IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 18 August 2026, accepted 4 October 2026, date of publication 12 October 2026, date of current version 16 October 2026.

Digital Object Identifier 10.1109/ACCESS.2026.3742950

RESEARCH ARTICLE

Understanding Blockchain Adoption Intensity in the Textile and Apparel Industry: Antecedents and Sustainable Performance Implications

SAIPING CHENG[1], MINJEONG OH[2], AND SUNGYONG CHOI[1]
[1]School of Business, Hanyang University, Seoul 04763, South Korea
[2]Global Elite Division, Yonsei University, Wonju-si 26493, South Korea

Corresponding author: Sungyong Choi (sungyongchoi@hanyang.ac.kr)

ABSTRACT Although the potential of blockchain technology has been widely recognized, existing research has insufficiently explored the factors influencing blockchain adoption intensity and its implications for sustainable performance. To address this gap, this study positions blockchain adoption intensity as the focal organizational-level construct. Focusing on the Chinese textile and apparel industry as the empirical context, this study develops an integrated research model that examines the antecedents and sustainable performance outcomes of adoption intensity based on the Technology–Organization–Environment (TOE) framework, institutional theory, and the Natural-Resource-Based View (NRBV). Using 291 firm-level responses, partial least squares structural equation modeling (PLS-SEM) is employed to test the proposed relationships involving higher-order constructs, while artificial neural network (ANN) analysis is used to identify key predictors. The results indicate that technological benefits, organizational enablers, external environmental drivers, and institutional pressure are significantly and positively associated with blockchain adoption intensity, which in turn is positively linked to sustainable performance. The ANN results highlight organizational enablers, external environmental drivers, and institutional pressure as relatively important predictors. Exploratory multi-group analysis indicates that several relationships vary across value-chain positions. This study extends the focus of blockchain adoption research from adoption intention and binary adoption decisions to organizational-level adoption intensity, deepening theoretical understanding of its antecedents and performance associations while enriching research on digital technology adoption. The findings provide practical insights for firms and policymakers in managing and supporting blockchain adoption intensity.

INDEX TERMS Artificial neural network (ANN), blockchain adoption intensity, higher-order constructs, partial least squares structural equation modeling (PLS-SEM), sustainable performance, textile and apparel industry.

I. INTRODUCTION

In multi-tier industrial networks, interorganizational information asymmetry, process opacity, and traceability difficulties have long constrained operational efficiency, value-chain transparency, and sustainable governance capacity. Blockchain technology, characterized by distributed ledgers, data immutability, and smart contracts, is regarded as an important tool for enhancing interorganizational information sharing, collaborative verification, and automated execution [1], [2]. Its potential to improve operational visibility and traceability has attracted considerable attention from both academia and industry [3], [4].

High levels of attention to blockchain or strong adoption intentions, however, do not necessarily translate into substantial implementation. Blockchain adoption often involves challenges such as cost pressures, scalability constraints, insufficient technical capabilities, and regulatory

The associate editor coordinating the review of this manuscript and approving it for publication was Ghufran Ahmed.

© 2026 The Authors. This work is licensed under a Creative Commons Attribution 4.0 License.
For more information, see https://creativecommons.org/licenses/by/4.0/

uncertainty [5], [6]. Industry reports also suggest a persistent gap between firms' strategic attention to blockchain and production-level deployment [7], [8]. Accordingly, blockchain research needs to move beyond whether firms adopt the technology and examine the extent to which they invest in, integrate, and use it.

The existing literature has identified various factors influencing blockchain adoption, mainly focusing on adoption intention, adoption decisions, or general usage status [9], [10], [11]. This research stream helps explain why firms accept, plan to adopt, or begin using blockchain, but pays insufficient attention to the degree of adoption and the conditions shaping it. Technology adoption research has increasingly examined the degree of actual technology adoption by organizations, giving rise to related concepts such as the degree of technology assimilation and adoption intensity [12], [13]. In the blockchain context, prior studies have also examined different organizational-level manifestations of blockchain adoption [14], [15], but a comprehensive characterization of firms' overall degree of blockchain adoption remains relatively limited. As an interorganizational digital technology, blockchain adoption is shaped by firms' internal technological, resource, and organizational conditions, as well as by external environmental forces and institutional pressures [11], [16]. Therefore, this study incorporates these conditions into a unified framework to systematically examine the factors influencing blockchain adoption intensity.

Examining only the factors influencing adoption intensity is insufficient; the actual value of blockchain also needs to be assessed through performance outcomes. Sustainable performance has become an important indicator of firms' long-term competitiveness, typically encompassing economic, operational, environmental, and social dimensions [17], [18]. From the natural-resource-based view (NRBV), technology investment alone does not necessarily generate sustainable competitive advantage. Sustainable performance may improve only when such investment is transformed into firm capabilities through resource allocation, capability development, and organizational embedding [19], [20]. Di Vaio and Varriale [21] also provide support for this view in their study of blockchain in the airport industry. The sustainable performance benefits of blockchain may not be associated solely with whether the technology is introduced, but also with the overall degree to which firms adopt it. Therefore, it is necessary to examine the relationship between blockchain adoption intensity and sustainable performance.

The textile and apparel industry provides a suitable context for examining blockchain adoption intensity and its implications for sustainable performance. The industry has a large market scale and a multi-tier, fragmented value chain characterized by intensive interorganizational collaboration. This value chain spans upstream raw material supply, midstream textile manufacturing, and downstream branded retail, involving numerous suppliers, manufacturers, and subcontractors [22], [23]. This structure exacerbates information asymmetry and low visibility, posing persistent challenges for supplier compliance monitoring, product traceability, and accountability [23], [24]. The industry also faces sustained scrutiny over carbon emissions, water consumption, and pollution control, while tightening regulations and growing stakeholder oversight further intensify sustainable governance pressure [25], [26]. These characteristics make blockchain highly applicable across different business processes and supply chain segments, while also highlighting the practical relevance of examining firms' blockchain adoption intensity and its performance associations.

This study focuses on firms in the Chinese textile and apparel industry. China has a comprehensive textile and apparel industrial system with a complex hierarchical structure. Government support has also been identified as an important environmental factor influencing blockchain adoption in Chinese firms' supply chains [27], providing a valuable empirical basis for examining variations in blockchain adoption and their implications for sustainable performance in complex industrial networks. Based on the foregoing discussion, the following research questions are addressed:

RQ1: What factors influence blockchain adoption intensity among textile and apparel firms?

RQ2: How does blockchain adoption intensity affect the sustainable performance of textile and apparel firms?

RQ3: Do these relationships vary across firms at different value-chain positions?

To address these questions, this study develops and empirically tests an integrated analytical framework centered on blockchain adoption intensity. The Technology–Organization–Environment (TOE) framework organizes technological, organizational, and environmental antecedents [16], institutional theory captures external institutional pressures [28], and the NRBV explains the theoretical link between blockchain adoption intensity and sustainable performance [19]. Methodologically, partial least squares structural equation modeling (PLS-SEM) is used to test structural relationships, artificial neural network (ANN) analysis is employed to identify key predictors, and multi-group analysis (MGA) is applied to explore path differences across value-chain positions.

This study extends the focus of blockchain adoption research from adoption intention and binary adoption decisions to blockchain adoption intensity as an organizational-level, degree-based construct, thereby complementing existing understanding of firms' blockchain adoption. A model centered on blockchain adoption intensity simultaneously examines its antecedents and performance outcomes, providing a more comprehensive explanation of firms' blockchain adoption and value realization. The exploratory examination of firms at different value-chain positions provides preliminary evidence of value-chain

heterogeneity in blockchain adoption intensity. The findings also provide practical guidance for textile and apparel firms and policymakers in identifying key factors and developing differentiated adoption and support strategies.

