a firm's dynamic capabilities in sensing, integrating, and reconfiguring resources, which are critical amid growing external threats like natural disasters, pandemics, geopolitical strains, and energy deficiencies (Teece et al. 1997). In practice, the DCT entails a firm's capacity to detect environmental shifts (sense), combine cross-functional knowledge (integrate), and swiftly absorb or redirect new technologies (reconfigure) (Teece 2007; Leso et al. 2024). Within this concept, firms' dynamic capabilities enable them to transform digital resources into efficient output. Hence, SCD is simultaneously a digital resource and a channel for dynamic capabilities, as it allows firms to sense change in real time, quickly assimilate internal and external assets, and dynamically modify technological directions (Seyedghorban et al. 2020).

Environmental sustainability has become a central element for corporate strategy. It requires firms to align their economic objectives with ecological responsibilities. By implementing efficient resource utilization and pollution control, firms can ensure their adherence to green regulatory frameworks (Sun et al. 2024; Wang and Zhang 2025). In this context, GTFP serves as a valuable benchmark in sustainability as it captures both resource efficiency and environmental performance (Kuosmanen and Maczulskij 2024). Resource efficiency reflects the firm's ability to minimize energy consumption and raw material waste, while environmental performance evaluates efforts to reduce emissions and comply with environmental regulations (Tian et al. 2025). These two dimensions are directly linked to SDG 9, 12, and 13, which emphasize sustainable industrialization, efficient resource use, and corporate responsibility in addressing climate change and reducing carbon emissions (Hao et al. 2023).

Viewed through RBV and DCT, SCD functions as a strategic digital resource that improves a firm's ability to sense environmental changes, integrate knowledge across operations, and reconfigure processes in response to sustainability demands. These dynamic capabilities are essential for improving GTFP. AI-driven analytics sharpen demand forecasts and production plans. This prevents overproduction and excess inventory; consequently. They streamline the distribution of energy, materials, and labor, minimizing wastage and pollution (Seyedghorban et al. 2020). Internet of Things (IoT) sensors, meanwhile, track energy use, equipment conditions, and material distribution in real time, enabling firms to quickly identify inefficiencies. (Wang et al. 2025). Accordingly, Singh and Maheswaran (2024) found that digitalization spurs green innovation, and Nguyen et al. (2023) demonstrated that SCD's real-time energy monitoring decreases emissions. Hence, a growing body of theoretical and empirical study acknowledges SCD's value in sustainability.

Beyond that, it is relevant to understand how firms convert SCD's technological assets and dynamic capabilities into sustainable outcomes. Escalating external threats pose uncertainties and systemic risks for firms pursuing green performance (Ao et al. 2023). SCR refers to a firm's capacity to identify threats in real time. Whether a firm can effectively relieve disruptions and rapidly restore the structure and functioning of its supply chain is crucial (Di Vaio and Varriale 2020). As disruptions become more frequent and complex, SCR has gained growing attention as a key indicator of a firm's ability to sustain operations under adverse conditions (Belhadi et al. 2024). In turbulent external environment, digital resources facilitate close coordination with upstream and downstream partners. The real-time analysis of supply–demand shifts and agile operational process adjustments help firms sense and react to emerging threats so they can reconfigure their processes, and adapt to environmental fluctuations (Tiwari et al. 2024). These can increase SCR (Zhao et al. 2023). Such resilience strengthens firms' continuity and ability to deal with environmental challenges, in turn, raising GTFP. In other words, SCR functions as a key mechanism through which SCD improves GTFP output.

To better demonstrate the effect of SCR, this study adopts resilience theory, which highlights adaptability, recovery, and reconfiguration competencies of a system facing unexpected events (Holling 1973). In the supply chain context, resilience theory explains a supply network's response channels and structural agility (Dubey et al. 2023), thereby extending the RBV-DCT framework to complex environments (Pettit et al. 2010). Combining DCT with resilience theory, we operationalize SCR into three dimensions: (i) demand–supply matching efficiency, where firms use real-time data to track market shifts and respond swiftly, preventing overproduction and energy wastage (Yang et al. 2022); (ii) demand–supply relationship stability, where firms assimilate upstream and downstream resources to sustain their stable coordination and response pathways, decreasing wastage from sudden shocks (Gu et al. 2022); and (iii) supply quality, where firms reconfigure their green procurement pathways and quality standards using technology, making the production process more eco-friendly (Liu et al. 2024).

The three dimensions of SCR align theoretically with the DCT's core mechanisms of sensing, integration, and reconfiguration, while also embodying the adaptability, recoverability, and flexibility emphasized in resilience theory. Collectively, they influence GTFP from different angles. For example, during the COVID-19 pandemic, Alibaba Group leveraged its Cainiao logistics platform to integrate cloud-based warehouse resources and implement data-driven resource allocation. This not only improved the supply chain's responsiveness to sudden demand shocks but also reduced carbon emissions through optimized transportation routes and warehouse configurations. Alibaba's case demonstrates the practical pathway through which SCD enhances SCR to improve GTFP.

Existing studies have explored the determinants of GTFP from both firms' governance and macroeconomic perspectives. Within firm governance, profitability reflects a firm's ability to convert assets into profits, indicating efficient asset utility (Fan et al. 2022); firm size captures the firm's capacity to acquire and allocate key resources such as capital and labor (Guo et al. 2024); firm age represents the accumulation of experience in processes, systems, and technological paths (Gao et al. 2024); and the shareholding ratio of the largest shareholder reflects ownership concentration, which facilitates the coordination of strategic resources (Jiakui et al. 2023). These distinct firm-level resources contribute to the enhancement of GTFP, aligning with the RBV. From a macroeconomic perspective, the marketization index represents the institutional environment; a more mature market system enables more efficient resource allocation and capability development (Guo et al. 2024). In addition, money supply reflects firms' access to financing and their investment willingness, while producer price captures cost pressure fluctuations (Xu and Deng 2022; D'Adamo and Rossi 2025). As both firm governance and macroeconomic factors influence firms' capacity to acquire resources and respond to external shocks, consistent with the logic of the DCT, they are likely to impact GTFP. Therefore, these variables were incorporated into our empirical analysis.

In addition, prior studies have shown that firms differ significantly in terms of production and operation resource endowments, risk awareness, and external environmental pressures (Li 2025). However, whether such differences significantly affect the relationship between SCD and GTFP remains insufficiently examined. From the perspective of the RBV, firms across different ownership types, industries, and regions vary in their access to key strategic resources such as capital, technology, and digital infrastructure (Sun et al. 2024). The effectiveness of SCD implementation is influenced by these resources (Tiwari et al. 2024). The intensity of environmental pressures also differs across firms (Li 2025). For instance, firms in heavily polluting industries or economically developed regions tend to have higher risk awareness and stronger technological foundations, making them more likely to activate their dynamic capabilities (Wang and Su 2025). As a result, they are better positioned to transform SCD into improvements in GTFP.

China is a manufacturing powerhouse and produces one of the world's largest carbon emissions. In response, the government has enacted a series of SCD pilot programs, setting up a unique environment for firms to test digital governance and sustainable development (Dong and Yang 2024). Consequently, Chinese firms are involved in a complicated system of policies on digitalization and sustainability. These multiple overlapping requirements significantly impact firms' decision-making; therefore, causing high-dimensional covariates and nonlinear relationships. Conventional regression models are not able to adequately capture such data, often leading to endogeneity and biased estimates (Bia et al. 2024; Chernozhukov et al. 2018). To overcome this shortcoming, we adopted the DML method, which combines cross-fitting approaches with machine learning (ML) algorithms, to assess the SCD–SCR–GTFP link among Chinese firms. In the unique environment of digitalization and sustainability interventions in China, the DML approach yields more precise causal inferences on the net impact of SCD while minimizing model bias.

2.2 | Hypothesis Development

2.2.1 | SCD And GTFP

Implementing SCD requires firms to integrate AI tools within their supply chain architectures. This creates technological systems driven by data (Zhao et al. 2023). Over time, firms with SCD accumulate and combine key digital resources like tech platforms, information-sharing mediums, and decision-making systems, resources that meet the RBV criteria (Wang et al. 2025). SCD boosts firms' capacity to acquire information and allocate production resources efficiently by these assets, improving productivity and decision quality (Le et al. 2024). For instance, IoT sensors perform real-time tracking of equipment performance, energy use, and emissions, allowing rapid immediate operational modifications (Bienhaus and Haddud 2018). Blockchain technology also strengthens transparency and traceability along the supply chain, guaranteeing environmental policy compliance and mitigating ecological risks (Di Vaio and Varriale 2020; Seyedghorban et al. 2020). Similarly, big-data platforms assimilate inputs from suppliers and customers, heightening market sensing and data-processing abilities to produce more precise product demand forecasts (Wu et al. 2024). Overall, SCD systems support automated decision-making, dynamic production resource allocation (e.g., raw materials, energy, and labor), and optimized ordering, inventory, and logistics processes, thus jointly raising organizational productivity defined as the improvement in operational efficiency and output performance achieved by the focal firm through its decisions.

