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Drivers of Digital Traceability System Adoption for Greenhouse Gas Emissions in Complex Supply Chains

Sukrit Vinayavekhin[1] | Aneesh Banerjee[2] | Feng Li[2] | Davide Luzzini[3,4]

[1]Thammasat Business School, Thammasat University, Bangkok, Thailand | [2]Bayes Business School (formerly Cass), City St George's University of London, London, UK | [3]EADA Business School, Barcelona, Spain | [4]Business School, LUT University, Lappeenranta, Finland

Correspondence: Aneesh Banerjee (aneesh.banerjee@citystgeorges.ac.uk)

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ABSTRACT

The global climate crisis is pushing firms toward sustainable supply chain practices, with digital technology offering a vital pathway to track greenhouse gas (GHG) emissions. This research investigates the factors influencing the adoption of digital traceability systems for managing these emissions, focusing on implementation scope and supply chain complexity (SCC). Drawing on Institutional Theory and Transaction Cost Economics, we conducted a choice-based conjoint experiment with managers in manufacturing sectors to capture the trade-offs in their decision-making process. Our results show that firms are more likely to consider technology solutions when (a) those solutions cover Scope 1, 2, and 3 GHG emissions, and (b) there is greater SCC due to 'detail-numerousness' (number of elements in a system) and 'detail-variety' (heterogeneity of these elements). However, dynamic complexity (changing nature of elements) has an ambiguous impact on technology adoption. "Detail-numerousness" (e.g., number of products produced) is the most critical attribute for internal operations, while "detail-variety" (e.g., geographical dispersion and supplier heterogeneity) has the greatest impact on upstream supply chains. This research extends the supply chain technology adoption literature by providing a nuanced empirical understanding of how distinct dimensions of SCC at both internal and upstream levels shape the adoption of digital traceability.

1 | Introduction

The global climate crisis, driven by a dramatic increase in greenhouse gas (GHG) emissions, represents one of the most significant challenges of our time (Zhang et al. 2024). Although supply chains are recognized as the primary locus for environmental sustainability intervention, empirical research regarding the management of supply chain emissions remains nascent (Wieland and Creutzig 2025). Central to the work of building sustainable supply chains is the requirement for transparency and traceability of supply chain data (c.f., Vinayavekhin et al. 2024). However, as most emissions (particularly, the Scope 3 emissions) stem from upstream supply chain activities, they frequently reside beyond the focal firm's direct visibility, making accurate and comprehensive traceability a major challenge (Hettler and Graf-Vlachy 2024).

We argue that supply chain complexity (SCC) serves as a formidable structural barrier to these efforts, wherein the high number, variety, and dynamic nature of supply chain elements (Choi et al. 2001) complicate the collection and verification of emissions data. As a consequence, digital traceability systems (DTSs) are often seen as the foundational step toward developing a true understanding of supply chains' environmental impact and ultimately reducing overall emissions (El Hathat et al. 2023). Evidence shows that DTSs assist in the pivot from symbolic sustainability (i.e., relying on industry averages and secondary proxies) to substantive sustainability (i.e., based on primary data) (Shalique et al. 2022). However, despite the potential to leverage technologies such as automation, blockchain, and Artificial Intelligence (AI) to improve supply chain traceability via real-time data sharing (Sanders et al. 2019) and to reduce information asymmetry among supply chain actors (Kurpjuweit et al. 2021), adoption rates of DTSs remain paradoxically low. This implementation gap necessitates a more rigorous investigation into the drivers of DTS adoption (George et al. 2022).

In this paper, we contribute to the literature by examining the drivers of DTS adoption for GHG-emissions traceability, particularly how this decision is shaped by the complexity of supply chains. We investigate how the scope of supply chain technology adoption and the complexity of firms' internal operations and upstream supply chains influence firms' implementation of digital technologies for tracing GHG emissions. Our research is therefore guided by the following research questions:

1. How does the scope of GHG emissions (i.e., Scope 1, 2, and 3) influence a firm's likelihood of adopting a DTS?
2. How do different dimensions of supply chain complexity influence the adoption of DTS?

Building on key concepts from Institutional Theory and Transaction Cost Economics (TCE), we employ a choice-based conjoint (CBC) experimental design that combines both quantitative and qualitative responses from managers with decision-making responsibilities in their operations and supply chains. Our findings reveal the importance of adopting digital technologies for tracing not only direct emissions (i.e., Scope 1) but also indirect emissions (i.e., including all Scopes 1, 2, and 3), achieving a more holistic understanding of the entire supply chain. Our research also highlights that the complexity of both firms' internal operations and their upstream supply chains affect the implementation of supply chain digital technologies.

Our research makes three primary theoretical contributions. First, we respond to the call by Yang et al. (2021) and empirically test how emissions scope and supply chain complexity shape DTS adoption. Second, we disentangle the effects of distinct SCC dimensions (i.e., detail-numerousness, detail-variety, dynamic complexity) at both internal and upstream levels (Akın Ateş et al. 2022). Third, we advance experimental approaches in supply chain decision-making by using CBC to quantify managerial trade-offs and derive actionable adoption guidance (c.f. Banerjee et al. 2021; Vinayavekhin et al. 2024). In addition, the findings of this research provide practical guidance for industry practitioners on how to strategically implement a DTS for improving sustainability within their supply chains.

2 | Literature Review

2.1 | GHG Emissions Traceability

GHG emissions traceability is crucial for understanding and minimizing the environmental impact of supply chains. In this paper, we follow Garcia-Torres et al.'s (2019) definition of GHG traceability as: "the ability to track and verify the origin, movement, and transformation of materials and products throughout a supply chain, specifically focusing on their associated greenhouse gas emissions". We follow the GHG Protocol's three-scope structure: Scope 1 (direct operational emissions), Scope 2 (indirect energy emissions), and Scope 3 (other indirect supply-chain emissions) (Downie and Stubbs 2012). Scope 3 is especially challenging because it depends on data from external partners and often lies beyond a focal firm's direct visibility (Patchell 2018). Notably, the three scopes can overlap within the same supply chain. For instance, a firm's Scope 3 emissions often coincide with its supplier's Scope 1 emissions, emphasizing the interconnected nature of supply chains.

Among the three scopes, Scope 3 emissions are often the most material, as they can constitute up to 80% of the total GHG footprint (Naqvi 2021). The Carbon Disclosure project (CDP) reports that firms' upstream emissions are, on average, 26 times higher than their direct operational emissions (CDP 2024), highlighting the substantial impact of Scope 3 in comprehensive emissions reduction strategies. However, tracing Scope 3 emissions remains a challenge. While legal requirements for mandatory disclosure are still evolving, a growing number of companies are voluntarily reporting their Scope 3 emissions, driven by factors such as investor pressure and sustainability commitments. Reporting rates vary, influenced by the varying regulatory landscapes across different regions. In Europe, the Corporate Sustainability Reporting Directive (CSRD) has come into force to mandate the reporting of Scope 3 emissions (European Commission 2023). This has led to regional disparities in reporting, with European firms showing higher rates of disclosure compared to those in other parts of the world (Hadziosmanovic et al. 2022).

Tracing Scope 3 emissions is difficult, leading to two main strategies for gathering data. The first and most common method relies on secondary data, which uses industry averages, financial estimates, or other proxies. Firms typically use this approach when they cannot access emission data from their upstream suppliers (Huang et al. 2009). In contrast, a more accurate approach uses primary data. This involves collecting actual emission details directly from suppliers through utility bills, purchase records, or direct equipment monitoring (Stenzel and Waichman 2023). DTSs are expected to be essential in this area, as they help companies efficiently collect, track, and share relevant GHG emission information across the supply chain (Chan 2022).

2.2 | Adoption of Digital Traceability Systems

A Digital Traceability System (DTS) is a type of supply chain technology whose implementation extends beyond the boundaries of an individual firm, covering processes and activities outside internal operations and often across the entire supply chain (Yang et al. 2021). This paper does not focus on specific technologies, but rather on the core functions of DTSs: capturing, storing, and sharing GHG emissions data. We conceptualize DTSs as socio-technical configurations that include not only the digital infrastructure supporting these functions, but also the organizational processes, human decision-making, and collaborative norms required to ensure data integrity and system transparency.