The remainder of this paper is organized as follows. Section II reviews the relevant literature and develops the hypotheses; Section III describes the research methodology; Section IV reports the empirical results; and Section V concludes the study with theoretical and practical implications, limitations, and future research directions.

II. THEORETICAL BACKGROUND AND RESEARCH MODEL

This section reviews prior research on blockchain adoption and discusses the theoretical foundations underlying the proposed research model. Based on these foundations, the research model and hypotheses are developed.

A. REVIEW OF BLOCKCHAIN ADOPTION RESEARCH

Research on blockchain adoption has grown rapidly since 2019, expanding from individual acceptance to organizational adoption and industrial applications. At the individual level, studies are largely grounded in the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), focusing on cognitive factors such as perceived usefulness, perceived ease of use, and adoption intention [29], [30]. Organizational-level studies often apply the TOE framework to examine the effects of technological, organizational, and environmental factors on firms' blockchain adoption intentions, decisions, or actual use [11], [31]. Some studies incorporate institutional theory to analyze the influence of institutional pressures on firms' adoption behavior [32], [33]. Research on industrial applications focuses on the functions of blockchain in transparency, traceability, interorganizational collaboration, and sustainable governance [10], [34].

Viewed through the lens of innovation adoption research, blockchain adoption is not a single point-in-time decision but a dynamic process that unfolds progressively within organizations. Innovation adoption research has mainly developed along two research streams: the innovation variance perspective and the innovation process perspective [35]. Traditionally, the former has dominated innovation adoption research and primarily explains the formation of adoption intentions and decisions [36], [37], [38]. The latter views technology adoption as a continuous evolutionary process from awareness to actual application [35], [39]. In the blockchain context, research from the process perspective remains relatively limited [40]. Existing studies have employed stage-based models to examine blockchain adoption and describe its development as involving stages such as adoption intention, adoption decision, and routinization [40], [41].

Within this evolving process, technology adoption research has also examined the degree of technology adoption through several related concepts. Technology assimilation refers both to the process through which organizations absorb and integrate technologies into their operations and to the degree to which technologies become embedded in organizational practices [12], [42], [43]. Relatedly, adoption depth emphasizes the deeper use and integration of technologies after adoption and addresses the potential gap between technology adoption and actual application [44], [45]. Post-adoption use, in turn, focuses on actual use behavior and the extent of use following initial adoption [46], [47], [48]. More recently, studies in the artificial intelligence domain have begun to use adoption intensity to measure the degree of technology adoption at the organizational level, encompassing the scope of application across different AI technologies and coverage within specific business processes [13], [49].

Existing blockchain adoption studies have examined organizational adoption manifestations related to resource investment and business application requirements [14], [15], [50], providing a foundation for understanding the degree of blockchain adoption. Building on the above research, this study conceptualizes and operationalizes blockchain adoption intensity as a focal organizational-level construct that reflects the overall degree of blockchain adoption within a firm. The construct is reflected in three aspects: resource investment, application scope, and operational embedding. Table 1 summarizes the main research focuses of prior blockchain adoption studies and the theoretical positioning of this study.

In terms of performance outcomes, existing studies have mostly focused on a single outcome dimension, such as financial performance [50], [51], cost performance [52], or supply chain performance [14], [53]. Systematic evidence integrating economic, operational, environmental, and social dimensions remains limited [54]. Moreover, less attention has been paid to differences among firms at different value-chain positions within the same industry. Sustainable supply chain research has used different tiers of fashion supply chains as units of analysis and found significant differences in sustainable practices and governance tasks across tiers [55]. In multi-tier industries such as textile and apparel, firms at different value-chain positions may face different adoption conditions, and the relationships between antecedent conditions and blockchain adoption intensity, as well as between blockchain adoption intensity and sustainable performance, may also vary. These potential differences remain to be further explored.

B. PROPOSED RESEARCH MODEL

The TOE framework is a well-established theoretical model for explaining organizational technology adoption and implementation. It emphasizes that technological, organizational, and environmental conditions jointly influence firms' adoption behavior [16], [56]. The framework has been widely applied in blockchain adoption research and provides a basic classification structure for identifying antecedents of technology adoption at the firm level [11], [31].

TABLE 1. Positioning of this study within blockchain adoption research.

Research Focus	Conceptual Meaning	Key Studies	Distinction / Positioning
Adoption intention	Firms' willingness or behavioral intention to adopt blockchain before actual adoption.	[37], [38], [41], [57], [58]	Explains pre-adoption intention but not the subsequent adoption process.
Adoption-decision	The stage in which firms evaluate blockchain, make an adoption decision, and allocate initial resources for its acquisition and implementation.	[40], [59], [60], [61]	Focuses on the adoption-decision stage rather than the degree of blockchain adoption.
Assimilation	The process through which technologies are absorbed, integrated, and embedded in organizational practices, as well as the degree to which they become embedded in those practices.	[43], [53], [62], [63]	Focuses on the integration and embeddedness of technology within organizational practices, whereas BAI jointly captures resource investment, application scope, and operational embedding.
Routinization	The stage in which adopted technologies become stable components of organizational routines and operations.	[40], [41], [64]	Focuses on the later stage of the technology adoption process but provides limited insight into earlier stages and overall adoption progression.
Post-adoption use	Actual use behaviors and the extent of use following initial adoption.	[48], [65], [66]	Focuses on continued and extended use behaviors and the extent to which technology is used in organizational practices, whereas BAI reflects the overall degree of blockchain adoption at the organizational level.
Blockchain adoption intensity (BAI)	The overall degree of organizational blockchain adoption is reflected in resource investment, application scope, and operational embedding.	This study	Positions blockchain adoption intensity as a focal organizational-level construct that jointly captures resource investment, application scope, and operational embedding.

Note: "This study" indicates the positioning of the present research rather than prior literature.

Although the TOE framework incorporates the external environment into technology adoption analysis, it provides a relatively limited explanation of the specific sources and different forms of institutional influence [52], [67]. Firms' blockchain adoption is driven not only by efficiency logic but also by industry norms and peer imitation [28], [68]. This study incorporates institutional theory to explain the influence of normative and mimetic pressures on blockchain adoption intensity. Coercive institutional influences are typically manifested as government policies, regulatory requirements, and formal rules [28], [68]. Blockchain adoption studies commonly include government support, regulatory environment, and standards uncertainty as external environmental factors [31], [57]. To avoid overlap among related constructs, this study does not separately include coercive pressure and instead focuses on normative and mimetic pressures.

The NRBV provides theoretical grounding for the translation of adoption intensity into multidimensional sustainable performance. This view emphasizes that technological resources must be organized, embedded in processes, and developed into capabilities before they can be converted into long-term performance outcomes [19], [20].

Based on this theoretical integration, the research model is presented in Figure 1, with blockchain adoption intensity as the central variable linking antecedent conditions to performance outcomes. The TOE framework is used not only to categorize technology adoption antecedents but also to describe the multidimensional contextual conditions surrounding firms' technology adoption [56], [69]. To reflect the multidimensional structure of technology adoption antecedents and sustainable performance, this study applies higher-order construct (HOC) modeling to integrate relevant first-order dimensions into HOCs. This approach has been used in technology adoption research to consolidate multidimensional constructs and help enhance model parsimony and theoretical clarity [70], [71].

C. HYPOTHESIS DEVELOPMENT

The antecedents of blockchain adoption intensity can be organized into technological, organizational, environmental, and institutional factors, with a distinction between facilitating and constraining factors. Table 2 summarizes the constructs, first-order dimensions, and measurement sources.