Shen et al. (2025) further reported that China's SCD policies accelerate the development of blockchain-enabled digital platforms for supply chains. Firms can flexibly engage with diverse suppliers and distributors to create dynamic networks. Such flexibility helps firms react swiftly to upstream or downstream demands, boosting adaptability in the face of external uncertainties (Seyedghorban et al. 2020). By curbing transaction and operating costs and optimizing the allocation efficiency of key resources, these SCD-enabled capabilities coincide with the dynamic capabilities highlighted in the DCT.

Research has confirmed that SCD enhances firms' economic performance (Wang and Zhang 2025; Le et al. 2024); however, few studies have simultaneously considered environmental factors. Di Vaio and Varriale (2020) emphasized that SCD facilitates data management in firms, thereby enhancing environmental performance. For instance, supply chain data platforms enable intelligent scheduling, route optimization, and energy efficiency management, effectively reducing carbon emissions and energy consumption to achieve environmental protection goals (Tian et al. 2025; D'Adamo 2025). Essentially, SCD facilitates improvements in productivity and environmental performance, which are key dimensions of GTFP. Therefore, we propose the following hypothesis:

H1. *SCD significantly improves the GTFP of firms.*

2.2.2 | Mediating Role of SCR

SCR corresponds with the resilience theory, which underscores a firm's capacity to sustain core operations during external shocks and then to rebound and adapt swiftly after the disruption (Dubey et al. 2023). This resilience is contingent on how well the firm can sense, integrate, and reconfigure its digital resources, aligning with the DCT (Teece et al. 1997). Referring to prior research (Ge and Bao 2024), we categorize SCR into three components: (i) supply–demand matching efficiency, (ii) supplier-quality enhancement, and (iii) supply–demand relationship stability.

2.2.2.1 | Optimizing Supply–Demand Matching. Optimizing supply–demand matching is a vital aspect of SCR. It governs how flexible and responsive the entire chain is (Chopra et al. 2021). Because supply–demand variations are highly sensitive to external shocks, rapidly detecting market shifts and reacting to them effectively is vital for avoiding supply shortages, surpluses, and other related disruptions (Dubey et al. 2023). By combining IoT sensors with AI, SCD delivers real-time monitoring and forecasting of market demand and production scope (Wang et al. 2025). These capabilities markedly improve the sensing dimension of DCT (Xu et al. 2025). Dynamic adjustments to production and inventory also lower operating costs and allow firms to pivot quickly when environmental disruptions strike, reiterating sensing capability (Chong et al. 2024). Improving the alignment between supply and demand strengthens firms' capacity for risk mitigation and market responsiveness, fostering a proactive foundation for environmentally sustainable and operationally efficient practices (Di Vaio et al. 2024). We thus hypothesize that:

H2. *SCD significantly improves the GTFP of firms by optimizing supply–demand matching.*

2.2.2.2 | Enhancing Supply Quality. A high-quality supplier network is fundamental to SCR. Complying with stricter environmental laws and evolving customer demands requires continuous quality upgrades across the network (Razak et al. 2023). SCD accelerates this process by embedding digital tools (e.g., real-time traceability, supplier assessment platforms) in procurement and quality management systems (Zouari et al. 2021). Achieving higher quality standards often necessitates the redesign of inefficient or noncompliant networks, the strategic selection of more capable partners, the revision of collaborative frameworks, and the modernization of delivery processes, all aimed at establishing a more resilient, environmentally friendly, and sustainable supply chain (Wang et al. 2024). Such restructuring of the digital resource base and supplier network reflects the reconfiguring capability in the DCT, helping firms reach new quality targets and enhance adaptability (Leso et al. 2024). To summarize, SCD improves overall supply chain quality and, concurrently, creates a strong basis for productivity improvements within environmental considerations. Accordingly, we predict that:

H3. *SCD significantly improves the GTFP of firms by enhancing supply quality.*

2.2.2.3 | Maintaining Stable Supply–Demand Relationships. Resilience theory suggests that stable supply–demand network relationships and coordination processes are essential for continuous system operations, uninterrupted material flows, and smooth communication (Sheffi and Rice 2005). Building resilience requires such robust connections and effective collaboration, for which SCD is a key enabler (Dubey et al. 2023). For instance, platform-based collaboration tools and data-sharing networks improve the quality of upstream and downstream links by uniting suppliers, distributors, and logistics providers on a common digital platform (Belhadi et al. 2024). With this continuous information exchange, firms can capture external marketing resources proactively, coordinate efficiently, and respond quickly, while also securing lower transaction costs, fewer supply disruptions, and more stable, long-term partnerships in dynamic settings (Mishra and Singh 2023). Additionally, stable supply–demand networks, driven by SCD, aid firms' critical production resource acquisition, crisis recovery, and operating resource allocation efficiency, ultimately leading to sustainable growth (Li et al. 2023). This study thus postulates that:

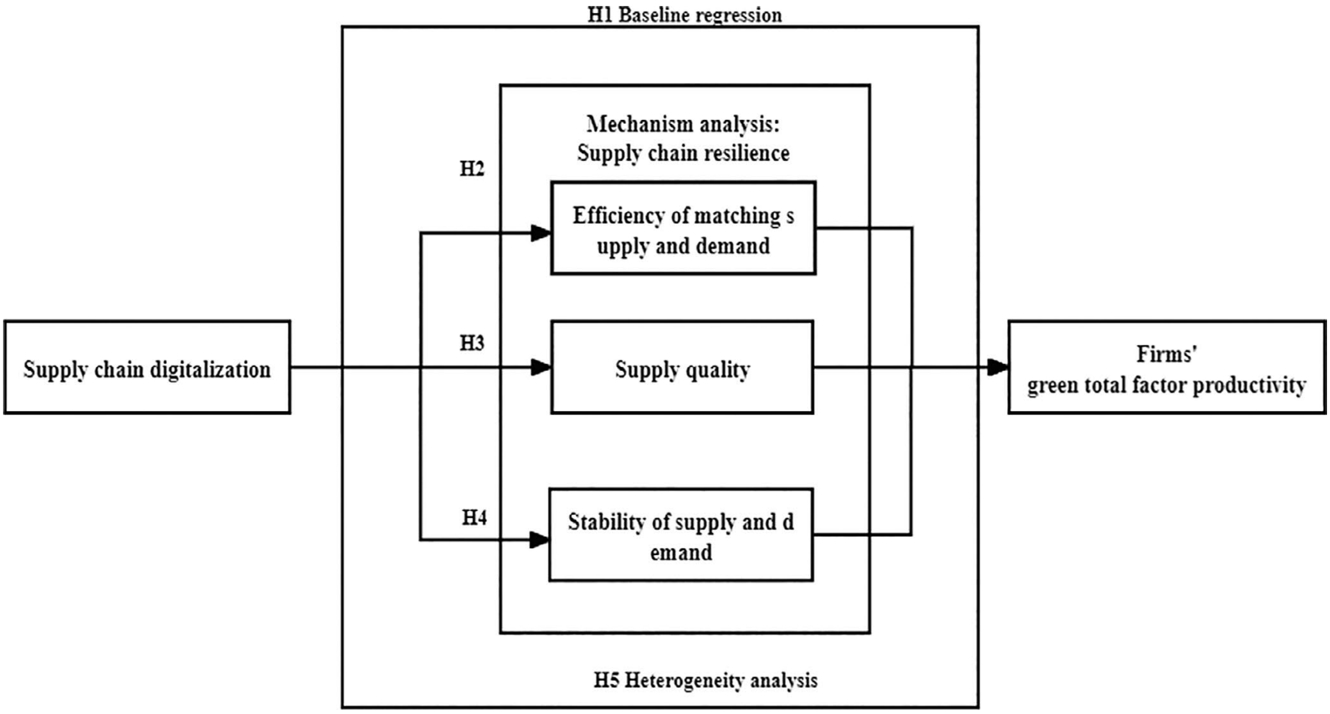

FIGURE 1 | Research framework.