Compared with traditional paper-based methods, DTSs enable faster, more accurate, and more cost-effective traceability (Gligor et al. 2021). Using digital technologies such as sensors and radio frequency identification (RFID), DTSs can efficiently capture and retrieve relevant data (Hastig and Sodhi 2020). Their standardized data formats and communication protocols also facilitate information exchange among supply chain partners (Roeck et al. 2020). In addition, implementation costs may be lower because DTSs are less sensitive to scale and can reduce repetitive manual processes such as paperwork (Kamble et al. 2020). Another key advantage is real-time data sharing, which improves visibility across the supply chain (Sanders et al. 2019). Furthermore, novel technologies such as blockchain can enhance data security and transparency through decentralized and tamper-resistant architectures (Saberi et al. 2019).

Despite these benefits, the academic literature on the adoption of digital traceability in supply chains has notable limitations. Most extant studies are either literature reviews or conceptual papers (Chang et al. 2020; Pournader et al. 2020; Queiroz et al. 2019; Schilling and Seuring 2024; Wang et al. 2018). A limited number of papers have empirically examined the drivers of DTS adoption in supply chains, including managerial and technical factors (Kim et al. 2012); organizational readiness and company size (Clohessy and Acton 2019); perceived usefulness (Kamble et al. 2019); relative advantage, compatibility, and complexity of technology (Agi and Jha 2022); and ability to enhance job-related tasks (Queiroz and Fosso Wamba 2019). However, these studies have largely focused on technological characteristics or firm-level organizational factors (Yang et al. 2021), while overlooking the characteristics of the supply chain itself.

This omission represents an important research gap, particularly in the context of GHG traceability, where the success of implementation depends on data sharing across the supply chain. Although the focal firm formally decides whether to adopt a DTS, the value of that decision depends on the willingness and capability of upstream partners to exchange reliable emissions data. This makes DTS adoption an inter-organizational governance problem rather than a purely intra-firm technology decision. For example, upstream suppliers, many of which are SMEs, often lack the resources, technical expertise, and financial capacity required to participate effectively (Garcia-Torres et al. 2019). This challenge is further compounded by limited data interoperability, as the absence of harmonized standards and integrated data structures across suppliers remains a major obstacle (Jaeger et al. 2022). In practice, firms such as American Tire Distributors have partnered with CO2AI by BCG to develop digital platforms that monitor emissions while facilitating collaboration among suppliers and retailers. Such initiatives highlight the importance of collaborative platforms and resource-sharing mechanisms in strengthening supplier capabilities (Meinecke et al. 2022). Therefore, the existing technology adoption literature remains underdeveloped for inter-organizational settings, where supply-chain-level barriers play a central role.

2.3 | Supply Chain Complexity (SCC)

Most of the SCC literature connects to Simon's systems theory, which defines a complex system as "a system that includes a large number of varied elements that interact in a non-simple way" (Simon 1962, 468). Perspectives on SCC might vary, but it is common in the literature to split it into levels (i.e., upstream, internal, and downstream) and sub-dimensions (i.e., detail and dynamic), as confirmed by the most cited studies (Bozarth et al. 2009; Bode and Wagner 2015) and some recent literature reviews on the topic (Akın Ateş and Luzzini 2024; Akın Ateş et al. 2022).

In terms of the various levels of SCC, Bozarth et al. (2009) argue that complexity can originate from three distinct levels. At the firm level, complexity refers to the firm's internal operational processes, reflecting for instance the number of product variants. It can also arise from interactions beyond the firm's boundaries, involving its upstream suppliers and downstream customers. The authors argue that different levels deserve to be considered independently, as a firm may possess a highly complex upstream supply chain while maintaining relatively less complex internal operations and vice versa.

Building on these seminal studies and the most recent meta-analysis on the topic (Akın Ateş et al. 2022), we focus our investigation on upstream and internal SCC (in line with the scope of our research) and consider its sub-dimensions as summarized in Table 1. In particular, SCC as detail-numerousness refers to the number of elements defining the system (Bozarth et al. 2009), detail-variety represents the variety of elements defining the system (Fernández Campos et al. 2019), and dynamic SCC captures

TABLE 1 | Dimensions of SCC (adapted from: Akın Ateş et al. 2022; Akın Ateş and Luzzini 2024; De Stefano and Montes-Sancho 2024).

SCC	Internal	Upstream
Detail-numerousness	• Number of products shipped by plant • Number of active parts • Number of services	• Number of tier-1 suppliers • Number of strategic suppliers
Detail-variety	• Variety of products produced • Percentage of customized products	• Location variety of tier-1 suppliers • Variety of tier-1 suppliers' size
Dynamic	• Changes in product varieties • Redesign changes • Core production processes changes	• Changes in number of suppliers • Delivery changes from suppliers

Source: Authors' own work.

the unpredictability, randomness, or frequent changes caused by interactions between the elements of the system (Bode and Wagner 2015). These sub-dimensions have been analyzed by previous studies both in terms of internal operations and upstream supplier management, allowing us to borrow specific measures for each level-type combination (see Table 1).

Up to date, few or no empirical studies have been conducted on the relationship between SCC and the implementation of digital traceability (Wissuwa et al. 2022). The prevailing assumption is that firms use digital technologies to manage the challenges of SCC (Liu et al. 2022; Nižetić et al. 2019). For example, a recent study suggests that the benefits of technologies are more pronounced in complex supply chains with numerous processes and stakeholders, highlighting SCC's role as a significant moderator for technology adoption (Bakici et al. 2025). However, some studies, especially those related to resilience and disruption, also argue that high complexity can undermine resilience and increase the risk of supply chain disruptions (Wiedmer et al. 2021). This creates a critical ambiguity: does complexity primarily encourage or discourage the implementation of digital systems? Moreover, the simultaneous investigation of different complexity dimensions at different levels remains scarce (Akın Ateş et al. 2022). For these reasons, in the next section, we develop specific hypotheses on the effect of these distinct levels and dimensions of SCC.

3 | Hypothesis Development

In this research, we adopt a dual-theory approach to examine the drivers of DTS adoption: Institutional Theory and Transaction Cost Economics (TCE). While Institutional Theory explains the external social and regulatory pressures that motivate firms to seek legitimacy (DiMaggio and Powell 1983), TCE focuses on the internal governance structures and efficiency considerations required to manage complex supply chain transactions (Williamson 1981). By integrating these perspectives, we distinguish between two mechanisms shaping DTS adoption. Institutional Theory explains why firms face external pressure to extend GHG traceability beyond organizational boundaries, whereas TCE explains how the costs of coordinating, monitoring, and verifying emissions data shape the feasibility and attractiveness of DTS adoption under different forms of supply chain complexity.

3.1 | Impact of Technology Scope on the Adoption of DTSs

In the context of GHG traceability, the scope of emissions covered across the supply chain is an important determinant of DTS adoption. As mentioned earlier, Scope 1 emissions are generally the easiest to trace, followed by Scope 2 and Scope 3 emissions (Downie and Stubbs 2012). However, limiting traceability efforts to Scope 1 and Scope 2 emissions provides only a partial representation of a firm's environmental impact, as emissions generated by external supply chain stakeholders can account for up to 80% of a firm's total GHG footprint (Naqvi 2021).