1) TECHNOLOGICAL CONTEXT

The technological context covers the technological characteristics and implementation conditions that affect the adoption process [16]. Firms' blockchain adoption intensity is influenced by their assessment of Technological Benefits and is also constrained by Technological Barriers. Technological Benefits reflect positive evaluations of Relative Advantage and Compatibility, whereas Technological Barriers reflect implementation resistance arising from Complexity and Technical Risk [72].

The adoption of technological innovation is generally driven by perceived advantage [73]. When organizations perceive that the benefits of a new technology outweigh its costs and risks, they are more likely to advance digital transformation [74]. In the blockchain context, Relative Advantage reflects the potential of blockchain to improve operational efficiency, information transparency, and process traceability, while Compatibility reflects its fit with firms' existing systems, processes, and business practices. Many processes in the textile and apparel industry still rely on manual verification and decentralized documentation, resulting in high information verification costs and lengthy dispute resolution

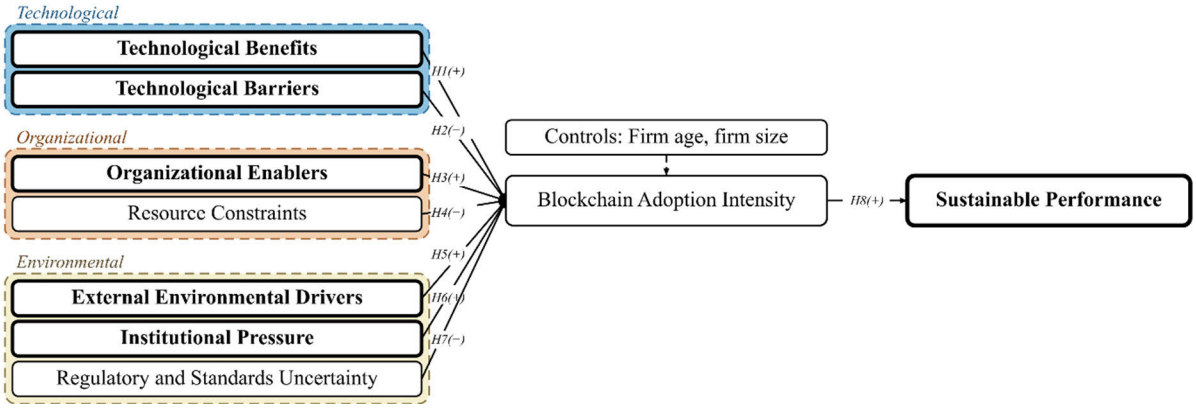

FIGURE 1. Proposed research model. Notes: bold boxes indicate higher-order constructs.

TABLE 2. Constructs, dimensional structure, and representative literature.

Category	Construct	Modeling	Dimensions / Indicators	Sources
Technological	Technological Benefits (TBE)	HOC	Relative advantage; compatibility	[11], [38], [50], [76], [77]
	Technological Barriers (TBA)	HOC	Complexity; technical risk	[11], [38], [50], [76], [78]
Organizational	Organizational Enablers (OEN)	HOC	Organizational innovativeness; top management support	[31], [38], [50], [77], [79]
	Resource Constraints (RC)	FOC	Financial constraints; human resource constraints; IT infrastructure limitations; technical capability limitations	[11], [38], [50]
Environmental	External Environmental Drivers (EED)	HOC	Government support and policy; market turbulence	[31], [38], [50], [80], [81]
	Regulatory and Standards Uncertainty (RSU)	FOC	Unclear compliance requirements; hard-to-predict regulatory changes; unstable industry standards; immature standards	[31], [57]
	Institutional Pressure (INS)	HOC	Mimetic pressure; normative pressure	[81]
Focal construct	Blockchain Adoption Intensity (BAI)	FOC	Resource investment; application scope; operational embedding	[14], [53]
Performance	Sustainable Performance (SP)	HOC	Economic performance; operational performance; environmental performance; social performance	[17], [82]

Note: HOC = higher-order construct; FOC = first-order construct. Dimensions/indicators refer to each construct's conceptual basis or measurement focus.

cycles [1], [23]. When blockchain can alleviate these pain points and fit existing systems, firms are more likely to increase related resource investment, expand its application across business processes, and embed it in daily operations. Prior research has confirmed the positive effects of Relative Advantage and Compatibility on blockchain adoption [37], [75]. Accordingly:

H1: Technological Benefits have a positive effect on Blockchain Adoption Intensity.

Technology adoption is also influenced by ease of implementation and the complexity of required changes [83]. When adoption requires substantial effort to learn new processes or modify existing systems, the likelihood of advancing adoption and embedding the technology in daily operations may decline. Blockchain involves a high technical threshold, and for textile and apparel firms with limited technical capabilities, learning, training, and coordination costs are non-trivial. The inhibiting effect of Complexity on technology adoption is well documented [37], [84]. Beyond Complexity, Technical Risk also constitutes an important implementation barrier. Firms introducing blockchain may face uncertainty regarding system reliability, data security, privacy protection, and interface security [1], [11], which can weaken their willingness to initiate blockchain projects and limit subsequent resource investment and deployment scope. Complexity and Technical Risk together constitute major Technological Barriers faced by textile and apparel firms in adopting blockchain. Therefore:

H2: Technological Barriers have a negative effect on Blockchain Adoption Intensity.

2) ORGANIZATIONAL CONTEXT

The organizational dimension reflects the internal conditions that shape technology adoption, including Top Management Support, Organizational Innovativeness, and Resource Constraints [16]. The textile and apparel industry encompasses firms of varying size and value-chain position, with differences in resource allocation and managerial capacity [85]. Organizational Enablers comprising Top Management Support and Organizational Innovativeness, together with Resource Constraints, may jointly influence firms' Blockchain Adoption Intensity.

Blockchain adoption typically involves a continuing process of solution evaluation, pilot implementation, and business embedding, requiring sustained management attention and clear strategic direction. Top management support creates a favorable organizational climate for the adoption process, provides necessary personnel and budget resources, and enhances the firm's capacity to cope with implementation uncertainty [31]. When management regards blockchain as strategically important, firms are more likely to continue advancing its application rather than remain at the stage of preliminary evaluation or limited piloting. Organizational innovativeness similarly affects the progression of adoption. Firms with stronger innovation orientation are generally more willing to explore emerging digital tools, test application feasibility through pilots, and institutionalize effective practices into routine processes [31], [77], [86]. This facilitates the transition of blockchain from limited application to broader and deeper application. This reasoning supports the following hypothesis:

H3: Organizational Enablers have a positive effect on Blockchain Adoption Intensity.

Blockchain deployment often places high demands on firms' financial, human, and technical capabilities. Firms lacking internal expertise or IT infrastructure typically rely on external service providers, increasing implementation costs and coordination complexity [74], [83]. Prior research indicates that resource insufficiency, talent scarcity, and limited technical capability are important barriers to advancing technology adoption [74], [87]. For textile and apparel firms already in the evaluation or pilot stage, resource constraints may not entirely prevent initial engagement with blockchain, but can limit investment scale, system integration depth, and business embedding, thereby constraining improvements in Blockchain Adoption Intensity. The fourth hypothesis is:

H4: Resource Constraints have a negative effect on Blockchain Adoption Intensity.

3) ENVIRONMENTAL AND INSTITUTIONAL CONTEXT

The environmental dimension reflects the influence of external ecosystem conditions on technology adoption, encompassing Market Turbulence, Government Support and Policy, and Regulatory and Standards Uncertainty [74], [88]. The textile and apparel industry faces rapidly changing consumer demand, intense market competition, and an evolving digital policy environment, all of which affect the timing and extent of firms' blockchain adoption. Regulations and industry standards related to blockchain have yet to fully mature, which may also increase uncertainty as firms advance blockchain adoption.