H4. *SCD significantly improves the GTFP of firms by maintaining stable supply–demand relationships.*

2.2.3 | Heterogeneity Analysis of SCD and GTFP

Chinese firms can be classified into SOFs and non-SOFs. Compared to non-SOFs, SOFs have inherent advantages in resource acquisition due to their political embeddedness, such as easier access to capital and stronger government support (Li 2025). SOFs have larger scale and operate in monopolistic or strategically important industries, resulting in higher credit ratings, lower financing costs, and greater access to bank loans (Li et al. 2023). In addition, as key vehicles for policy implementation, SOFs are selected as pilot or demonstration units and receive preferential policy support (Dong and Yang 2024). These institutional advantages enhance their ability to integrate and apply digital technologies, thereby amplifying improvements in productivity and environmental performance, and ultimately strengthening their sustainable competitive advantage (Wang and Zhang 2025). This is consistent with the core idea of the RBV. This study thus postulates that:

H5a. *The positive effect of SCD on GTFP is stronger in SOFs.*

DCT emphasizes that for firms operating in dynamic and uncertain environments, the ability to sense opportunities and threats must be developed for seizing relevant production and operation resources and reconfigure operations accordingly (Leso et al. 2024). Heavily polluting industries are under increasing pressure of regulatory and social scrutiny to improve environmental performance, this necessitates the development of capabilities to dynamically adapt and transform (Wang and Su 2025). SCD enables these firms to sense changes in environmental regulations and by utilizing digital tools, supply chain efficiency can be improved and operations can be optimized toward cleaner production (Zouari et al. 2021). Consequently, firms in high-polluting sectors may show more motivation to leverage SCD for environmental and productivity gains. This study therefore proposes that:

H5b. *The positive effect of SCD on GTFP is more pronounced in heavily polluting industries.*

Based on RBV, firms in developed regions have access to stronger digital infrastructure, more advanced human capital, better developed market institutional systems (Wang et al. 2025). These advantages allow firms to allocate their production resources with higher efficiency and to optimize production process by enhancing their ability to integrate and utilize digital technologies. (He et al. 2025). In addition, according to DCT, firms in developed regions are faced with strong regulatory pressure, fast-shifting markets, and high demands for sustainability (Xu et al. 2025). These external conditions encourage the development of dynamic capabilities, allowing firms to better apply SCD for green innovation and efficiency improvements (Singh and Maheswaran 2024). This study then assumes that:

H5c. *The effect of SCD on GTFP is greater in economically developed regions.*

To test the above hypotheses, we utilized a dataset of China A-share listed firms. The DML approach was employed to address high-dimensional covariates and endogeneity issue for a robust estimation of both direct and mediating effects. The key variables—SCD, SCR, and GTFP—were constructed with public firm-level data, as explained in the following section. Figure 1 illustrates the study framework and hypotheses.

3 | Methodology

3.1 | Sample Selection and Data Sources

We utilized the data of A-share listed firms from 2013 to 2023 as the study sample. The year 2013 was chosen as the starting point to ensure sample symmetry by including a balanced time range before and after the 2018 launch of the SCD pilot policy. In addition, the year 2013 marked the starting point of China's digital infrastructure development, with the launch of the Broadband China strategy laying the foundation for subsequent SCD. Since the data for 2024 was not yet available at the time of our analysis, it was not included in the study. Data on the SCD pilot cities was obtained from the Chinese government's official website. GTFP was calculated using the SBM-ML index based on data from firms' corporate social responsibility reports, including employment, net fixed assets, electricity use, operating revenue, and emissions of sulfur dioxide, wastewater, and dust. Additional firm-level information was acquired from the CSMAR database and the Chinese Bureau of Statistics. The data sources used in this study have been widely adopted in empirical study and are considered authoritative and accessible (e.g., Guo et al. 2024; Yang et al. 2025a).

To ensure the accuracy and reliability of the findings, the criteria of which sample was screened follow the approach of Sun et al. (2024). Specifically, firms in the financial sector were excluded due to their distinct financial reporting structures; observations with missing values and ST/PT firms were removed to reduce data bias, and 1% of key continuous variables were winsorized to mitigate the influence of outliers. The final dataset consisted of 3509 observations. This methodological approach is consistent with previous empirical studies on corporate sustainability and digital transformation, which also apply strict sample screening in firm-level panel data and focus on post-policy impact analysis (Wang and Zhang 2025). To enhance robustness and reduce potential endogeneity, we employed propensity score matching with varied ML algorithms to exclude confounding policy effects and adjusted model parameters accordingly.

3.2 | Variable Measurements

3.2.1 | Dependent Variable

Referring to Wu et al. (2022) and Gao et al. (2024), we utilized the Slack-Based Measure Malmquist-Luenberger (SBM-ML) index, which includes unfavorable outputs when measuring firms' GTFP. This comprehensive index accounts for both input and output efficiency and is particularly suitable in evaluating production systems with undesirable outputs (e.g., pollution emissions). The objective function is as follows:

$$\min \hat{p} = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} s_i^-}{1 - \frac{1}{s_1 + s_2}\left(\sum_{i=1}^{S_1} \frac{s_i^g}{y_{ik}^k} + \sum_{i=1}^{S_2} \frac{s_i^b}{y_{ik}^k}\right)} \tag{1}$$

In this function, the $\hat{p}$ value represents productivity efficiency, where a lower value reflects an improvement in productivity; S^- denotes the slack variable for undesirable outputs, indicating the difference between actual and expected outputs; M represents the number of decision-making units; S_1 and S_2 are the weights for expected and undesirable outputs, respectively; y_1 stands for the expected output variable, which in this study was measured via operating revenue; and y_2 represents the undesirable output variables (emissions of sulfur dioxide, wastewater, and dust).

To accurately reduce the $\hat{p}$ value, we established the following constraints:

1. Constraints on inputs and expected outputs

$$\sum_{k=1}^{K} \lambda_k x_{ij} + s_i^- = s_{ik} \tag{2}$$

where λ represents the weight and X represents the factor inputs, which in this study were measured using firms' inputs of labor (employment number), capital (net fixed assets), and energy (electricity use).

$$\sum_{j=1}^{S1} \lambda_j y_{uj}^g + s_u^g = s_{ik}^g \tag{3}$$

$$\sum_{j=1}^{n} \lambda_j y_{vj}^b + s_v^b = y_{vk}^b \tag{4}$$

2. Constraints on expected and undesirable outputs

The parameters and constraints within the formula ensure a balance between different outputs and inputs. The slack variables were used to adjust and reflect changes in actual productivity, thereby providing a more accurate depiction of productivity variations.

3.2.2 | Independent Variable

This study used the SCD pilot policy as the independent variable. In 2017, China's State Council issued an inaugural document titled Guiding Opinions on Actively Promoting Supply Chain Innovation and Application, urging regulatory authorities to leverage digital technology to enhance green supervision and establish a unified green product standard system. To implement these guidelines, the Ministry of Commerce selected pilot cities and firms; pilot cities' objective was to explore new models of cross-departmental and cross-regional supply chain governance, while pilot firms' goal was to adopt digital technology to create comprehensive, efficient, and green supply chains, thereby reducing costs, improving efficiency, and promoting green development. In October 2018, a rigorous selection process resulted in 55 cities and 266 firms being chosen as pilot entities. Following Wang and Li (2024), we defined two dummy variables to capture the policy setting: 'Post', which equals 1 for periods after the policy implementation and 0 otherwise; and 'Treated', which equals 1 if a firm is located in an SCD pilot city and 0 otherwise.

3.2.3 | Mediating Variable

Measuring SCR remains challenging and lacks standardization in the literature, as previous studies have often relied on surveys which are subject to respondent bias (Ozdemir et al. 2022; El Baz and Ruel 2024). Instead, based on the definitions and objectives of SCR outlined in previous studies (Ge and Bao 2024; Wang et al. 2024), this study analyzed it as three components: the optimization of supply–demand matching, the improvement of supplier quality, and the stability of supply–demand relationships. Previous theoretical analyses have demonstrated that these dimensions align with DCT (sensing, reconfiguring, integration) and resilience theory (adaptive, flexibility, recovery). First, supply–demand matching efficiency was evaluated using supply chain efficiency and transparency. Supply chain efficiency assesses a firm's supply management effectiveness, as measured by inventory turnover days. This indicator effectively overcomes potential miscalculations stemming from safety stock, as it reports upstream-downstream firms' interaction and transaction levels; as such, it captures the supply chain's flexibility and responsiveness. Supply chain transparency, on the other hand, indicates data accessibility based on the disclosure ratio of major supply partners and customers. A greater transparency level suggests better supply–demand predictive ability, as all partners can access and distribution information quickly. This reduces supply–demand imbalances caused by information asymmetry, again enhancing the supply chain's flexibility and responsiveness.