From a theoretical perspective, Institutional Theory suggests that coercive (e.g., regulatory and buyer mandates), normative (e.g., industry standards and certifications), and mimetic (e.g., peer benchmarking) pressures define the socially constructed boundaries of corporate responsibility (DiMaggio and Powell 1983). In the context of GHG traceability, these pressures increasingly dictate that legitimate transparency must extend beyond a firm's internal operations to include Scope 3 emissions (Hettler and Graf-Vlachy 2024). While a TCE perspective might suggest that firms should limit adoption to the most cost-efficient and easily monitored scope such as Scope 1 emissions, institutional isomorphism creates a mandate for broader implementation (Zhu et al. 2013). Thus, firms adopt a full-scope DTS (i.e., Scopes 1, 2, and 3) not solely for operational efficiency, but to bridge the legitimacy gap created by coercive regulatory frameworks, such as the EU Corporate Sustainability Reporting Directive (European Commission 2023), as well as normative pressures from industry initiatives such as the Science Based Targets initiative (SBTi) and CDP supply chain programmes (CDP 2022). Therefore, the selection of implementation scope represents a strategic response to institutional demands for comprehensive supply chain disclosure, leading to the following hypothesis:

H1. *Firms are more likely to implement DTSs when the implementation scope extends beyond Scope 1 emissions to include Scope 2 and upstream Scope 3 emissions.*

3.2 | Impact of Internal Complexity on Digital Traceability Adoption

Building on the dual-theory approach, we argue that Institutional Theory and TCE are integrated through a sequential decision-making logic. While institutional pressures identify the need for DTS adoption to maintain legitimacy, TCE explains the operational feasibility of such adoption. According to TCE, firms select governance structures designed to minimize transaction costs (Williamson 1981). In the context of GHG reporting, internal transaction costs rise when firms must repeatedly collect emissions data across many products, processes, and facilities. They also rise when firms need asset-specific investments such as emissions-accounting routines, specialized data architectures, and trained personnel that have limited value outside GHG traceability. This is because firms must invest in specialized human capital and systems tailored to unique reporting requirements that typically hold little value outside of this specific application (Ketokivi and Mahoney 2020). Thus, firms may adopt DTSs as novel governance mechanisms to manage these costs more effectively.

To develop hypotheses about the impact of internal complexity, we build on the meta-analysis by Akın Ateş et al. (2022) and summarize representative examples of three dimensions of complexity, namely detail-numerousness, detail-variety, and dynamic complexity, for internal operations and upstream supply chain in Table 1. We acknowledge that the three dimensions of complexity can also lead to high implementation costs and extended timelines for implementation (Bode and Wagner 2015). However, we propose that holding these factors constant, firms with high internal complexity are more likely to consider implementing DTSs as follows.

Firstly, the internal detail-numerousness refers to the number of elements involved (Akın Ateş et al. 2022). An example includes the high number of products produced and services offered (Bozarth et al. 2009; Saldanha et al. 2013), leading to an increased frequency of GHG-related data transactions that must be managed. When internal detail-numerousness is high, the frequency of GHG-related data transactions increases substantially because there would be multiple data touchpoints. According to TCE, such high transaction frequency justifies creating specialized governance structures to achieve economies of scale in management and control (Williamson 1981). Compared with manual data collection and monitoring, which are inefficient for high-frequency transactions, DTSs automate these recurrent transactions, significantly lowering the marginal cost of monitoring each product and process (Kamble et al. 2020). Moreover, by facilitating easier data collection, processing, and analysis, such a DTS can also significantly reduce the risk of errors such as missing information and double-counting (Ivanov et al. 2019). Thus, we hypothesize that:

H2a. *Keeping the implementation cost and time constant, the higher the internal SCC in terms of detail-numerousness, the more likely firms are to implement DTSs.*

Secondly, detail-variety captures the complexity caused by the variety of elements involved within firms' internal operations. Representative examples are the range of product varieties and the number of customized products (Gray and Handley 2015; Roscoe et al. 2020). Each product variant may demand unique methodologies for GHG measurement and reporting, complicating data integration and increasing the transaction costs of coordination across different data points (Garcia-Torres et al. 2019). Thus, the higher the range of product varieties, the more difficult it is to maintain consistent standards and accurate aggregation of emissions data within internal operations. However, several prior studies have provided evidence that manufacturing firms with strong digital capabilities can collect and manage a wider variety of data (Bharadwaj et al. 2007). DTSs can mitigate these costs by imposing standardized data protocols and communication formats (Roeck et al. 2020), lowering the transaction costs of ensuring data integrity and comparability across a varied product portfolio. Thus, we hypothesize that:

H2b. *Keeping the implementation cost and time constant, the higher the internal SCC in terms of detail-variety, the more likely firms are to implement DTSs.*

Lastly, the dynamic dimension captures the unpredictability and changing nature of internal operations. This can be influenced by factors such as changes in the number of product varieties and frequent alterations in manufacturing processes (Gray and Handley 2015; Merschmann and Thonemann 2011). High operational dynamic complexity makes it challenging to manually collect and maintain accurate emissions data. According to TCE, monitoring costs escalate when internal process uncertainty is high, as constant changes require more frequent and complex oversight (Williamson 1981). In response, digital technologies can collect data continuously and provide early detection of changes in manufacturing processes, such as electricity usage, machine conditions, and resource productivity (Nižetić et al. 2019). In such contexts, digital traceability serves as an efficiency-enhancing governance mechanism. It reduces the administrative burden and supports adaptive coordination by ensuring that emissions data is up-to-date (Liu et al. 2022). Thus, we hypothesize that:

H2c. *Keeping the implementation cost and time constant, the higher the internal SCC in terms of dynamic complexity, the more likely firms are to implement DTSs.*

3.3 | Impact of Upstream Complexity on Digital Traceability Adoption

In managing GHG emissions, the challenge extends beyond a firm's internal operations. From a TCE perspective, the complexity arising from upstream supply chains increases coordination and monitoring costs because firms must exchange, verify, and enforce information across organizational boundaries (Choi and Krause 2006). Managing upstream GHG emissions is therefore fundamentally a challenge of governing inter-firm transactions to mitigate contractual hazards. In response, DTSs provide a structural solution by enabling supply chain partners to share standardized data, improve transparency, and reduce opportunistic behavior (Queiroz et al. 2019; Raj Kumar Reddy et al. 2021). Thus, DTSs should be viewed not only as technological tools, but also as governance mechanisms that help reduce transaction costs in complex external environments (Ketokivi and Mahoney 2020; Roeck et al. 2020).

Building on this argument, we propose that, similar to complexity within a firm's internal operations, upstream SCC significantly influences a firm's decision to adopt digital technologies for tracing GHG emissions. In the following sections, we distinguish between structural forms of upstream complexity (i.e., detail-numerousness and detail-variety), and dynamic complexity. This distinction is important because structural complexity increases the number and heterogeneity of data exchanges, whereas dynamic complexity increases uncertainty about whether stable data-sharing routines can be developed (see Table 1). Although these dimensions may also increase implementation costs and extend implementation timelines (Bode and Wagner 2015), we argue that, holding these factors constant, firms facing greater upstream complexity are more likely to adopt DTSs.

The first dimension, detail-numerousness in this context, refers to the quantity of elements within an upstream supply chain (Akın Ateş et al. 2022). Examples include the total number of upstream suppliers across all tiers (Dong et al. 2020), key suppliers (Vanpoucke et al. 2014), or tier-1 suppliers (De Stefano and Montes-Sancho 2024). According to TCE, as the number of upstream suppliers increases, so do the transaction costs associated with searching, negotiating, and monitoring supplier relationships and their GHG emissions (Williamson 1981). A larger supplier base also increases behavioral uncertainty regarding data integrity and expands the number of data-sharing interactions that must be governed (Schmidt and Wagner 2019). To address these challenges, digital technologies can provide scalable governance solutions that reduce the marginal transaction costs of managing supplier relationships (Kamble et al. 2020). By standardizing supplier onboarding and data collection processes, DTSs enable firms to manage large and complex upstream supply chains more efficiently than traditional manual approaches (Ivanov et al. 2019). Thus, we hypothesize that higher upstream numerousness strengthens the economic argument for implementing DTSs:

H3a. *Keeping the implementation cost and time constant, the higher upstream SCC in terms of detail-numerousness, the more likely firms implement DTSs.*

Another dimension, detail-variety, refers to the heterogeneity of elements within an upstream supply chain (Akın Ateş et al. 2022). Examples include supplier dispersion across countries (Dong et al. 2020) and differences in supplier characteristics such as firm size, industry, sustainability performance, and technological capabilities (Steven et al. 2014). According to TCE, this variety increases the difficulty and cost of establishing common reporting standards and verifying data from disparate sources. In response, digital solutions serve as a potent governance tool by creating a standardized framework for data exchange (Roeck et al. 2020). By imposing a common language and set of rules on all suppliers, these systems reduce the transaction costs associated with coordinating a heterogeneous network (Schmidt and Wagner 2019). Thus, we hypothesize that:

H3b. *Keeping the implementation cost and time constant, the higher the upstream SCC in terms of detail-variety, the more likely firms implement DTSs.*

The third dimension, dynamic complexity, refers to unpredictability and frequent changes within upstream supply chains (Akın Ateş et al. 2022). Examples include fluctuations in delivery quantities from suppliers (Brandon-Jones et al. 2015) and frequent supplier switching (Fernández Campos et al. 2019). According to TCE, such volatility represents a high degree of environmental uncertainty, which significantly increases the costs of monitoring and enforcement (Williamson 1981). Focal firms must contend with the constant need to renegotiate terms and verify compliance under these volatile conditions (Brandon-Jones et al. 2015). When the supplier base is constantly shifting, the redeployability of specialized investments is low, making the asset specificity of traditional manual integration risky and expensive. DTSs may address this uncertainty by transforming volatile supplier information into more timely and trusted data. However, because dynamic upstream environments also make supplier relationships less stable, the benefits of DTS adoption depend on whether firms can develop sufficient relational and technical routines to support data sharing. Holding implementation cost and time constant, we nevertheless expect the information-processing benefits to dominate (Roeck et al. 2020). Furthermore, digital platforms empower suppliers through collaborative resource-sharing, such as cloud-based data pools, building the relational capital necessary to navigate volatility collectively (Morgan et al. 2018). Thus, we hypothesize that:

H3c. *Keeping the implementation cost and time constant, the higher the upstream SCC in terms of dynamic complexity, the more likely firms implement DTSs.*

4 | Methodology

4.1 | Choice-Based Conjoint (CBC) Experimental Design

This research uses an experimental design to test the hypotheses because such an approach enables researchers to control extraneous variables by creating an artificial decision environment (Siemsen 2011). Experimental methods are particularly suitable for examining forward-looking contexts, such as the adoption of emerging technologies, where real-world data are often limited or inconsistent (Shang and Rönkkö 2022; Ta et al. 2025). Among available experimental approaches, we selected a choice-based conjoint (CBC) design because it aligns closely with our research objectives. CBC allows the simultaneous examination of multiple attributes related to technology and supply chain complexity, while also capturing trade-offs that resemble real-world managerial decision-making (Orme 2010). Respondents evaluate several alternatives with different attribute combinations and must make trade-offs before selecting a preferred option (Banerjee et al. 2021). In addition, CBC can be integrated into a survey format, enabling the collection of demographic information that can later be used as control variables in the regression analysis (Ta et al. 2025).

The CBC design was developed following the guidelines proposed by Orme (2010). The proposed theoretical constructs, the attributes, and their levels are shown in Table 2. Attributes related to SCC were derived from the meta-analysis by Akın Ateş et al. (2022). The initial design was based on conditions used in prior CBC studies (Banerjee et al. 2021; Vinayavekhin et al. 2024; Yan et al. 2020), and subsequently refined through a multi-stage expert validation process to ensure content and face validity. Initially, four scholars and four industry practitioners specializing in supply chain traceability reviewed the experimental logic, survey flow, and choice sets. They also evaluated the realism of the design, including the thresholds for high and low complexity and the focus on Tier-1 suppliers as a representative proxy for upstream GHG traceability. This stage ensured that the tasks were clear, technically sound from both academic and practitioner perspectives, and structured to minimize respondent fatigue. After revisions based on their feedback, four additional scholars conducted a final review to ensure alignment between the experimental design, theoretical constructs, and hypotheses (Ta et al. 2025).

The final design includes nine attributes with three levels each (Table 2). The attributes correspond to the variables in the theoretical framework: the scope of digital GHG traceability systems (i.e., Scope 1, 2, and 3) and the dimensions of internal and upstream SCC (i.e., detail-variety, detail-numerousness, and dynamic complexity). Cost and time, key factors in technology adoption (Hastig and Sodhi 2020), were included as control attributes. The finalized CBC design received approval from the ethics committee, reflecting adherence to ethical guidelines for human subjects research (Eckerd et al. 2021).

The experiment was framed around a firm's decision to implement a DTS for tracing GHG emissions. Using Sawtooth software, we generated ten orthogonal choice sets for each

TABLE 2 | List of attributes and levels for the CBC.

Attributes	Level 1	Level 2	Level 3
Cost of implementation	Low (less than £500k)	Moderate (£750k)	High (more than £1m)
Time needed for implementation	Low (less than 6 months)	Moderate (1 year)	High (more than 2 years)
Scope of implementation	Scope 1	Scope 1 and 2	Scope 1, 2, and 3
Internal SCC detail-numerousness (e.g., no. of product produced per day)	Low (less than 500 products)	Moderate (1000–2000 products)	High (more than 5000 products)
Internal SCC detail-variety (e.g., no. of product varieties)	Low (less than 10 product varieties)	Moderate (20–30 product varieties)	High (more than 50 product varieties)
Internal SCC dynamic (e.g., yearly change rate in no. of product varieties)	Low (less than 5%)	Moderate (10%–20%)	High (more than 25%)
Upstream SCC detail-numerousness (e.g., no. of tier-1 Suppliers)	Low (less than 10 suppliers)	Moderate (20–30 suppliers)	High (more than 50 suppliers)
Upstream SCC detail-variety (e.g., location variety of tier-1 suppliers)	Low (single country)	Moderate (3–5 countries)	High (more than 10 countries)
Upstream SCC dynamic (e.g., yearly change rate in no. of tier-1 suppliers)	Low (less than 5%)	Moderate (10%–20%)	High (more than 25%)

Source: Authors' own work.

respondent. Each choice set included two firm profiles and a no-choice option, with attribute levels randomly assigned by the software. Such randomization is essential for establishing causality because it reduces systematic bias and ensures that observed effects are attributable to the manipulated variables rather than pre-existing differences (Knemeyer and Naylor 2011). Respondents were asked to indicate which firm was more likely to implement a DTS, or whether neither firm would do so. Both firms were assumed to operate within the same industry, and the levels of complexity (i.e., high, moderate, and low) were defined relative to industry norms. Figure 1 presents an example of a CBC choice set. To reduce social desirability bias, respondents were guaranteed anonymity and the design adopted a projective approach. Participants were instructed to answer based on how firms would realistically behave, rather than how they should behave (Knemeyer and Naylor 2011). A detailed description of the experimental procedure is provided in the supplementary document in Appendix S1.

Overall, the procedure began with participant information and informed consent, followed by a 2.5-min introductory video explaining DTSs, GHG emissions, and SCC to establish a common baseline of understanding. Respondents were subsequently introduced to the experimental scenario and completed ten CBC choice tasks. To ensure data quality, we embedded three attention checks throughout the survey: two after the introductory video and one after the CBC tasks (Carter et al. 2024). The survey concluded with demographic questions adapted from prior studies, including firm-level variables (e.g., firm size and industry) (Yan et al. 2020) and individual-level variables (e.g., age, gender, education, years of experience, and decision-making experience) (Banerjee et al. 2021; Vinayavekhin et al. 2024).

4.2 | Experiment Respondent

Respondents were recruited through the online panel platform Prolific, which has been widely used in prior studies in the field of operations and supply chain (see e.g., Banerjee et al. 2021; Vinayavekhin et al. 2024). Following the recommendations by Shang and Rönkkö (2022), we employed a two-stage screening process. First, Prolific filters were used to target individuals located in the UK and USA who worked in the manufacturing sector and held decision-making responsibilities in operations or supply chain management. Secondly, survey-based demographic questions were used to validate these criteria.

The initial screening by the Prolific platform yielded 150 qualified respondents who consented to participate for a compensation of £3. After data collection, we excluded 28 incomplete responses. Out of 122 fully completed responses, 20 respondents (17%) failed one or more attention checks. This data-cleaning process yielded a final, valid sample of 102 respondents.