Market turbulence and government support and policy are important external environmental drivers of blockchain adoption intensity. Consumer preferences in the textile and apparel industry are evolving rapidly, and competitive dynamics are shifting continuously, requiring firms to respond to demand changes more promptly and improve operational flexibility [38], [81]. Blockchain's verifiability and collaborative features make it a viable technology choice for enhancing operational responsiveness. Government support and policy measures create more favorable external conditions for firms' blockchain application through policy incentives, project partnerships, training guidance, and financial assistance [31], [50]. When Market Turbulence generates digital transformation pressure and Government Support and Policy provides external support, firms are more likely to increase their investment in blockchain and expand its application across key business processes. Based on the foregoing analysis:

H5: External Environmental Drivers have a positive effect on Blockchain Adoption Intensity.

Institutional theory emphasizes that organizational behavior is not solely driven by internal technological and resource conditions but is also shaped by isomorphic pressures in the external institutional environment [28]. Mimetic pressure arises from firms' observation of and learning from peer practices. Under conditions of high technological and market uncertainty, firms may imitate industry leaders to reduce decision risk and maintain competitive legitimacy [81], [83]. Normative pressure derives from industry expectations formed by supply chain partners, customers, and industry associations. As blockchain is increasingly regarded as a legitimate practice for improving transparency and sustainable governance, firms may expand blockchain application scope and resource commitment to gain industry recognition and sustain cooperative relationships [28], [84]. Unlike external environmental drivers, which operate primarily through market dynamics and policy support, institutional pressure acts through social expectations, industry norms, and interorganizational comparisons. This leads to:

H6: Institutional Pressure has a positive effect on Blockchain Adoption Intensity.

Blockchain applications in data sharing, on-chain recording, and audit tracing require firms to address compliance requirements and regulatory constraints. Rules related to blockchain, however, continue to evolve [1], [89]. When compliance requirements lack clarity, regulatory changes are difficult to anticipate, and industry standards remain unstable, firms face difficulty accurately assessing the scope and costs of project implementation [31], [57]. Insufficient standards maturity and interoperability issues further amplify decision risk in technology selection and system integration [90]. For textile and apparel firms in the evaluation or pilot stage, regulatory and standards uncertainty may not entirely prevent initial engagement, but can make firms more cautious in resource investment, system scaling, and cross-organizational data sharing, thereby constraining Blockchain Adoption

Intensity. Dehghani et al. [57] also found that regulatory and standards uncertainty inhibits organizations' willingness to adopt blockchain. This study thus proposes:

H7: Regulatory and Standards Uncertainty has a negative effect on Blockchain Adoption Intensity.

4) BLOCKCHAIN ADOPTION INTENSITY AND SUSTAINABLE PERFORMANCE

The performance implications of digital technologies are closely associated with their adoption intensity within organizations rather than adoption status alone [49]. Low-level deployment often remains confined to limited pilot applications, making it difficult to realize substantial benefits in cost control, process transparency, and interorganizational coordination. As Blockchain Adoption Intensity increases, the potential of blockchain in supply chain data sharing, process tracking, and transaction verification can be more fully realized, helping reduce information asymmetry, improve operational efficiency, and strengthen sustainable governance capabilities [3], [34]. The NRBV suggests that technological investment must be translated into organizational capabilities through resource allocation and capability development before it can improve sustainable performance [19], [20]. In the textile and apparel industry, sustainable performance depends strongly on interorganizational information transparency, supply chain traceability, and accountability coordination. Higher blockchain adoption intensity supports broader business application and performance benefits across economic, operational, environmental, and social dimensions [54], [91]. The final hypothesis is stated as follows:

H8: Blockchain Adoption Intensity has a positive effect on Sustainable Performance.

III. METHODOLOGY

To examine the proposed research model and hypotheses, this section describes the research methodology, including data collection, measurement development, bias assessment, and analytical procedures.

The empirical analysis employs a combined PLS-SEM and ANN approach. PLS-SEM is used to test the theoretically specified structural relationships, but it primarily estimates linear path relationships and has limitations in capturing more complex or nonlinear patterns among constructs [38]. ANN is therefore employed as a predictive complement to assess the relative importance of key antecedents through sensitivity analysis within a nonlinear framework, rather than as a substitute for the theoretical path testing of PLS-SEM [38], [92]. This methodological combination balances explanatory power with predictive capability and supports a more comprehensive interpretation of the findings. In addition, exploratory MGA based on value-chain position is conducted to address RQ3. The overall research method and analytical procedure are illustrated in Figure 2.

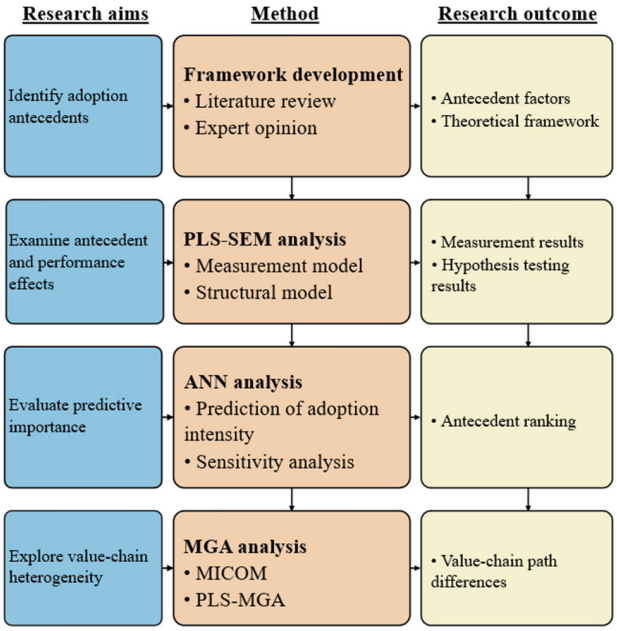

FIGURE 2. Research method and analytical procedure.

A. SAMPLE AND DATA COLLECTION

This study targeted firms in China's textile and apparel industry. Following the key informant approach [93], [94], respondents included senior managers, blockchain project leaders, and key personnel familiar with supply chain operations or digital practices. Data were collected using a structured questionnaire comprising background information and construct measurement items. Firms were classified into upstream, midstream, and downstream categories based on their primary value-creating activities in the textile and apparel value chain. Upstream firms primarily supply raw materials and basic materials; midstream firms are mainly engaged in processing, manufacturing, and production conversion; downstream firms focus on branding, distribution, sales, and market-facing functions.

The questionnaire was developed and distributed through Credamo (https://www.credamo.com/#/), a professional online survey platform. The platform supports targeted screening based on industry, job title, and firm characteristics, improving the match between the sample and the research population. Deng et al. [93] also used this platform for blockchain technology research in Chinese manufacturing and supply chain contexts, indicating that the platform has been used in comparable research settings. Targeted invitations through industry networks were supplemented by outreach via social media, email, and direct messaging, expanding sample coverage through snowball sampling. Front-end screening items were embedded at the beginning of the questionnaire, covering industry affiliation, blockchain awareness, and comprehension of core concepts; respondents who did not meet the criteria were automatically excluded. A blockchain adoption status item was included to ensure that the sample consisted only of firms that had initiated organizational blockchain adoption activities, including evaluation, planning, pilot projects, or implementation stages. Attention check items were included to identify invalid or careless responses.