Second, supply quality was measured using innovation input intensity and innovation output, where innovation input (R&D) was represented by ln(R&D + 1) and innovation output (Patent) was represented by ln(Patent grants+1). Third, the stability of supply–demand relationships was measured by customer stability, using the proportion of stable customers and the proportion of stable customer sales as proxy variables. The proportion of stable customers (Stable_cus) was calculated as the number of top five customers that also appeared in the previous year divided by five, and the proportion of stable customer sales (Stable_sale) was computed as stable customer sales divided by total sales. Figure 2 depicts the construction of the SCR indicators.

3.2.4 | Control Variables

This study incorporated the following control variables: (i) firm size, measured using ln(total assets); (ii) leverage, defined by the debt-to-asset ratio; (iii) profitability, assessed via return on assets (ROA); (iv) firm age, quantified as ln(number of years in operation); (v) largest shareholder ownership, measured by the percentage of shares held; (vi) gross domestic product (GDP), measured by growth rate; (vii) money supply, represented by the M^2 growth rate; and (viii) marketization index, measured using the NERI index which captures multiple high-dimensional macroeconomic factors (e.g., government intervention, market competition, legal environment, market liberalization, and economic development).

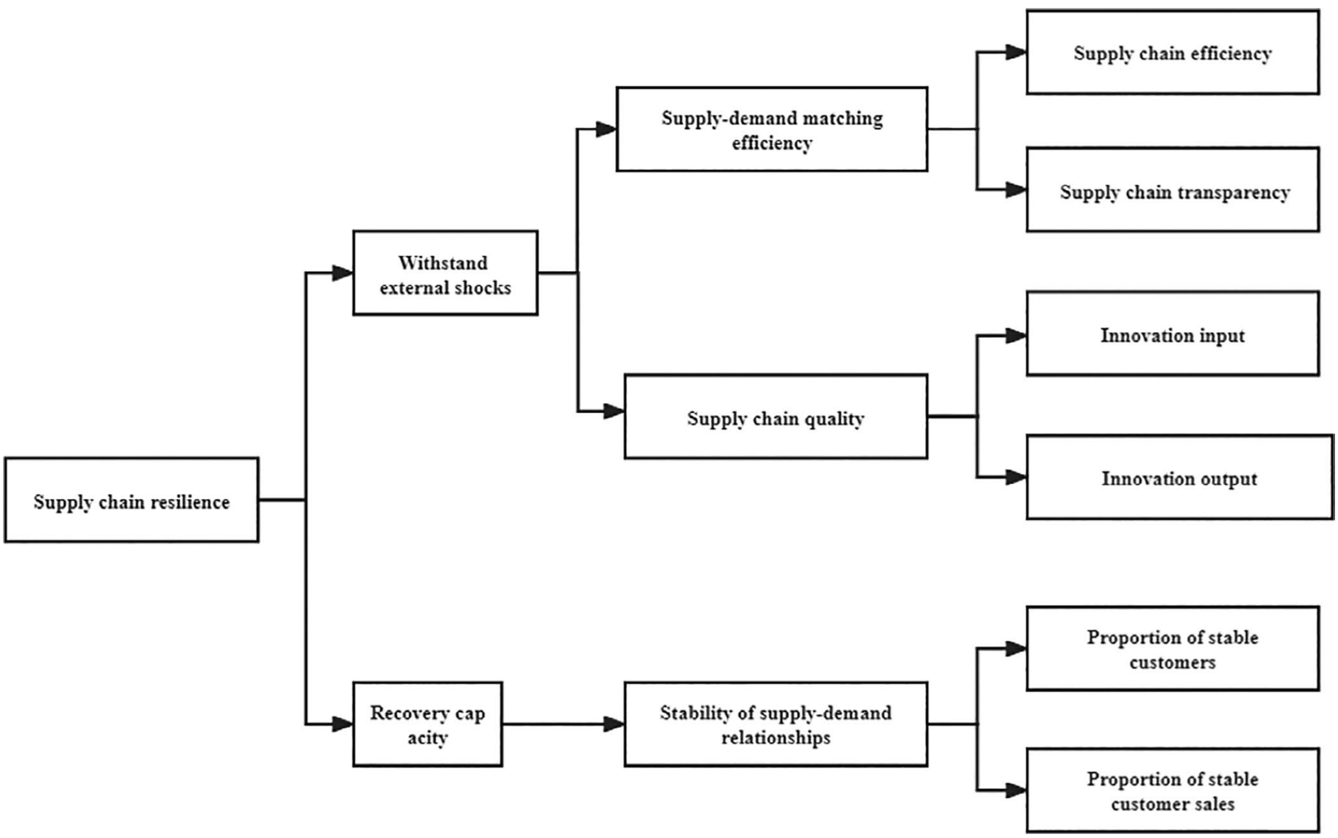

FIGURE 2 | SCR indicator construction.

3.3 | DML Approach

Study on firm-level policy impacts has mainly employed conventional analytical techniques such as the difference-in-difference model and logistic regression (Liu et al. 2022). Although these methods clearly report coefficients and significance levels, making them easy to interpret, they suffer from several limitations (Xue et al. 2024). These methods rely on predefined functional forms and can lead to misspecification and estimation bias (Jia and Xue 2022). They also require testing the parallel trend assumption to ensure a consistent trend exists in the absence of policy intervention, treatment, and control groups (Liu et al. 2022). Moreover, conventional models also struggle to handle high-dimensional relationships. Multicollinearity can also occur (Yin et al. 2025). To overcome these limitations, an advanced algorithm via the DML approach was introduced by Chernozhukov et al. (2018) and since then numerous studies have confirmed that it delivers better robustness and improved model fit (Xue et al. 2024; Jiang and Sun 2025). This makes DML a viable alternative compared to conventional methods. DML combines traditional causal analysis and modern ML techniques; a two-stage problem-solving procedure is proposed (Yang et al. 2025a). First, separate ML models are cross-fitted to test the relationship of both treatment and outcome variables, yielding residuals free of confounding influence. Second, residuals are input into a regression model to estimate causal effects (Farbmacher et al. 2022).

Compared to conventional regression methods, the two-level DML process greatly reduces specification errors (Bia et al. 2024) and causal inference biases that occur with omitted variables or mis-specified paths (Ahrens et al. 2025). DML provides curse of dimensionality as the first stage employs a regularization algorithm. This avoids the preset biases. It does not enforce the linearity assumption and provides better estimates of real data-generating mechanisms (Chernozhukov et al. 2018). Overall, DML can handle complex nonlinear data with high-dimensional confounders. These benefits of DML were particularly valuable for model estimation and variable selection in this study. First, GTFP is a comprehensive index shaped by many high-dimensional control variables (e.g., economic development and government intervention) (Gao et al. 2024). Traditional regression techniques cannot capture the links between firm-specific factors and high-dimensional data. This can result in multicollinearity and inaccurate estimations (Chernozhukov et al. 2018). DML's regularization algorithms filter such data effectively, excluding potential multicollinearity and ensuring unbiased results (Farbmacher et al. 2022). Moreover, the RBV and DCT perspectives suggest that as a new digital resource form, SCD not only improves firms' information flow but also enhances their adaptability and responsiveness towards external market shifts (Zhao et al. 2023). Given the complex market environment and economic conditions, the SCD–GTFP link is likely nonlinear. The DML approach can be utilized to effectively capture this characteristic (Yang et al. 2025a). The corresponding equations are as follows:

$$GTFP_{i,t} = \theta_0 SCD_{i,t} + g(X_{i,t}) + \varepsilon_{\mathrm{i},t} \tag{5}$$

$$E(\varepsilon_{\mathrm{i},t} | X_{i,t} SCD_{i,t}) = 0 \tag{6}$$

X represents the multidimensional control variables. The functional form of g is unknown and is derived from the ML model. θ_0 is the estimated coefficient.