The adequacy of the sample size was assessed using the guideline proposed by Orme (2010). This guideline suggests multiplying 500 by the ratio of the highest number of attribute levels (C) to the product of the number of choice sets (T) and the number

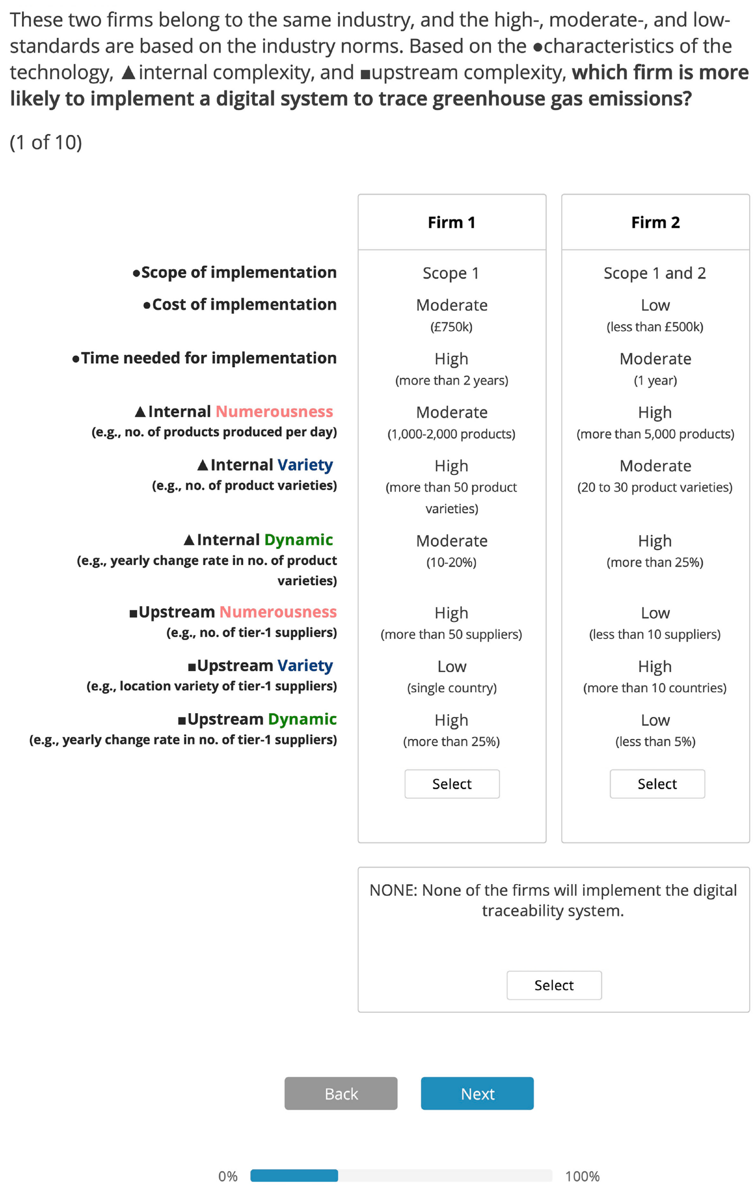

FIGURE 1 | Example of a single choice set and CBC design components.

of alternatives per task excluding a “none” option (A). In our CBC design, C = 3, T = 10, and A = 2, resulting in a minimum required sample size of 75. The final sample of 102 respondents therefore exceeded this threshold.

Furthermore, demographic characteristics are presented in Table 3. The sample consisted of experienced professionals, with 77% (n = 79) reporting more than 10 years of industry experience. Most respondents were male (82%), and 72% held university degrees. To assess potential selection bias, we compared respondents excluded because of failed attention checks (n = 20) with those retained in the final sample (n = 102). The distributions across age, gender, education, experience, firm size, and industry were broadly similar between the two groups, although the excluded subsample skews toward lower-education and smaller-firm respondents (Appendix S2).

4.3 | Analysis

Using the valid responses, we first conducted a part-worth utility analysis to evaluate hypotheses H1, H2, and H3. This analysis estimates the relative influence of each attribute level on respondents' choices compared with other levels within the same attribute. All nine attributes were included in the analysis. Part-worth utilities were estimated using a hierarchical Bayes model and adjusted using an arbitrary additive constant to ensure that utilities within each attribute summed to zero. The results are presented in Table 4.

We then conducted logistic regression analyses to estimate the likelihood of preference for each attribute level relative to the base and “none” options. The base option represented a firm positioned at level two across all nine attributes. Following prior CBC

TABLE 3 | Demographic characteristics of the respondents.

	Counts ($N = 102$)	Percentage
Age		
1. Less than 20 years	0	0%
2. 20–29 years	14	14%
3. 30–39 years	35	34%
4. 40–49 years	34	33%
5. 50–59 years	14	14%
6. More than 60 years	5	5%
7. Prefer not to say	0	0%
Gender		
1. Male	84	82%
2. Female	18	18%
3. Non-binary	0	0%
4. Prefer not to say	0	0%
Education		
1. Up to high school	21	21%
2. Undergraduate (Bachelor degree)	48	47%
3. Postgraduate (Master degree)	25	25%
4. PhD degree	0	0%
5. Other professional qualification or certification	8	8%
6. Prefer not to say	0	0%
Years of experience		
1. Less than 1 year	0	0%
2. 1–5 years	13	13%
3. 6–10 years	10	10%
4. More than 10 years	79	77%
5. Prefer not to say	0	0%
Experience of decisions		
1. Yes—both internal operations and supply chain	81	79%
2. Yes—only internal operations	13	13%
3. Yes—only supply chain	8	8%
4. No	0	0%
5. Prefer not to say	0	0%

(Continues)

TABLE 3 | (Continued)

	Counts ($N = 102$)	Percentage
Firm size		
1. Less than 5 employees	2	2%
2. 5–50 employees	8	8%
3. 51–100 employees	17	17%
4. 101–500 employees	28	27%
5. 501–1000 employees	10	10%
6. 1001–5000 employees	22	22%
7. More than 5000 employees	14	14%
8. Prefer not to say	1	1%
Firm industry		
1. Manufacture of food products	18	18%
2. Manufacture of beverages	2	2%
3. Manufacture of tobacco products	0	0%
4. Manufacture of textiles	2	2%
5. Manufacture of wearing apparel	3	3%
6. Manufacture of leather and related products	0	0%
7. Manufacture of wood and of products of wood and cork	1	1%
8. Manufacture of paper and paper products	3	3%
9. Printing and reproduction of recorded media	0	0%
10. Manufacture of coke and refined petroleum products	0	0%
11. Manufacture of chemicals and chemical products	8	8%
12. Manufacture of basic pharmaceutical products and pharmaceutical preparations	5	5%
13. Manufacture of rubber and plastic products	6	6%

(Continues)

TABLE 3 | (Continued)

	Counts ($N=102$)	Percentage
14. Manufacture of other non-metallic mineral products	0	0%
15. Manufacture of basic metals	6	6%
16. Manufacture of fabricated metal products	7	7%
17. Manufacture of computer, electronic and optical products	11	11%
18. Manufacture of electrical equipment	4	4%
19. Manufacture of machinery and equipment n.e.c.	6	6%
20. Manufacture of motor vehicles, trailers and semi-trailers	8	8%
21. Manufacture of other transport equipment	1	1%
22. Manufacture of furniture	1	1%
23. Other manufacturing	9	9%
24. Repair and installation of machinery and equipment	1	1%
25. Prefer not to say	0	0%

Source: Authors' own work.

studies (see e.g., Banerjee et al. 2021; Vinayavekhin et al. 2024), we estimated three logistic regression models with respondent-clustered robust standard errors to account for intra-respondent correlation. Model 1 includes seven demographic control variables: five individual-level variables (i.e., age, education, years of experience, primary functional experience, and decision-making experience) and two firm-level variables (i.e., firm size and industry). Model 2 includes the nine focal attributes, while Model 3 combines both the control variables and focal key attributes. The regression results are presented in Table 5. As a robustness check, we also estimated linear mixed models, which confirmed the stability and reliability of our primary findings. (Appendix S3).

Finally, we calculated attribute importance scores using CBC utility estimates. These scores indicate the relative contribution of each attribute to overall choice utility and are expressed as percentages summing to 100%. This analysis was conducted to identify the most influential dimensions of complexity within both internal operations and upstream supply chains. The results are presented in Table 6. We additionally performed *t*-tests to examine whether differences in average attribute importance were statistically significant.