Research descriptions and completion guidelines were provided to participants before data collection, and informed

consent was obtained. All data were collected anonymously and used solely for academic research purposes. Data collection was conducted from November 20, 2025, to January 13, 2026. A total of 797 questionnaires were distributed and 357 were returned, yielding a response rate of 44.8%. After removing 66 responses that failed the attention checks, 291 valid responses were retained, representing 81.5% of the returned sample. This sample size exceeds the conventional ten-times-rule threshold commonly used in PLS-SEM [95]. Basic sample characteristics are presented in Table 3.

TABLE 3. Sample characteristics (n = 291).

	Variables	Frequency	Percent (%)
Job position	Specialist / Staff / Other	128	43.99
	Middle Management	120	41.24
	Top Management	43	14.78
Blockchain experience	Less than 1 year	18	6.19
	1 - 2 years	95	32.65
	3 - 4 years	122	41.92
	5 years or more	56	19.24
SCM experience	Less than 5 years	97	33.33
	5 - 10 years	135	46.39
	11 - 15 years	43	14.78
	More than 15 years	16	5.50
Gender	Male	155	53.26
	Female	136	46.74
Education	Below bachelor's degree	33	11.34
	Bachelor's degree	198	68.04
	Master's degree or higher	60	20.62
Age	Under 25	30	10.31
	25–34	127	43.64
	35–44	122	41.92
	45–54	8	2.75
	55 or above	4	1.37
Value chain position	Upstream	84	28.87
	Midstream	114	39.18
	Downstream	93	31.96
Firm age	Less than 5 years	22	7.56
	5 - 10 years	86	29.55
	11 - 20 years	119	40.89
	More than 20 years	64	21.99
Firm size	Small	37	12.71
	Medium	163	56.01
	Large	91	31.27

B. MEASUREMENT DEVELOPMENT

The measurement items were primarily based on established and validated scales from prior literature and adapted to the research context. The measurement indicators and their corresponding sources are summarized in the Appendix.

Specifically, the TOE framework-related constructs were mainly measured based on Wong et al. [38], Chittipaka et al. [11], and other blockchain technology adoption studies. The measurement of regulatory and standards uncertainty was based on Malik et al. [31] and Dehghani et al. [57], and the measurement of institutional pressure was based on Lin [81]. In terms of measurement content, the antecedent constructs retained the core elements of established scales, including relative advantage and compatibility, technological complexity and risk, organizational innovativeness and top management support, resource constraints, and government support and market turbulence. The item wording was adapted to the textile and apparel supply chain and firm-level blockchain application context. The institutional pressure items largely followed the established measurement logic of mimetic and normative pressures, whereas regulatory and standards uncertainty was contextualized in terms of blockchain-related compliance requirements, regulatory changes, and industry standards.

The measurement items for blockchain adoption intensity were primarily adapted from Wamba et al.'s [14] blockchain adoption measure and adjusted with reference to related blockchain application research [50]. Compared with prior measures, this study retained the resource investment item and adapted the prior item concerning the need for blockchain use in firms' business activities to assess blockchain application scope across key supply chain processes. An operational embedding item was also incorporated to reflect whether blockchain had become integrated into firms' day-to-day operations rather than remaining limited to demonstrations or one-off trials. Together, resource investment, application scope, and operational embedding capture the overall degree of blockchain adoption at the organizational level.

Sustainable performance was measured using items primarily based on Zailani et al.'s [17] sustainable supply chain performance scale, retaining its main measurement content for economic, operational, environmental, and social performance. Selected items were adapted to the textile and apparel supply chain context with reference to Baliga et al.'s [82] discussion of sustainable supply chain practices. The formal questionnaire used a seven-point Likert scale (1 = "strongly disagree", 7 = "strongly agree"), and firm size and firm age were included as control variables in the model.

Consistent with the HOC modeling approach introduced earlier, several multidimensional constructs were modeled as HOCs and operationalized as hierarchical component models (HCMs) in the PLS-SEM analysis [96]. Technological benefits, technological barriers, organizational enablers, external environmental drivers, institutional pressure, and sustainable performance were specified as reflective–formative Type II structures. In this structure, lower-order constructs (LOCs) are measured by reflective indicators, whereas HOCs are aggregated from their corresponding LOCs in a formative manner. Incorporating HCMs helps reduce the number of relationships in the structural model, lowers model complexity, and represents multidimensional constructs at a higher level of abstraction [96], [71].

Before the formal survey, 40 pretest questionnaires were distributed through the Credamo platform. Pretest respondents were managers from production, technology, and supply chain departments. The pretest assessed item clarity, wording accuracy, and questionnaire completion time. Items with ambiguity or unclear wording were revised based on respondent feedback and expert opinions from the fields of

supply chain management and digital transformation. Based on preliminary item diagnostics, two items with unclear wording and weak statistical performance, RSU4 and MT4, were removed. Pretest responses were excluded from the formal analysis.

C. NONRESPONSE BIAS AND COMMON METHOD BIAS

Given that data were collected from a single questionnaire survey relying on self-reported responses, potential common method bias (CMB) and nonresponse bias were assessed.

CMB was first mitigated through procedural controls, including anonymous completion, screening mechanisms, and attention checks. The questionnaire was also structured into separate sections covering antecedent variables, blockchain adoption intensity, sustainable performance, and background information to reduce psychological proximity among key constructs. These measures helped reduce systematic errors arising from single-source measurement, evaluation apprehension, and careless responses. Statistical assessment was then conducted using Harman's single-factor test. An unrotated principal component analysis did not yield a single dominant factor; the first common factor explained 36.205% of the total variance, indicating that no single factor dominated the data variance. Collinearity assessment showed that the variance inflation factors (VIFs) of all predictor constructs ranged from 1.191 to 3.034, all below the conservative threshold of 3.3 [97]. Although no single diagnostic test can completely rule out CMB, the combined procedural controls and statistical results suggest that CMB is unlikely to pose a serious threat.

Nonresponse bias was assessed using the early–late comparison method [98]. The 291 valid responses were divided into early and late respondents based on submission time, and the first 30% and last 30% were selected for comparison. Independent-samples t-tests on the means of key constructs revealed no significant differences, indicating no significant nonresponse bias in the sample.

D. DATA ANALYSIS PROCEDURE

PLS-SEM analysis was conducted in SmartPLS 4. Compared with covariance-based structural equation modeling (CB-SEM), PLS-SEM is better suited for research models involving HCMs and complex path relationships [71], [99]. HCMs were estimated following the repeated indicator approach recommended by Sarstedt et al. [71]; Mode B was used for measurement with path weighting as the internal weighting scheme, a combination that demonstrates good parameter recovery in reflective–formative models [96]. Measurement model assessment followed a two-step procedure. The first step assessed internal consistency, convergent validity, and discriminant validity of the reflective LOCs; the second step evaluated multicollinearity, outer weights, and their significance for the formative higher-order layer of HCMs [71]. Following structural model assessment, the MICOM procedure was applied to test measurement invariance across groups, providing the basis for MGA path comparison [100].

ANN analysis was implemented using a multilayer perceptron (MLP) model in the neural network module of IBM SPSS 27. MLP is suitable for handling potentially complex nonlinear relationships between input and output variables and can serve as a predictive complement to PLS-SEM. Input layer nodes corresponded to the significant antecedent variables identified by PLS-SEM, and the output layer node was blockchain adoption intensity. A sigmoid activation function was applied to the hidden layer and an identity function to the output layer; the number of hidden layer nodes was determined automatically by the software. To reduce the risk of overfitting, a training–testing split was applied, with approximately 90% of the sample used for training and 10% for testing. Multiple training runs were conducted to obtain stable results, and model predictive performance was evaluated using the root mean square error (RMSE) for the training and testing samples. A sensitivity analysis was further conducted to assess the relative predictive contribution of each input variable based on normalized importance. Normalized importance was obtained by scaling the importance value of each variable relative to the highest importance value [92].