To prevent biased estimation of the coefficient θ_0, we included the following auxiliary equations:

$$SCDP_{i,t} = m(X_{it}) + V_{i,t} \tag{7}$$

$$E(V_{i,t} | X_{i,t}) = 0 \tag{8}$$

We also introduced an ML model to estimate the function m, obtaining $\hat{m}$. Subsequently, we computed the residual $\hat{V}$ and used it to estimate the function g, denoted as $\hat{g}$, thereby obtaining the estimator $\hat{\theta}_0$. The process is modeled below:

$$\hat{\theta}_0 = \left(\frac{1}{\mathrm{n}} \sum_{i \in I, \mathrm{t} \in \mathrm{T}} \hat{V}_{i,t} SCD_{\mathrm{i},t} \right)^{-1} \frac{1}{\mathrm{n}} \sum_{\mathrm{i} \in I, \mathrm{t} \in \mathrm{T}} \hat{V}_{i,t} \{ GTFP_{\mathrm{i},t} - \hat{g}(X_{i,t}) \} \tag{9}$$

4 | Findings

4.1 | Baseline Regression

Table 1 shows the regression results on the impact of SCD on GTFP using the DML method. The coefficients of Post*Treated are 0.09136, 0.01882, and 0.01895, respectively (all significant at the 1% level), indicating a positive relationship between SCD and GTFP. This finding can be explained from a theoretical perspective. SCD drives firms to widely adopt digital technologies, enabling them to accumulate and integrate key digital resources (Wang and Prajogo 2024). This enhances information acquisition and the efficiency of operational resource allocation, thereby boosting productivity (Tiwari et al. 2024). Meanwhile, SCD helps reduce carbon emissions and energy consumption during transportation and production, enhancing environmental friendliness and ultimately boosting GTFP, which aligns with the core tenets of the RBV. Furthermore, SCD strengthens firms' capacity to sense green market demand, regulatory changes, and resource supply risks, enabling them to better adapt to external uncertainties and achieve sustainable transformation (Zhao et al. 2023). This is consistent with the DCT. Overall, these findings provide support for H1.

4.2 | Robustness Tests

4.2.1 | Re-Specifying the ML Model

To avoid biases from model specification, we re-specified the DML model's SCD-GTFP link using Gradient Boosting Trees, LassoCV, and Neural Network models, following prior studies that adopted similar robustness strategies (Jia and Xue 2022; Jiang and Sun 2025). Comparing the estimation results across these models helps assess whether the findings depend on a specific algorithm, thereby validating the robustness of the results (Yang et al. 2025a). The results are presented in Table 2. This approach of using multiple ML models to enhance the robustness of empirical results has been validated by numerous studies (Chernozhukov et al. 2018).

TABLE 1 | Basic regression results.

	(1)	(2)	(3)
	Gtfp	**Gtfp**	**Gtfp**
Post*Treated	0.09136***	0.01882***	0.01895***
	(0.00442)	(0.00504)	(0.00496)
_cons	−0.00048	0.00057	0.00085
	(0.00112)	(0.00078)	(0.00073)
Control variables	NO	YES	YES
Control variables^2	NO	YES	YES
Time fixed effect	NO	NO	YES
Industry fixed effect	NO	NO	YES
Learning model		Random forest	
Folds		5 times	
N	3509	3509	3509

Note: Standard errors in parentheses. *$p<0.1$; **$p<0.05$; ***$p<0.01$.

TABLE 2 | Robustness test (re-specified ML models).

	(1)	(2)	(3)
	Gtfp	**Gtfp**	**Gtfp**
Post*Treated	0.03514***	0.06363***	0.04971***
	(0.00500)	(0.00496)	(0.00539)
_cons	−0.00007	0.00005	−0.00074
	(0.00088)	(0.00115)	(0.00136)
Control variables	YES	YES	YES
Control variables^2	YES	YES	YES
Time fixed effect	YES	YES	YES
Industry fixed effect	YES	YES	YES
Learning model	Gradboost	Lassocv	Nnet
Folds		5 times	
N	3509	3509	3509

Note: Standard errors in parentheses. *$p<0.1$; **$p<0.05$; ***$p<0.01$.

The findings are shown in Table 2, where the coefficients of Post*Treated are 0.03514, 0.06363, and 0.04971, respectively, and are all positive and significant. These consistent results across fundamentally different model architectures—tree-based, regularized linear, and nonlinear—indicate that the positive impact of SCD on GTFP is not driven by any particular model. The findings confirm that after re-specifying the ML models, the conclusion that SCD enhances GTFP remains unaffected. This finding can be explained from a theoretical perspective. As a strategic digital resource, SCD enhances firms' ability to allocate and utilize key production resources more efficiently (Le et al. 2024). By improving the visibility, traceability, and responsiveness of supply chain activities, SCD facilitates the optimal use of materials, energy, labor, capital, and information, contributing directly to the enhancement of GTFP, in line with the RBV. From the perspective of the DCT, SCD enables firms to sense environmental changes, seize sustainable innovation opportunities, and reconfigure production processes accordingly (Seyedghorban et al. 2020). These capabilities enable firms to support long-term improvements in GTFP. Therefore, the results align with H1.

4.2.2 | Excluding the Influence of Concurrent Policies

To ensure the estimated impact of the SCD on GTFP is robust, we further consider the potential confounding effects from other implemented policies, following Wu et al. (2024). The 2015 National Big Data Pilot policy promoting digital infrastructure development has been tested to improve GTFP (Lyu et al. 2024). We included this variable in the regression analysis to exclude its potential effect.

Based on the findings in Table 3, the coefficient of Post*Treated is estimated at 0.01909; the positive effect of SCD on GTFP remains robust. This indicates that SCD plays a key role in enhancing firms' GTFP, rather than the effect of other concurrent policies. Through SCD, firms build blockchain and information-sharing platforms. This allows them to accumulate key digital resources such as high-quality data assets and transparent tracking systems (Di Vaio and Varriale 2020). These resources effectively reduce information asymmetry within the supply chain and enhance environmental compliance. This reflects the role of scarce and valuable resources emphasized by the RBV in supporting green governance (Wang et al. 2025). These initiatives enable the rapid application of green innovation resources into production practices, in line with the principles of the DCT. Overall, the robustness of H1 can be supported by the above findings.

4.2.3 | Adding Control Variables

To improve the model specification and reduce omitted variable bias, we optimized several control variables based on relevant

TABLE 3 | Robustness tests (policy influence, control variables, fixed effects).

	(1) Policy Influence	(2) Adding Control Variables	(3) Adding Fixed Effects
Post*Treated	0.01909***	0.01627***	0.00941**
	(0.00490)	(0.00507)	(0.00467)
_cons	0.00072	0.00066	0.00109
	(0.00072)	(0.00074)	(0.00067)
Control variables	YES	YES	YES
Control variables^2	YES	YES	YES
Time fixed effect	YES	YES	YES
Industry fixed effect	YES	YES	YES
Province fixed effect	NO	NO	YES
Learning model	Random forest		
Folds	5 times		
N	3509	3509	3509

Note: Standard errors in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

literature (Gao et al. 2024; Zhou et al. 2024). Initially, we controlled eight variables: firm size, leverage, profitability, largest shareholder ownership, firm age, money supply, marketization, and GDP. To avoid omitted variable bias, we made the following changes: board size was added as a control variable to reflect corporate governance structure, as previous studies have highlighted its significance on firm productivity (Guo et al. 2024); firm age was replaced with listing year, which helps reduce multicollinearity with firm size (Hao et al. 2023); and the largest shareholder ownership was replaced with the ownership of the top five shareholders to better capture control structure (Javeed et al. 2024).

As reported in Table 3, after including board size and substituting the original control variables, the regression outcomes did not undergo substantial changes, validating the model's robustness. The coefficients of Post*Treated is 0.01627. This is because SCD integrates digital technologies and the supply chain to optimize raw material procurement, green supplier selection, and energy efficiency management, enabling more precise control of input resources and thus improving firms' GTFP. This aligns with the RBV, which highlights the importance of valuable and scarce resources in enhancing firm performance (Bienhaus and Haddud 2018). Moreover, SCD strengthens sensing capabilities through real-time data collection, market monitoring, and environmental scanning, allowing firms to identify regulatory shifts and sustainability demands at an early stage (Seyedghorban et al. 2020). This contributes to long-term improvements in GTFP, consistent with the DCT. This finding provides support for the robustness of H1.