5 | Findings

5.1 | Impact of Implementation Scope on Digital Traceability Adoption

The part-worth utility analysis (Table 4) provides insights into the extent to which each attribute level influences the likelihood of DTS implementation. Regarding the implementation scope, full-scope implementation is preferred (42.53%, SE = 5.88) over partial implementation covering Scopes 1 and 2 only (−2.05%, SE = 3.20) or Scope 1 alone (−40.48%, SE = 5.25). The regression results in Model 3 of Table 5 reinforce this finding. Compared with the base condition of Scope 1 only, the coefficients for Scope 1 and 2 implementation (0.52, SE = 0.09) and full-scope implementation covering Scopes 1, 2, and 3 (1.09, SE = 0.14) are both significant at $p < 0.001$. Therefore, H1 is supported.

5.2 | Impact of Internal SCC on Digital Traceability Adoption

Higher internal detail-numerousness is associated with a stronger preference for DTS implementation. The utility analysis shows the highest utility for high detail-numerousness (58.51%, SE = 7.34), while low detail-numerousness produces a substantial decline in utility (−49.72%, SE = 5.72). The regression analysis supports this pattern, with coefficients of 0.51 (SE = 0.08) for the moderate level and 1.43 (SE = 0.18) for the high level. These findings support H2(a).

A similar pattern is observed for internal detail-variety. Table 4 shows the highest utility for high detail-variety (20.40%, SE = 4.17) and the lowest utility for low detail-variety (−24.96%, SE = 4.82). The regression analysis further supports this relationship. Compared with the low-level condition, moderate detail-variety is associated with a coefficient of 0.35 (SE = 0.08), which increases to 0.56 (SE = 0.11) at the high level. Thus, H2(b) is supported.

For internal dynamic complexity, the high level yields the highest utility score (11.14%, SE = 2.47). In Model 3 of Table 5, the coefficient for the high level is 0.29 (SE = 0.06; $p < 0.001$), while the moderate level has a smaller but still significant coefficient of 0.15 (SE = 0.06; $p = 0.011$). These findings provide support for H2(c).

5.3 | Impact of Upstream SCC on Digital Traceability Adoption

Higher upstream detail-numerousness is associated with a stronger preference for DTS implementation. The utility analysis shows the highest utility for high detail-numerousness (11.62%, SE = 3.39), whereas low detail-numerousness results in a substantial decline in utility (−17.49%, SE = 2.30). The regression analysis further supports this finding, with coefficients of 0.25 (SE = 0.05) for the moderate level and 0.35 (SE = 0.06) for the high level. Thus, H3(a) is supported.

For upstream detail-variety, Table 4 indicates the highest utility for high detail-variety (21.71%, SE = 2.64) and the

TABLE 4 | Part-worth utility analysis for each attribute and related levels.

Attributes and levels	Part-worth utility (%)	Standard error	Lower 95% CI	Upper 95% CI
Scope				
1. Scope 1	−40.48	(5.25)	−50.78	−30.18
2. Scope 1 and 2	−2.05	(3.20)	−8.31	4.22
3. Scope 1, 2 and 3	42.53	(5.88)	31	54.05
Internal SCC detail-numerousness				
1. Low	−49.72	(5.72)	−60.94	−38.51
2. Moderate	−8.79	(2.70)	−14.08	−3.50
3. High	58.51	(7.34)	44.13	72.90
Internal SCC detail-variety				
1. Low	−24.96	(4.82)	−34.42	−15.51
2. Moderate	4.56	(2.27)	0.12	9.01
3. High	20.40	(4.17)	12.22	28.58
Internal SCC dynamic				
1. Low	−11.61	(2.54)	−16.59	−6.63
2. Moderate	0.47	(2.50)	−4.43	5.37
3. High	11.14	(2.47)	6.30	15.98
Upstream SCC detail-numerousness				
1. Low	−17.49	(2.30)	−22.01	−12.98
2. Moderate	5.87	(3.18)	−0.37	12.11
3. High	11.62	(3.39)	4.98	18.27
Upstream SCC detail-variety				
1. Low	−29.78	(4.20)	−38.02	−21.54
2. Moderate	8.07	(3.16)	1.88	14.26
3. High	21.71	(2.64)	16.53	26.88
Upstream SCC dynamic				
1. Low	−0.04	(2.84)	−5.61	5.52
2. Moderate	−8.03	(2.96)	−13.82	−2.24
3. High	8.07	(2.75)	2.68	13.46
Cost				
1. Low	52.24	(6.18)	40.13	64.34
2. Moderate	7.94	(2.68)	2.68	13.19
3. High	−60.17	(6.44)	−72.79	−47.55
Time				
1. Low	54.71	(4.53)	45.83	63.59
2. Moderate	−3.69	(2.77)	−9.11	1.74
3. High	−51.02	(5.89)	−62.57	−39.48

Source: Authors' own work.

lowest utility for low detail-variety (−29.78%, SE = 4.20). The regression analysis shows a similar pattern. Compared with the low-level condition, moderate detail-variety is associated with a coefficient of 0.49 (SE = 0.09), while the coefficient increases to 0.65 (SE = 0.09) at the high level. Therefore, H3(b) is supported.

TABLE 5 | Logistic regression results of preference likelihood of each level in the same attribute.

	Model 1	Model 2	Model 3
Independent variables	**Coefficient (SE)**	**Coefficient (SE)**	**Coefficient (SE)**
Scope of implementation (base scope 1)			
Scope 1 and 2		0.49*** (0.08)	0.52*** (0.09)
Scope 1, 2, and 3		1.02*** (0.14)	1.09*** (0.14)
Internal SCC detail-numerousness (base low)			
Moderate		0.48*** (0.07)	0.51*** (0.08)
High		1.34*** (0.17)	1.43*** (0.18)
Internal SCC detail-variety (base low)			
Moderate		0.33*** (0.07)	0.35*** (0.08)
High		0.53*** (0.11)	0.56*** (0.11)
Internal SCC dynamic (base low)			
Moderate		0.14** (0.06)	0.15** (0.06)
High		0.27*** (0.05)	0.29*** (0.06)
Upstream SCC detail-numerousness (base low)			
Moderate		0.23*** (0.05)	0.25*** (0.05)
High		0.33*** (0.06)	0.35*** (0.06)
Upstream SCC detail-variety (base low)			
Moderate		0.46*** (0.09)	0.49*** (0.09)
High		0.61*** (0.08)	0.65*** (0.09)
Upstream SCC dynamic (base low)			
Moderate		−0.11* (0.06)	−0.12* (0.07)
High		0.09 (0.06)	0.09 (0.06)
Cost for implementation (base low)			
Moderate		−0.59*** (0.10)	−0.63*** (0.10)
High		−1.34*** (0.17)	−1.43*** (0.18)
Time for implementation (base low)			
Moderate		−0.68*** (0.06)	−0.73*** (0.07)
High		−1.25*** (0.13)	−1.33*** (0.14)
Control variables	Yes	No	Yes
Constant	0.44 (0.39)	−1.02*** (0.25)	−0.27 (0.56)
Pseudo R^2	0.035	0.157	0.201
Respondents	102	102	102

Note: Control variables: age, education, year of experience, primary functional experience, experience of decision making, firm size, firm industry; Robust standard errors clustered by respondent in parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
Source: Authors' own work.

For upstream dynamic complexity, the high level produces the highest utility score (8.07%, SE = 2.75). The moderate-level coefficient is marginally significant and negative (−0.12, SE = 0.07, $p = 0.066$), while the high-level coefficient is non-significant and positive (0.09, SE = 0.06, $p > 0.1$). Taken together, the upstream dynamic coefficients do not form a coherent monotonic pattern, and H3(c) is not supported.

5.4 | Relative Worth of Different Dimensions of SCC

According to Table 6, among all attributes, internal detail-numerousness emerges as the most important attribute (16.17%, SE = 0.98), followed by implementation cost (15.99%, SE = 1.02) and implementation time (14.53%, SE = 0.82).

TABLE 6 | Average importance of attributes.