IV. RESULTS

Based on the proposed research model and analytical procedures described in the previous section, this section reports the empirical results. The PLS-SEM results are presented first, followed by the ANN and exploratory MGA results.

A. PLS-SEM RESULTS

The PLS-SEM analysis comprised the assessment of the measurement and structural models.

1) MEASUREMENT MODEL

Measurement model assessment was conducted separately for the reflective LOCs and the formative layer of HCMs.

Table 4 presents the assessment results for the first-order reflective constructs, covering indicator reliability, internal consistency reliability, and convergent validity. All factor loadings exceeded 0.70 (range: 0.702–0.930), meeting the indicator reliability criterion [99]. The average variance extracted (AVE) for all constructs exceeded 0.50 (range: 0.591–0.822), supporting convergent validity. Cronbach's alpha and composite reliability (CR) for all constructs exceeded the 0.70 threshold, indicating satisfactory internal consistency.

Discriminant validity was assessed using the heterotrait-monotrait ratio (HTMT) method [99], [100]. As shown in

Table 5, all construct pairs yielded HTMT values below the conservative threshold of 0.85, indicating sufficient distinction among constructs and supporting discriminant validity. The reliability, convergent validity, and discriminant validity of the reflective LOCs all met the recommended criteria.

TABLE 4. Measurement model results (reflective constructs).

Construct	Items	Loadings	Cronbach's α	ρ_A	CR (ρ_C)	AVE
BAI	BAI 1–BAI 3	0.819–0.917	0.853	0.863	0.911	0.773
CLX	CLX1–CLX5	0.784–0.798	0.852	0.854	0.894	0.627
COMP	COMP1–COMP4	0.702–0.841	0.769	0.781	0.852	0.591
ECO	ECO1–ECO4	0.772–0.890	0.868	0.880	0.910	0.717
ENV	ENV1–ENV4	0.832–0.858	0.868	0.868	0.910	0.716
GSP	GSP1–GSP3	0.891–0.918	0.892	0.892	0.933	0.822
MT	MT1–MT3	0.866–0.930	0.879	0.887	0.926	0.806
MP	MP1–MP4	0.816–0.850	0.845	0.853	0.896	0.682
NP	NP1–NP3	0.826–0.914	0.841	0.871	0.903	0.757
OI	OI1–OI4	0.846–0.879	0.883	0.884	0.920	0.741
OPE	OPE1–OPE4	0.847–0.883	0.880	0.881	0.918	0.736
RA	RA1–RA4	0.750–0.842	0.821	0.832	0.881	0.650
RC	RC1–RC4	0.799–0.830	0.831	0.836	0.887	0.663
RSU	RSU1–RSU3	0.730–0.912	0.739	0.877	0.843	0.645
SOC	SOC1–SOC4	0.794–0.879	0.867	0.870	0.910	0.716
TR	TR1–TR4	0.781–0.860	0.859	0.862	0.904	0.703
TMS	TMS1–TMS4	0.759–0.881	0.858	0.865	0.904	0.703

TABLE 5. Discriminant validity assessment using the HTMT ratio.

Construct	BAI	CLX	COMP	ECO	ENV	GSP	MT	MP	NP	OI	OPE	RA	RC	RSU	SOC	TR	TMS
BAI	—																
CLX	0.46																
COMP	0.58	0.34															
ECO	0.72	0.36	0.65														
ENV	0.79	0.33	0.59	0.81													
GSP	0.73	0.41	0.55	0.70	0.75												
MT	0.71	0.32	0.52	0.64	0.73	0.70											
MP	0.64	0.28	0.67	0.75	0.71	0.64	0.64										
NP	0.65	0.32	0.62	0.70	0.64	0.64	0.57	0.58									
OI	0.76	0.34	0.51	0.66	0.77	0.74	0.74	0.61	0.58								
OPE	0.72	0.32	0.59	0.71	0.76	0.74	0.70	0.64	0.66	0.77							
RA	0.66	0.29	0.65	0.67	0.64	0.59	0.58	0.57	0.63	0.60	0.65						
RC	0.49	0.73	0.34	0.43	0.44	0.49	0.40	0.29	0.31	0.43	0.42	0.37					
RSU	0.07	0.08	0.07	0.09	0.08	0.12	0.03	0.10	0.10	0.12	0.06	0.08	0.07				
SOC	0.73	0.36	0.65	0.78	0.82	0.70	0.64	0.64	0.65	0.72	0.76	0.66	0.47	0.11			
TR	0.50	0.68	0.35	0.36	0.35	0.49	0.34	0.33	0.38	0.45	0.40	0.44	0.68	0.09	0.38		
TMS	0.69	0.29	0.57	0.64	0.67	0.68	0.62	0.63	0.62	0.74	0.71	0.57	0.30	0.06	0.67	0.40	—

Note: HTMT = heterotrait–monotrait ratio. All HTMT values are below the conservative threshold of 0.85, with the highest value being 0.82, indicating adequate discriminant validity.

Table 6 summarizes the assessment results for the formative layer of HCMs. All VIF values were below the threshold of 3.3, all outer weights were significant ($p < 0.001$), and all outer loadings were within the acceptable range, indicating that the LOCs effectively form their corresponding HCMs. Overall, the formative-layer results support the HCM modeling approach used in this study.

2) STRUCTURAL MODEL

The structural model evaluation results are presented in Table 7. The structural model was evaluated using path coefficients, coefficients of determination (R^2), effect sizes (f^2), and predictive relevance (Q^2predict). Path coefficients were estimated using 5,000 bootstrap samples [99]. R^2 assesses the explanatory power of endogenous constructs, f^2 evaluates the relative effect size of each exogenous variable on endogenous constructs, and Q^2predict values above 0 indicate predictive relevance [101].

TABLE 6. Summary of formative measurement model assessment.

Assessment item	Result range	Assessment standard	Conclusion
VIF	1.326 – 2.696	< 3.3	No serious multicollinearity
Outer weight	0.279 – 0.618	$p < 0.001$	Significant contribution
Outer loading	0.846 – 0.918	High loading	Adequate absolute contribution

The model showed good explanatory capability. The antecedents and control variables jointly explained 60.2%

TABLE 7. Structural model results.

Hypothesis / Path	β	t-value	p-value	R^2 (Adj. R^2)	Q^2predict	f^2 (Effect size)	Result
H1: TBE → BAI	0.135	2.362	0.018	BAI = 0.602 (0.590)	BAI = 0.572	0.022 (small)	Supported
H2: TBA → BAI	−0.105	2.029	0.042			0.014 (very small)	Supported
H3: OEN → BAI	0.281	4.753	< 0.001			0.074 (small)	Supported
H4: RC → BAI	−0.056	1.031	0.303			0.004 (negligible)	Not supported
H5: EED → BAI	0.232	3.526	< 0.001			0.046 (small)	Supported
H6: INS → BAI	0.147	2.162	0.031			0.02 (small)	Supported
H7: RSU → BAI	−0.016	0.487	0.626			0.001 (negligible)	Not supported
H8: BAI → SP	0.737	29.889	< 0.001	SP = 0.544 (0.542)	SP = 0.664	1.192 (large)	Supported

Note: β denotes the standardized path coefficient. BAI = blockchain adoption intensity; SP = sustainable performance. Adjusted R^2 values are reported in parentheses. Q^2predict > 0 indicates predictive relevance. f^2 effect sizes follow Cohen's thresholds.

TABLE 8. ANN prediction accuracy and sensitivity analysis.