4.2.4 | Adding Fixed Effects

Different regions in China possess unique characteristics, such as policy implementation capacity, industrial foundations, and environmental governance levels, which influence firms' GTFP (Gao et al. 2024). To rule out potential biases caused by unobserved regional heterogeneity, this study follows prior research and incorporates provincial fixed effects in the robustness check (Wang et al. 2023). Provinces are essential administrative units in China's governance system, such that cities within the same province share similarities in policy environments, geographical characteristics, and historical and cultural contexts (Yang and Liu 2024). Table 3 presents the findings, which again corroborate the initial findings on SCD and GTFP. As a digital resource, SCD facilitates intelligent manufacturing, equipment condition monitoring, and process tracking, thereby reducing defect rates, minimizing energy redundancy, and enhancing the overall efficiency of production systems (El Baz and Ruel 2024). These improvements not only reduce unnecessary environmental burdens but also optimize the allocation and use of key production inputs, which are essential components of GTFP, thereby contributing to the achievement of SDG 9. This evidence aligns with the RBV. Moreover, from the perspective of the DCT, SCD enhances firms' ability to sense operational inefficiencies, seize technological upgrading opportunities, and reconfigure their production processes toward greener and more sustainable practices (Nguyen et al. 2023). Together, these findings provide strong support for the robustness of H1.

4.2.5 | Endogeneity Test

This study employs Propensity Score Matching as an endogeneity test. This is to address the potential endogeneity issues stemming from the non-random implementation of the SCD. This method constructs comparable samples based on observable characteristics to simulate a quasi-experimental setting, thereby effectively mitigating selection bias (Liu et al. 2022). This method has been widely used to address endogeneity issues in SCD effect evaluations (Zhou et al. 2024; Lyu et al. 2024; Wang et al. 2025).

Table 4 shows that all coefficients are significant (0.106, 0.0902, 0.0600). These findings confirm the reliability of the outcomes obtained through DML. This result also supports H1 and is in line with the RBV and the DCT, indicating that as a strategic digital resource, SCD helps firms improve the allocation efficiency of operational resources and production. This, in turn, enhances their ability to adapt to environmental changes and policy adjustments, promoting the improvement of GTFP. More importantly, the significant improvement in GTFP is also aligned with several SDGs (Tian et al. 2025). By incorporating technologies such as big data, artificial intelligence, and the Internet, SCD pushes digital transformation and enhances industrial technological capabilities. This contributes to the achievement of SDG 9 (D'Adamo 2025). Meanwhile, SCD reduces resource waste and pollution in production, transportation, and other processes,

TABLE 4 | Endogeneity test.

	(1)	(2)	(3)
	Gtfp	Gtfp	Gtfp
Post*Treated	0.106***	0.0902***	0.0600***
	(0.00463)	(0.00458)	(0.00476)
size		0.0106***	0.0121***
		(0.00180)	(0.00192)
lev		−0.0298**	−0.0293**
		(0.0116)	(0.0115)
roa		−0.101***	−0.101***
		(0.0300)	(0.0289)
firmage		0.0843***	0.108***
		(0.00734)	(0.00744)
top1		−0.000486***	−0.000509***
		(0.000128)	(0.000127)
Mi		0.00140	0.00140
		(0.00135)	(0.00135)
GDP		0.00888***	0.00888***
		(0.000747)	(0.000747)
Time fixed effect	NO	NO	YES
Industry fixed effect	NO	NO	YES
_cons	0.969***	0.513***	0.403***
	(0.00210)	(0.0420)	(0.0694)
N	2084	2084	2084
adj. R^2	0.199	0.267	0.385
F	520.1	127.4	18.62
p	5.94e-103	1.72e-137	7.31e-176

Note: Standard errors in parentheses. $*p<0.1$; $**p<0.05$; $***p<0.01$.

thereby promoting SDG 12, 13. Furthermore, SCD improves firms' responsiveness to environmental policies, which supports progress toward SDG 13 (Hao et al. 2023).

4.3 | Mediation Analysis

To investigate the indirect mechanism linking SCD to GTFP, SCR was chosen as a mediating variable with three components: optimizing supply–demand matching, improving supply quality, and maintaining stable supply–demand relationships. To avoid potential endogeneity issues, we employed a two-step method for mechanism testing according to the approach of Shi et al. (2024). This method is widely recognized in recent empirical studies due to its clear causal logic and compatibility with various modeling frameworks (Jiang and Sun 2025; Yin et al. 2025). The results are reported in Table 5.

4.3.1 | Optimization of Supply–Demand Matching

The first and second columns of Table 5 present the DML analysis results for supply–demand matching as a mediator between SCD and GTFP, whereby efficiency and transparency were employed as proxies. The significant (at the 1% level) coefficients of Post*Treated (0.04039 and 0.16688) show that SCD improves the optimization of supply–demand matching, thus increasing GTFP. This finding can be explained from the DCT and resilience theory. SCD enables the integration of artificial intelligence technologies into the supply chain to achieve real-time monitoring and forecasting of market demand and production processes, allowing firms to detect shifts in customer needs or regulatory requirements more rapidly and accurately (Yang et al. 2025b). These capabilities significantly enhance the sensing dimension within the DCT (Leso et al. 2024). At the same time, the result supports resilience theory, as improving supply–demand matching allows firms to maintain operational continuity and reduce vulnerability to external shocks. H2 is supported.

4.3.2 | Improvement of Supply Quality

The Table 5 shows the findings of supply quality as a mechanism. The coefficients of Post*Treated are 0.00334 and 0.33628, respectively, both demonstrating statistical significance. This finding can be explained by resilience theory and supports H3. From the reconfiguration perspective of DCT, SCD helps restructure inefficient or non-compliant supplier networks by embedding digital tools into procurement and quality management systems (Ao et al. 2023; Nguyen et al. 2023). This enables firms to assess, select, and collaborate with more capable and environmentally responsible suppliers, thereby reducing the risk of supply chain disruptions (Zouari et al. 2021). These improvements ultimately promote the enhancement of GTFP.

4.3.3 | Stability of Supply–Demand Relationships

The fifth and sixth columns of Table 5 show the mediating effect of maintaining supply–demand relationships. The coefficients are 0.03213 and 0.01660 (significant at the 10% and 5% levels). These findings elucidate that SCD can boost the ratio of stable customers and their sales, increasing the stability of supply–demand relationships, which improves GTFP and supports H4. This mechanism mirrors the focus on integration capability in DCT-SCD, enabling firms to assimilate customer relationship data and enhance coordination with important customers, stabilizing the supply–demand network and enhancing GTFP, thereby contributing to the achievement of SDG 12, 13. In parallel, the findings are consistent with resilience theory. Specifically, SCD can integrate suppliers, distributors, and logistics providers into a unified digital platform, enabling firms to proactively access external market resources, achieve efficient coordination and rapid response, reduce transaction costs, minimize supply disruptions, and establish more stable long-term partnerships in dynamic environments (Mishra and Singh 2023). Ultimately, this contributes to the improvement of GTFP.

4.4 | Heterogeneity Analysis

4.4.1 | Heterogeneity by Firm Ownership

Considering the significant differences in governance structure, resources, capabilities, and policy dependence between SOFs and private firms, the effects of SCD may vary. As such, referring to an existing study (Javeed et al. 2024), we conducted a group test. As shown in Columns (1) and (2) of Table 6, the positive effect of SCD on GTFP is significant for SOFs, with a coefficient of 0.02785. However, the policies do not have an impact on private firms' GTFP. The reason may be that SOFs are more dependent on policy initiatives, enjoying greater resources and support to implement SCD (Dong and Yang 2024). Additionally, SOFs are usually subject to stringent regulatory oversight when executing policies (Li 2025). In contrast, private firms are more market-oriented; despite having greater flexibility, they face limited resources and market pressures that may delay or diminish their response to policy impacts (Shen et al. 2025). These findings support H5a.

4.4.2 | Industry Heterogeneity

Given that firms in different industries face varying pressures and demands regarding environmental governance and green transformation, the relationship between SCD and GTFP may exhibit heterogeneity. Referring to Wang et al. (2023), we divided

TABLE 5 | Mechanism test results.