Attributes and levels	Average importance of each attribute (%)	Standard error	Lower 95% CI	Upper 95% CI
Scope	13.03	(0.87)	11.34	14.73
Internal detail-numerousness	16.17	(0.98)	14.24	18.09
Internal detail-variety	10.31	(0.49)	9.35	11.26
Internal dynamic	6.29	(0.31)	5.68	6.89
Upstream detail-numerousness	7.69	(0.37)	6.97	8.41
Upstream detail-variety	9.24	(0.49)	8.29	10.20
Upstream dynamic	6.75	(0.35)	6.07	7.44
Cost	15.99	(1.02)	13.99	17.99
Time	14.53	(0.82)	12.92	16.15
	100%			

Source: Authors' own work

TABLE 7 | Summary of topic modeling from responses to open text questions.

Question	Emergent themes	Representative quote
Please tell us what criteria influenced your decision within a choice set and why?	Implementation practicality	"I chose mostly by looking at a balance between cost and time to implement…"
	Supply chain complexity	"…It stands to reason that if a company is using a lot of different suppliers that has a high variability, the company is already concerned about different issues with the supply chain—including traceability"
	Firm-level considerations	"…because companies can invest more in technologies when they have higher gross profit"
If you have chosen "NONE: None of the firms will implement the digital traceability system.", what criteria influenced your decision to reject the two presented firms?	Realism of experimental design (Low uptake of the "NONE" option)	"I didn't choose NONE"
	Cost–Benefit analysis	"…cost-benefit analysis, perceived irrelevance, high risk"
	Log-term view	"…minimal long-term impact, resource limitations, alternative solutions, misalignment with strategy, or lack of market demand, collectively suggesting the digital traceability system isn't a viable choice for my company's objectives and circumstances"

Source: Authors' own work.

Within internal complexity, detail-numerousness is the most influential dimension (16.17%, SE = 0.98), followed by detail-variety (10.31%, SE = 0.49) and dynamic complexity (6.29%, SE = 0.31). In contrast, upstream SCC shows a different pattern. Detail-variety ranks highest (9.24%, SE = 0.49), followed by detail-numerousness (7.69%, SE = 0.37) and dynamic complexity (6.75%, SE = 0.35).

5.5 | Further Insights From Qualitative Sources

In this section, we present analysis from two qualitative sources to better interpret and contextualize the quantitative results. First, we analyzed open-text responses collected from CBC respondents using Latent Dirichlet Allocation (LDA) topic modeling in Python, followed by manual coding to identify emergent themes. Table 7 presents the three most prominent themes alongside representative quotes. The findings support the robustness of the quantitative results, showing that implementation effort and supply chain complexity are the main factors influencing participant choices.

Secondly, we discussed the finalized quantitative findings with two senior executives. These interviews served as an ex-post interpretive triangulation tool, providing practical explanations for the results rather than independent confirmatory evidence for the hypotheses. Representing the buyer perspective, R1 is a Vice President at the UK subsidiary of a German retailer. The firm regularly works with more than 700 UK suppliers and over 2000 suppliers serving the UK market. It

TABLE 8 | Summary of interview quotes used for ex-post interpretive triangulation.

Hypothesis	Interview quote used for ex-post interpretive triangulation
H1	"Large businesses have to do it anyway... Purely voluntary participation is not common" (R1)
	"Our clients want accreditations... we have all the top sustainability accreditations" (R2)
	"If a large client wants a new reporting tool – yes, we will consider it... use it. We can report anything... but it [cost-benefit] must make sense" (R2)
	"Reporting is...common and we have standard practices [that] we use... influenced by industry practices" (R2)
H2	"Complexity of the [internal operations] influences our choice of a software solution" (R1)
	"Cost, which is also the time and change management... influences our choice" (R1)
H3	"We deal with many small regional suppliers... so we work with each of them to onboard them on the platform" (R1)
	"You also want something simple enough so that your suppliers, some are very small businesses, so they do not have the capability, [can] join" (R1)
	"Supplier onboarding requires both change management effort as well as company policy updates" (R1)
	"The choice [to adopt] is influenced by the cost of implementing and managing any new software [requested by customers], as you find [in your study]" (R2)

Source: Authors' own work.

has already implemented a digital solution to track GHG emissions as part of its net-zero strategy and is currently onboarding all UK tier-1 suppliers onto the platform. Representing the supplier perspective, R2 is the Managing Director of a manufacturing SME with approximately 50 employees specializing in industrial ventilation manufacturing, assembly, installation, and maintenance. Key quotes related to the hypotheses are presented in Table 8.

6 | Discussion

Our research provides several insights into the multifaceted factors influencing the adoption of DTSs for managing GHG emissions in complex supply chains. In this section, we discuss the implications for the technology adoption and supply chain complexity literatures, as well as implications for practitioners.

6.1 | Theoretical Implications

Our research responds to a call for research on factors influencing the adoption of supply chain technology (Yang et al. 2021). The conceptual framework and summary of empirical results are shown in Figure 2. These findings advance our understanding of how supply chain complexity influences the adoption of digital GHG traceability systems through the lens of institutional theory and TCE.

From an Institutional Theory perspective, our results for H1 demonstrate that firms are more likely to implement digital GHG traceability systems when the implementation scope extends to the upstream supply chain. This supports the premise that institutional pressures influence full-scope DTS adoption through three mechanisms: coercive pressures from regulators and powerful buyers, normative pressures from certifications and sustainability-reporting standards, and mimetic pressures created when firms benchmark against peers that disclose broader supply chain emissions (DiMaggio and Powell 1983). This interpretation is further contextualized by R2, who noted that suppliers are often willing to adopt any tool if "a large client wants it". Furthermore, R2 noted that "Our clients want accreditations...

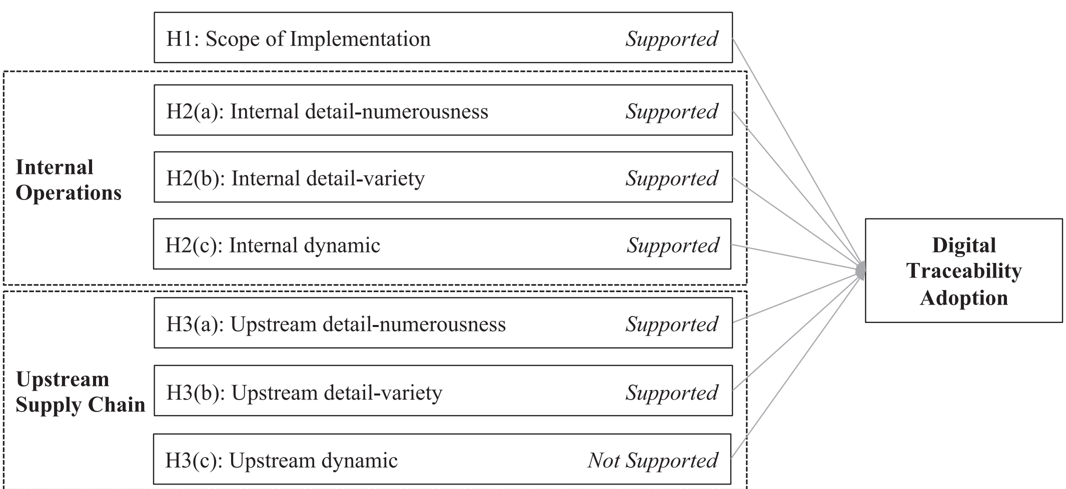

FIGURE 2 | Conceptual framework and summary of empirical results. *Source:* Authors' own work.

we have all the top sustainability accreditations". In this context, normative pressures, such as industry certifications and professional standards, create a baseline expectation for comprehensive emissions disclosure (Garcia-Torres et al. 2019).

We also use TCE to motivate how DTSs mitigate transaction costs in complex supply chains. High levels of detail-numerousness and detail-variety, both within the focal firm's internal operations and across its upstream supply chain, create coordination challenges (Williamson 1981). Traditional paper-based or manual reporting increases monitoring-related transaction costs and the likelihood of errors as complexity increases. In contrast, DTSs lower coordination and monitoring costs by standardizing reporting formats and enabling real-time data exchange (Roeck et al. 2020). These results suggest that technology adoption is motivated not only by institutional pressures but also by the expected efficiency gains from reducing the transaction costs of managing GHG data across complex supply chains.