No.	Train RMSE	Test RMSE	EED (NI)	INS (NI)	OEN (NI)	TBA (NI)	TBE (NI)
1	0.44	0.46	96.50	100.00	78.20	49.40	45.30
2	0.43	0.51	100.00	65.00	73.20	58.40	55.50
3	0.49	0.39	24.70	12.50	100.00	19.90	77.00
4	0.46	0.37	100.00	73.70	55.90	65.10	39.70
5	0.43	0.37	81.40	65.10	100.00	60.90	71.60
6	0.43	0.42	80.10	81.30	100.00	51.50	62.10
7	0.44	0.44	87.50	86.80	100.00	49.60	48.30
8	0.43	0.44	64.90	67.70	100.00	68.90	66.30
9	0.45	0.36	63.20	64.70	100.00	41.90	76.10
10	0.44	0.42	93.20	100.00	84.60	55.70	59.50
Avg.	0.45	0.42	79.15	71.68	89.19	52.13	60.14

Note: RMSE = root mean square error; NI = normalized importance; Avg. = average. Normalized importance values are reported across ten ANN runs.

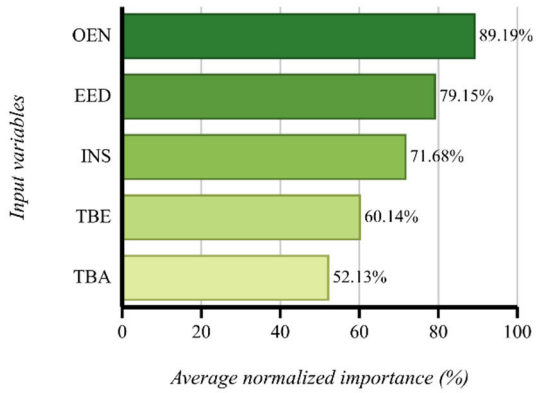

FIGURE 3. Ranking of average normalized importance of ANN input variables.

of the variance in blockchain adoption intensity (R^2 = 0.602, adjusted R^2 = 0.590), while blockchain adoption intensity explained 54.4% of the variance in sustainable performance (R^2 = 0.544, adjusted R^2 = 0.542), indicating satisfactory explanatory levels for both endogenous constructs. The Q^2predict values for blockchain adoption intensity and sustainable performance were 0.572 and 0.664, respectively, both exceeding 0 and indicating predictive relevance.

The structural model results show that H1–H3, H5, H6, and H8 were supported, while H4 and H7 were not supported. Among the antecedents, organizational enablers showed

TABLE 9. Significant MGA results for hypothesized paths.

Comparison	Path	β1	β2	Δβ	p
UP vs. MID	TBE → BAI	-0.150	0.276	-0.427	0.002
UP vs. DOWN	BAI → SP	0.760	0.595	0.164	0.004
UP vs. DOWN	OEN → BAI	0.512	0.163	0.349	0.020
UP vs. DOWN	TBE → BAI	-0.150	0.173	-0.323	0.032

Note: $p < 0.05$. β1 and β2 denote the group-specific path coefficients following the order shown in the comparison column; Δβ = β1 − β2. UP = upstream, MID = midstream, and DOWN = downstream. Only significant differences in hypothesized paths are reported. No significant differences were found for MID vs. DOWN.

the strongest positive relationship with blockchain adoption intensity ($\beta = 0.281$, $p < 0.001$, $f^2 = 0.074$), followed by external environmental drivers ($\beta = 0.232$, $p < 0.001$, $f^2 = 0.046$) and institutional pressure ($\beta = 0.147$, $p = 0.031$, $f^2 = 0.020$), all representing small effect sizes. Technological benefits were positively related to blockchain adoption intensity ($\beta = 0.135$, $p = 0.018$, $f^2 = 0.022$), also with a small effect size. Technological barriers were negatively related to blockchain adoption intensity ($\beta = -0.105$, $p = 0.042$, $f^2 = 0.014$), although the effect size fell below the threshold for a small effect. These results indicate that although technological benefits and technological barriers were significantly related to blockchain adoption intensity, their effect sizes were smaller than those of organizational enablers and external environmental drivers. Resource constraints ($\beta = -0.056$, $p = 0.303$) and regulatory and standards uncertainty ($\beta = -0.016$, $p = 0.626$) were not significantly related to blockchain adoption intensity. Blockchain adoption intensity

Construct	Code	Measures	Source
Relative Advantage	Stem: In our view, blockchain can…		[11], [38], [50], [76], [77]
	RA1	make product-related information clearer and easier to verify and trace (e.g., provenance/batch records, composition and labeling information, compliance records).	
	RA2	help us respond faster to changes or unexpected issues in the supply chain (e.g., tracing quality issues, batch recalls, returns handling, or demand fluctuations).	
	RA3	make information communication and collaboration smoother with brands, suppliers, manufacturers/OEMs, or logistics providers (e.g., reconciliation and information synchronization).	
	RA4	streamline information inquiry and verification processes, helping employees handle inquiries, verification, and reconciliation tasks faster and with less effort.	
Compatibility	Stem: In our view,…		
	COMP1	blockchain is generally compatible with our existing IT infrastructure and information systems (e.g., ERP, PLM, MES, WMS, TMS).	
	COMP2	using blockchain in supply chain scenarios (e.g., traceability, authenticity checks, compliance records, order/logistics data sharing) fits our existing business processes and operating routines.	
	COMP3	blockchain-related working and collaboration practices are compatible with employees' current (or commonly used) ways of working.	
	COMP4	blockchain applications can be well aligned with our existing management rules and governance mechanisms (e.g., approvals, access rights, data standards, responsibility allocation).	
Technical Risk	Stem: We are concerned that…		[11], [38], [50], [76], [78]
	TR1	during supply chain data sharing, blockchain use may lead to privacy leakage or exposure of sensitive business information.	
	TR2	security issues in blockchain-related systems/interfaces may negatively affect online transactions or operational coordination.	
	TR3	during data transmission, on-chain recording, and storage, blockchain systems may still have vulnerabilities or be exposed to cyberattacks.	
	TR4	blockchain use still involves considerable uncertainty regarding security, privacy, and system reliability.	
Complexity	Stem: In our view,…		
	CLX1	learning how to use blockchain-related systems/tools is not simple.	
	CLX2	substantial training and ramp-up time are needed for relevant employees to use blockchain-related systems/tools proficiently.	
	CLX3	using blockchain-related systems/tools has a high skill threshold and requires strong professional capability.	
	CLX4	further clarification and optimization are still needed to stably integrate blockchain-related systems/tools into existing business processes.	
	CLX5	blockchain-related systems/tools are not easy to use in practice.	
Organizational Innovativeness	Stem: In our view, our company…		[31], [38], [50], [77], [79]
	OI1	typically searches for and evaluates new management methods or digital practices.	
	OI2	usually pilots new management methods or digital tools on a small scale before deciding whether to scale up.	
	OI3	can usually learn quickly and apply new methods or tools to real business operations.	
	OI4	typically improves existing processes continuously and institutionalizes effective new practices into routine procedures or rules.	
Top Management Support	Stem: In our view, our top management…		
	TMS1	continuously pays attention to and is involved in advancing blockchain-related initiatives.	
	TMS2	considers blockchain a strategically important direction.	
	TMS3	is willing to provide necessary resources for blockchain-related work (e.g., staffing and budget).	
	TMS4	is willing to take risks and accept uncertainty when promoting blockchain-related initiatives.	
Resource Constraints	Stem: In our view, the following constraints hinder our firm from advancing blockchain-related initiatives:		[11], [38], [50]
	RC1	insufficient financial resources or budget constraints.	
	RC2	a lack of skilled personnel with blockchain-related knowledge and experience.	
	RC3	insufficient IT infrastructure.	
	RC4	insufficient data analytics capability or system development capability.	
Government Support and Policy	Stem: In our view,…		[31], [38], [50], [80], [81]
	GSP1	government policies generally encourage firms to pursue blockchain-related applications.	
	GSP2	the government provides support through projects, procurement, or cooperation programs, together with training, technical guidance, or financial support.	
	GSP3	blockchain-related government procedures are relatively clear, and firms can follow them when preparing or implementing supply chain applications (e.g., blockchain information service filing).	
Market Turbulence	Stem: In our view,…		
	MT1	customer needs or preferences in our industry change frequently.	
	MT2	changes in customer needs or preferences in our industry are often difficult to predict.	
	MT3	supply-chain-related digital technologies or platforms in our industry evolve rapidly (e.g., tracking, data sharing).	
Mimetic Pressure	Stem: In our view, after adopting blockchain-related practices, our main competitors…		[31], [57]
	MP1	have gained benefits.	
	MP2	are more likely to be favorably perceived within the industry.	
	MP3	are more likely to be favorably perceived by suppliers.	
	MP4	are more likely to be favorably perceived by customers.	