	(1)	(2)	(3)	(4)	(5)	(6)
	SCE	**SCT**	**R&D**	**Patent**	**Sta_cus**	**Sta_sale**
Post*Treated	0.04039***	0.16688***	0.00334**	0.33628***	0.03213**	0.01660***
	(0.01438)	(0.04634)	(0.00152)	(0.08493)	(0.01456)	(0.00479)
_cons	−0.00072	0.00054	−0.00025	−0.00975	−0.00169	−0.00021
	(0.00305)	(0.01464)	(0.00027)	(0.01723)	(0.00282)	(0.00110)
Control variables	YES	YES	YES	YES	YES	YES
Control variables^2	YES	YES	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES	YES	YES
Industry fixed effect	YES	YES	YES	YES	YES	YES
Learning model	Random forest					
Folds	5 times					
N	3509	3509	3509	3509	3509	3509

Note: Standard errors in parentheses. *$p<0.1$; **$p<0.05$; ***$p<0.01$.

TABLE 6 | Heterogeneity analysis results.

	(1)	(2)	(3)	(4)	(5)	(6)
	SOE	**Non-SOE**	**HPI**	**Non-HPI**	**EDR**	**Non-EDR**
Post*Treated	0.02785***	0.00942	0.03506***	0.01413*	0.01931***	0.01392
	(0.00666)	(0.00883)	(0.00663)	(0.00747)	(0.00608)	(0.00939)
_cons	0.00054	0.00145	0.00048	0.00051	0.00110	0.00063
	(0.00103)	(0.00111)	(0.00141)	(0.00098)	(0.00078)	(0.00149)
Control variables	YES	YES	YES	YES	YES	YES
Control variables^2	YES	YES	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES	YES	YES
Industry fixed effect	YES	YES	YES	YES	YES	YES
N	1444	2065	1001	2508	3061	448
Learning model	Random forest					
Folds	5 times					

Note: Standard errors in parentheses. *$p<0.1$; **$p<0.05$; ***$p<0.01$.

the sample into heavy-pollution industries and non-heavy-pollution industries to examine the specific effects of SCD across sectors with different environmental burdens. As detailed in Columns (3) and (4) of Table 6, the positive impact of SCD on GTFP is primarily concentrated in heavy-pollution industries, with a coefficient of 0.03506. The analysis confirms H5b. The reason is that these industries face greater environmental pressure and stricter regulatory oversight, creating an urgent need to enhance resource utilization efficiency and reduce emissions through digital technologies (Wang and Su 2025). Consequently, firms in these industries respond more actively to SCD policies, resulting in more noticeable effects. Conversely, firms in less polluting sectors endure limited environmental pressure, leading to lower dependence on and responsiveness to SCD policies.

4.4.3 | Regional Heterogeneity

Considering the substantial gaps in economic growth and infrastructure development across Chinese regions—the eastern region being more developed than the western and central regions—the effects of SCD may vary. By dividing the sample into economically developed regions and non-economically developed regions, we aimed to uncover the specific impacts of SCD in different economic contexts, providing a basis for more precise and regionalized policy formulation. In Columns (5) and (6) of Table 6, it can be observed that the impact of SCD on GTFP is significant for firms in economically developed regions, with a coefficient of 0.01931. In contrast, the impact is not significant for firms in economically underdeveloped regions. H5c is supported by the empirical results. This is because firms in central and western regions find it difficult to benefit greatly from the implementation of SCD through various subsidies, advanced green technologies, and management practices (He et al. 2025). Firms in developed regions, on the other hand, have well-established infrastructure, enhancing the additional benefits of these policies. Consequently, these policies have led to a notable improvement in GTFP in these regions.

5 | Discussion

The findings demonstrate that SCD significantly enhances firms' GTFP, verifying H1. This finding reinforces the RBV, demonstrating that SCD, as a scarce and difficult-to-imitate digital resource, is not merely an optimization tool for supply chains but a critical driver of sustainable development. Meanwhile, the promotion of SCD drives the development of digital infrastructure and enhances industrial technological capabilities, which aligns closely with SDG 9. While prior studies (Zekhnini et al. 2022; Wang and Prajogo 2024) have demonstrated that SCD improves production efficiency and supply chain performance, our findings go a step further by situating SCD within the broader framework of sustainable development, not just operational optimization. Furthermore, unlike previous studies that primarily focused on internal digital transformation within firms (e.g., Sun et al. 2024; Javeed et al. 2025), this study emphasizes that firm-level sustainable development is deeply embedded in the broader supply chain environment. A firm's environmental performance is influenced not only by its own digital initiatives but also by the digitalization of external stakeholders, that is, suppliers, distributors, logistics partners, and government institutions. Moving the focus from the digital initiatives of individual firms to those that span the entire supply chain, this study's analysis delivers a more thorough view of how digitalization advances sustainable development.

Moreover, we found that the SCR has a mediating influence within the SCD–GTFP pathway. As external threats intensify, firms are slowly transitioning from efficiency-based supply chain strategies to resilience-oriented models (Belhadi et al. 2024). In this shift, SCD helps firms sense, seize, and reconfigure to respond to unexpected events by several mechanisms to improve GTFP. Specifically, digital tools facilitate the optimization of demand–supply matching and strengthen the connection between producers and consumers, thereby reducing resource waste and securing the supply of critical raw materials, which ultimately improves GTFP. This aligns with the core objectives of SDG 12 and supports H2 as well as resilience theory, which expounds firms' resistance to and recovery from shocks. Previous studies have highlighted the role of SCD in enhancing market transparency (Tiwari et al. 2024). This study extends that perspective by demonstrating how such transparency also contributes to environmental sustainability. SCD enhances supplier quality by facilitating the monitoring of green compliance and enabling the reconfiguration of inefficient supply chains. Through these improvements, firms can recover swiftly after disruptions, preserve day-to-day operations, safeguard environmental goals, and ultimately, boost GTFP and SDG 12. This finding supports H3 and reflects the reconfiguration dimension of DCT. Additionally, SCD contributes to stabilizing partner relationships and maintaining production continuity in the face of external shocks, thereby enhancing firms' GTFP and contributing to the goals of SDG 13. This finding supports H4 and the integration capability emphasized in DCT. Therefore, the mediation of SCR resonates with the logic of resource reconfiguration and environmental adaptability advocated by the DCT and resilience theory. This study complements the works of Dubey et al. (2023) and Ghobakhloo et al. (2025), who revealed the relationship between SCD–SCR and the direct impact of digitalization on dynamic capabilities. We expand their perspective to sustainable development that is, GTFP.

In addition, the heterogeneity analysis reveals that the positive impact of SCD on GTFP is primarily concentrated in SOFs, firms in pollution-intensive industries, and those located in economically developed regions, thereby confirming H5. Firms that exhibit greater improvements in GTFP tend to have stronger access to critical resources such as funding, policy support, and infrastructure. Meanwhile, these firms are subject to more stringent environmental supervision (Wang and Su 2025) and demonstrate a higher sensitivity to external risks, which enhances the effectiveness of SCD implementation. Consequently, the development of digital infrastructure and technological capabilities is accelerated, contributing positively to the achievement of SDG 12 and SDG 13. These results indicate that the value of core resources in enhancing sustainable competitive advantage is not uniform but depends on the firm's specific contextual conditions. This insight extends the static perspective of the RBV by highlighting the interdependence between resource deployment and organizational context in driving sustainability outcomes. This study builds upon the findings of Li (2025);

Wang and Su (2025), who argue that SCD in SOFs has a stronger impact on environmental governance. By introducing GTFP as the dependent variable, we conceptualize digitalization as a means to simultaneously enhance environmental performance and production efficiency, thereby reflecting a broader perspective on the sustainable development potential of SCD.

5.1 | Theoretical Implications

This study reveals the significant positive impact of SCD on GTFP, expanding the RBV. It demonstrates that SCD is not merely a tool for optimizing supply chain management but also a scarce and inimitable strategic resource that empowers firms' environmentally sustainable development. In light of rapid digital advancements in China, our investigation of the link between SCD and GTFP is particularly timely. Additionally, by applying the DCT, this study constructs an SCD-SCR-GTFP theoretical framework, demonstrating how digital resources become key assets for firm-level sustainable development. Amid evolving environmental policies and market fluctuations, firms must enhance the adaptability of their supply chain to successfully achieve green development. To this end, we provide new theoretical support for the application of the DCT in sustainable development. In addition, our heterogeneity analysis establishes a more context-adaptive SCD–GTFP framework, reinforcing the resource heterogeneity principle within the RBV. Specifically, the value of resources is not universally applicable but depends on the alignment and support of the external environment, thereby challenging the traditional static assumption of resource value embedded in the RBV. This also echoes the central proposition of DCT, which emphasizes that the value of capabilities varies in different external environmental contexts.