Taken together, these findings extend prior supply chain technology adoption studies that have focused mainly on technological characteristics or firm-level readiness (Agi and Jha 2022; Kamble et al. 2019). We show that adoption decisions are shaped by both institutional legitimacy-seeking and transaction cost minimisation logics, providing a more nuanced understanding of why firms extend digital traceability beyond their focal boundaries. This dual-theory perspective highlights that institutional theory explains why firms face pressures to expand GHG traceability, while TCE explains how digital systems resolve the coordination and monitoring frictions that make such expansion feasible.

For SCC research, our results clarify how distinct complexity dimensions at internal versus upstream levels differentially shape the perceived value of DTS adoption (Akın Ateş et al. 2022). We provide strong evidence to support the impact of detail-numerousness and detail-variety for both internal operations (H2a and H2b) and the upstream supply chain (H3a and H3b). Our findings are in line with the prior literature showing that large and heterogeneous supplier bases create greater coordination needs with and between suppliers, resulting in greater operational loads and higher transaction costs (Bode and Wagner 2015; Wiedmer et al. 2021), and firms could mitigate the detrimental effects by improving the visibility of the supply chain (Brandon-Jones et al. 2015). It also highlights that standardized procedures, in this case, through the implementation of digital solutions, could potentially counteract the adverse impacts of SCC on supply chain GHG emissions (De Stefano and Montes-Sancho 2024). Our research provides further insights that digital systems are expected to alleviate the complexity caused by detail-numerousness and detail-variety but not the dynamic dimension.

The non-significance of upstream dynamic complexity (H3c) provides a distinct theoretical contribution by identifying a boundary condition for digital traceability as a governance tool. This suggests that digital traceability is perceived as an effective governance tool for structural complexity, where numerous or heterogeneous data points can be standardized and monitored at scale. By contrast, dynamic upstream complexity reduces the stability of the supplier relationships and data-sharing routines on which DTS implementation depends. According to TCE, high environmental uncertainty typically increases the information processing burden, as managers require monitoring mechanisms to reduce the risk of supplier opportunism (Williamson 1981). Since the upstream supply chain is more difficult to control than internal operations (Choi et al. 2001), frequent supplier switching reduces the value of asset-specific DTS investments. Firms may therefore hesitate to invest in tightly integrated traceability systems when supplier relationships are unstable and the data-sharing routines created for one supplier cannot easily be redeployed to another. This mismatch acts as a deterrent to adoption. This is further explained by the interplay between formal and relational governance. As argued by Zheng et al. (2008), formal governance mechanisms, in this case DTSs, often require a foundation of relational governance (e.g., trust and long-term collaboration) to be effective. In dynamic environments where suppliers are frequently replaced, there is insufficient time to develop the relational bonds and mutual trust necessary for transparent data sharing. These findings are echoed in the qualitative insights from R1, who observed that supplier onboarding requires both significant change management effort and company policy updates. This finding extends existing SCC theory by highlighting that "dynamic" complexity requires different governance approaches than "structural" complexity.

6.2 | Managerial Implications

The findings also provide practical guidance for upstream suppliers, focal manufacturing firms, and DTS providers seeking to accelerate credible GHG traceability.

For upstream suppliers, particularly SMEs, digital traceability sits on two distinct logics that managers should hold together. The first is defensive: as mandates such as the EU CSRD push focal firms to disclose Scope 3 emissions, buyers will increasingly screen out suppliers that cannot deliver primary emissions data. The strong support for H1 confirms this preference, and the practical implication is that suppliers who keep relying on industry averages or secondary proxies risk being quietly dropped from preferred supply bases. The second logic is proactive: the same data, once collected, becomes a strategic asset. Verified emissions records differentiate suppliers in conversations that would otherwise default to cost-only comparisons, open access to green-finance instruments, and create a credible basis for premium positioning with sustainability-conscious customers. SMEs can invest early in lean, interoperable reporting capabilities that integrate across multiple buyer platforms rather than rebuilding the same data layer for each client. As R2 noted, suppliers will adopt what large clients require, but those who treat the requirement as a capability, not a cost line, convert defensive compliance into competitive leverage.

For focal manufacturing firms, although both detail-numerousness (H2a and H3a) and detail-variety (H2b and H3b) significantly influence DTS adoption, internal detail-numerousness emerges as the most influential factor, with the highest relative attribute importance (Table 6). This suggests that firms are primarily motivated by the operational burden of managing large volumes of emissions-related data. Thus, managers should prioritize automating high-volume internal reporting through a standardized DTS before extending traceability requirements upstream. In addition, qualitative insights indicate that many SME suppliers face capability and resource constraints. Thus, focal firms should provide onboarding support through shared training programmes or subsidized DTS fees to reduce technical and financial barriers.

For DTS providers, the non-significant result for upstream dynamic complexity (H3c) suggests that firms may avoid highly integrated systems because of concerns related to asset specificity and technological lock-in. Providers should therefore focus on modular solutions that allow focal firms to onboard or offboard suppliers without disrupting the wider system. Since detail-variety is the most influential attribute within upstream complexity (Table 6), providers should prioritize features that standardize data across suppliers operating in different regions and industries. Marketing efforts should also emphasize the ability of DTSs to manage structural heterogeneity and coordination complexity.

7 | Limitations and Future Research

Our research provides novel insights into the implementation of a DTS, but it also has certain limitations that provide a foundation for a prioritized agenda for future research.

Firstly, our findings were contextualized within manufacturing sectors in the USA and the UK, and the sample was also skewed toward medium-to-large firms. While we statistically controlled for several demographic variables in our analysis, this focus limited the direct generalisability of our findings. In addition, we conducted sub-group analyses based on location (Appendix S4) and firm size (Appendix S5) as robustness checks. The purpose was to examine potential differences, such as variations in local regulatory maturity across regions (Hadziosmanovic et al. 2022). However, we observed a similar pattern in the direction of the effects across both locations and firm sizes. Although some differences in effect sizes were identified, we did not find a coherent monotonic pattern. As the results were contingent on the specific design of our CBC experiment, future research should replicate our research or employ alternative experimental designs to explore how disparate regulatory landscapes and cross-cultural differences influence the adoption of DTS (Carter et al. 2024).

Secondly, our research focused on internal and upstream supply chain complexity. As Bozarth et al. (2009) mentioned, complexity could also arise from downstream customers. Thus, a crucial next step is to investigate the role of downstream complexity, including factors such as the number of customers and the heterogeneity of customer demand. Moreover, as suggested by the reviewer team during the revision round, we conducted a post hoc analysis to explore potential interaction effects between the various dimensions of supply chain complexity (Appendix S6). While our primary focus remained on the direct impacts of individual complexity dimensions, this supplemental analysis did not yield a coherent monotonic pattern. Future research could employ more specific experimental designs to further isolate these subtle dynamics and determine if specific combinations of internal and upstream complexity might eventually lead to different adoption outcomes.

Lastly, while our research incorporated qualitative insights through open-text responses and targeted ex-post expert interviews to triangulate the quantitative findings, we acknowledge that the small number of interviews serves as a starting point for contextualisation. Future research should employ more extensive qualitative methodologies, such as focus groups or in-depth case studies, to further validate the decision-making trade-offs captured in our experiment. Given the interdisciplinary nature of sustainability research, future research should also incorporate literature from other disciplines and collect data from developing countries to develop a more holistic view of the context (Vinayavekhin et al. 2023).

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Conflicts of Interest

The authors declare no conflicts of interest.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Appendix S1:** Disclosure on the experiment design. **Appendix S2:** Comparison of demographics between the analytical sample and respondents excluded due to failed attention checks. **Appendix S3:** Comparison of respondent-clustered logistic regression and mixed-effects models. **Appendix S4:** Logistic regression models of preference for subgroup analysis by location (UK and USA). **Appendix S5:** Logistic regression models of preference for subgroup analysis by firm size. **Appendix S6:** Logistic regression models of preference with interaction effects.