5.2 | Practical Implications

Based on the findings, we propose several practical implications for firms seeking environmental sustainability. First, our findings show that firms with higher investment in digital procurement tools reported a 9.1% increase in GTFP, suggesting that management should regard SCD as a strategic investment in sustainable competitiveness, with the goal of advancing SDG 9. Specifically, firms should adopt concrete digital tools for supply chain management such as AI-driven demand forecasting systems, green supplier databases, and cloud-based production scheduling platforms. These improvements can be tracked through key environmental performance indicators such as carbon emissions and energy consumption, allowing firms to align digital upgrades with measurable sustainability outcomes. In doing so, they also support supply chain collaboration and the development of digital infrastructure, further contributing to the achievement of SDG9. However, especially for small and medium-sized firms, financial constraints, limited digital skills, and resistance to transformation pose real challenges. To address these issues, firms should adopt phased implementation strategies, begin with lightweight digital modules, provide employee training programs, and establish partnerships with local governments or third-party platforms to facilitate sustainable development. For example, SMEs can start with cloud-based invoice management, digital contract signing, or online supplier onboarding platforms, which require minimal investment but deliver high process efficiency.

Second, we find that SCR plays a mediating role in the relationship between SCD and GTFP. Accordingly, investments in SCD should prioritize the development of SCR. Firms should apply technologies such as the IoT and blockchain to establish automated supply–demand alignment systems and monitor supplier compliance. Specifically, firms can monitor key environmental metrics such as supplier carbon intensity, recycling rates, or energy efficiency via IoT-enabled devices and integrate them into digital dashboards for real-time decision-making. These technologies enhance firms' ability to adapt to and recover from external shocks, ensuring the continuity of supply chain operations. They also help build cleaner, more traceable, and more collaborative supply chain ecosystems, making a positive contribution to the achievement of SDG12. For instance, Alibaba's Cainiao Network used blockchain technology to verify suppliers' green certifications and applied digital scorecards to monitor partner performance, demonstrating exceptional effectiveness during the COVID-19 pandemic.

Third, SOFs in economically developed regions are advised to fully utilize their advantages in resource control, digital infrastructure, and policy support to promote broader and more systematic SCD strategies. For instance, firms can carry out green collaboration initiatives with suppliers through digital platforms and develop AI-powered tools for clean production scheduling. These strategies enable end-to-end sustainable supply chain management, further amplifying the environmental benefits of digitalization and supporting sustainable development. For small and medium-sized firms, especially those in less developed regions, weak infrastructure and limited digital capabilities present significant challenges. It is recommended to provide digital literacy training, subsidies for cloud platform access, or modular digital tools tailored to low-resource environments, thereby expanding the reach of digitalization and sustainable development, and supporting climate action in line with SDG13.

5.3 | Policy Recommendations

Our findings offer important policy implications as well. First, given the significant impact of SCD on improving firms' GTFP, policymakers should take the lead in gradually expanding pilot areas for SCD implementation. To stimulate digital investment, policymakers can introduce targeted instruments such as performance-based subsidies (e.g., tied to carbon reduction achievements) and tax incentives for digital infrastructure investment. Specifically, firms that procure green digital equipment and services such as carbon footprint calculation platforms should be eligible for corporate income tax deductions. Effective implementation also requires overcoming institutional barriers, including weak interagency coordination and inconsistent enforcement at the local level. Establishing coordination mechanisms across departments and piloting digital policies through regulatory sandboxes helps strengthen digital infrastructure and supports the realization of SDG9.

Moreover, SCR plays a mediating role in the relationship between SCD and GTFP, and policy should emphasize the importance of strengthening SCR. Specifically, the government can provide financial and resource support for firms to build data-driven real-time supply and demand matching platforms and AI-based inventory management systems through targeted subsidies, service voucher schemes, or by co-developing industrial infrastructure with platform firms. These efforts help strengthen the connection between producers and consumers, enable firms to better sense market dynamics and respond to sudden disruptions, and ultimately enhance environmental sustainability, thereby contributing to the achievement of SDG12.

Furthermore, it is crucial to adapt SCD to local contexts. Specialized policy support and funding should be provided for SOFs to lead the way in digital transformation, thereby elevating the overall level of industry digitalization. For example, the government supports SOFs in implementing blockchain-based emissions recording and digitalized supplier evaluation systems. For high-pollution industries such as steel, chemicals, and cement, the implementation of digital environmental compliance supervision mechanisms should be accelerated. Key firms should be required to adopt emission visualization platforms and undergo annual environmental audits. In addition, for firms in economically developed regions, the government should increase support by offering technical training, financial subsidies, and market promotion assistance to help them overcome difficulties in their SCD process. For small and medium-sized firms, especially those in less developed regions, the government should provide digital training programs and subsidies for access to cloud-based tools to lower the barriers to transformation and promote broad participation. For example, digital green operations training programs can be established at local vocational colleges, and local chambers of commerce can organize joint procurement of cloud services to reduce costs. These measures contribute to the realization of SDG13 by enabling a more inclusive and resilient low-carbon transition.

5.4 | Limitations

Despite addressing key literature gaps on the SCD-GTFP relationship and expanding the application of DML, some limitations remain in this study. First, this study does not account for other potential influencing factors such as market competition or regional culture. Future studies could incorporate these variables to deepen the understanding of the mechanisms affecting GTFP. Second, considering that the study addresses Chinese firms in the context of sustainable development and the SDGs, the lack of discussion on China's national strategies or contributions to the UN 2030 Agenda represents a notable gap. A clearer positioning of China's role in global sustainability efforts could provide important context and further reinforce the relevance of the study. Third, SCD and environmental sustainability provide a relevant and representative context for this study. Future studies could replicate the study design in other countries or regions, such as Europe and the United States, to further assess the generalizability and external validity of the findings. Fourth, given that the DML approach helps mitigate omitted variable bias and partially addresses endogeneity concerns, this study does not employ the GMM instrumental variable method. Instead, it uses propensity score matching for checks related to endogeneity. Future studies could consider incorporating GMM-based approaches to further validate the effectiveness of DML in addressing endogeneity issues. Additionally, as customer information disclosure in the supply chain is voluntary and many firms do not disclose such data, future studies could use alternative indicators or incorporate external data sources to supplement the analysis.

6 | Conclusion

The world is facing severe environmental challenges, making the promotion of sustainable development a critical goal for governments and firms alike. In this context, GTFP has emerged as a key metric for assessing sustainable development, as it comprehensively measures both economic efficiency and environmental impact. Meanwhile, the rapid development of digital technologies, particularly in the supply chain, is profoundly reshaping firm operations by enhancing inter-firm connectivity and collaborative efficiency. Meanwhile, as a country with one of the highest levels of pollution emissions and fastest growth in technological development, China's SCD practices hold significant value for global sustainable development. As such, it is imperative to understand how SCD in the Chinese market influences firms' GTFP.

To achieve this objective, we employed the DML technique to analyze the influence of SCD on GTFP among China's A-share listed firms, with a focus on SCR's mediating role and firm-based heterogeneity. Our results show that SCD significantly improves GTFP, suggesting that digitalization, as a unique digital resource, facilitates improvements in firms' operational efficiency and resource utilization. This finding extends the RBV, originally focused on economic performance, to encompass environmental performance, thereby enriching its relevance to sustainable development. We also establish SCR as a mediating mechanism in this process. This is because SCD provides data and technological foundations that enhance firms' ability to cope with external shocks and internal uncertainties, thereby ensuring the continuity and efficiency of green production and promoting improvements in GTFP. This mechanism clarifies the critical role of digitalization in the formation of dynamic capabilities and enriches the theoretical connotation of DCT. Finally, our heterogeneity analysis shows that SCD's positive effect on GTFP is strongest in SOFs, pollution-intensive industries, and economically advanced regions. Policy makers should therefore expand SCD programs in these priority areas, while firms should invest in their digital capabilities and supply chain management to enhance both environmental and operational performance. Although this study focuses on Chinese listed firms, its underlying mechanisms and methodological approach have broader applicability to other countries. While this study is rooted in China's institutional context, the DML approach offers a replicable empirical framework for assessing the complex interactions between digitalization and sustainability across different economies. Future research could further advance this line of inquiry by incorporating additional factors such as market competition and employing cross-national data to better support the achievement of the SDGs.

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Conflicts of Interest

The authors declare no conflicts of interest.

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