was positively related to sustainable performance ($\beta = 0.737$, $p < 0.001$, $f^2 = 1.192$), with a large effect size. The control variables firm age and firm size were both non-significant ($p > 0.05$).

Normative Pressure	Stem: In our view,…		
	NP1	our key suppliers or business partners generally believe that blockchain "should be adopted" in the supply chain.	
	NP2	our key customers generally believe that blockchain "should be adopted" in the supply chain.	
	NP3	advocacy from industry associations or professional bodies makes "blockchain should be adopted" a widely accepted view in the industry.	
Regulatory and Standards Uncertainty	Stem: In our view,…		
	RSU1	compliance requirements related to blockchain are not sufficiently clear (e.g., data, audit, and operational compliance).	[31], [59]
	RSU2	changes in blockchain-related laws or regulatory requirements are difficult to predict.	
	RSU3	blockchain-related industry standards/guidelines are not yet stable and may change.	
Blockchain Adoption Intensity	BAI1	Our firm has allocated clear resources and organizational support for blockchain applications in the supply chain (e.g., budget, dedicated personnel, IT infrastructure, and system integration support).	[14], [53]
	BAI2	Our firm has piloted or implemented blockchain in at least one key supply chain process and is gradually expanding its coverage (e.g., traceability, authentication, data sharing, regulatory disclosure).	
	BAI3	Within the piloted or implemented scope, blockchain systems or blockchain-recorded data support day-to-day operations or operational management (e.g., querying, verification, coordination, decision support), rather than only demonstrations or one-off trials.	
Sustainable Performance	Economic Performance (ECO): Over the past year (last 12 months), our firm has shown the following changes in supply chain economic performance:		[17], [82]
	ECO1	Manufacturing and delivery-related costs (overall supply chain operating costs) have decreased.	
	ECO2	Product sales have increased.	
	ECO3	Profit and profit margin have increased.	
	ECO4	Market performance has improved (e.g., higher market share or stronger ability to enter new markets).	
	Operational Performance (OPE): Over the past year (last 12 months), our firm has shown the following changes in supply chain operational performance:		
	OPE1	We can achieve "perfect order" delivery (complete, on-time, undamaged).	
	OPE2	We can respond quickly to unexpected demand fluctuations.	
	OPE3	Efficiency and productivity in manufacturing and delivery have improved.	
	OPE4	Inventory level and/or inventory management efficiency have improved.	
	Environmental Performance (ENV): Over the past year (last 12 months), our firm has shown the following changes in supply chain environmental performance:		
	ENV1	Solid and water waste have decreased.	
	ENV2	Use of hazardous/dangerous/toxic materials has decreased.	
	ENV3	Environmental compliance has improved (e.g., meeting environmental standards/regulatory requirements).	
	ENV4	The incidence of environmental accidents/incidents has decreased.	
	Social Performance (SOC): Over the past year (last 12 months), our firm has shown the following changes in supply chain social performance:		
	SOC1	Our image as a "good employer/good workplace" has improved.	
	SOC2	Our image as a "responsible/ethical organization" has strengthened.	
	SOC3	Health and safety of employees (or the community) have improved.	
	SOC4	Health-and-safety-related incidents (e.g., safety accidents/injuries) have decreased.	

B. ANN ANALYSIS RESULTS

As a predictive complement to the PLS-SEM results, ANN analysis incorporated the five antecedent variables that showed significant relationships with blockchain adoption intensity in the PLS-SEM results. The model was run ten times under identical parameter settings [92].

The ANN prediction results are presented in Table 8. The mean training RMSE was 0.45, and the mean test RMSE was 0.42. The two values were close and relatively low, indicating low prediction error, stable predictive performance, and acceptable generalization capability. Normalized importance was used to assess the relative predictive contribution of each input variable to blockchain adoption intensity. As visualized in Figure 3, organizational enablers showed the highest average normalized importance (89.19%), making them the most important predictor, followed by external environmental drivers (79.15%) and institutional pressure (71.68%). Technological benefits (60.14%) and technological barriers (52.13%) exhibited relatively lower predictive contributions.

The variable importance rankings from ANN sensitivity analysis were broadly consistent with the PLS-SEM path coefficient rankings. Organizational enablers ranked first in both analyses, and external environmental drivers and institutional pressure also demonstrated relatively high importance. The relatively low importance of technological barriers in ANN is consistent with its relatively small effect size in PLS-SEM, indicating limited predictive contribution.

C. EXPLORATORY MGA RESULTS

Exploratory MGA was performed using SmartPLS. MICOM testing established configural invariance (Step 1), and compositional invariance (Step 2) was supported for most constructs across pairwise group comparisons [100].

Although a few constructs did not fully meet the compositional invariance criterion, all constructs involved in the significant paths reported in Table 9 met the relevant requirements in their corresponding pairwise comparisons. Given the

relatively limited subgroup sample sizes and the incomplete compositional invariance for some constructs, the subsequent MGA results are treated as exploratory evidence of heterogeneity associated with value-chain position and should be interpreted with caution.

As shown in Table 9, significant path differences primarily emerged between upstream firms and midstream or downstream firms, while no significant differences were found between midstream and downstream firms. Between upstream and midstream firms, significant differences were found in the path coefficients for technological benefits–blockchain adoption intensity and firm age–blockchain adoption intensity. Between upstream and downstream firms, significant differences were found in the path coefficients for blockchain adoption intensity–sustainable performance, organizational enablers–blockchain adoption intensity, and technological benefits–blockchain adoption intensity. These findings suggest that differences related to value-chain position are mainly reflected in the strength of selected path relationships.

V. CONCLUSION AND IMPLICATIONS

Drawing on the empirical results, this section summarizes the major findings and discusses their theoretical, managerial, and policy implications. It also highlights the limitations of this study and provides directions for future research.

A. INTERPRETATION OF FINDINGS

The findings indicate significant relationships between blockchain adoption intensity and multiple antecedent conditions, as well as between blockchain adoption intensity and firms' sustainable performance. The exploratory MGA results provide preliminary insights into value-chain-related contextual differences. The following discussion interprets these findings in terms of antecedent factors, performance outcomes, and value-chain-related differences.

1) ANTECEDENTS

The antecedent analysis shows that organizational enablers, external environmental drivers, institutional pressure, technological benefits, and technological barriers are all significantly associated with blockchain adoption intensity, although their individual effect sizes are small or very small. Thus, statistical significance does not necessarily imply a large substantive effect for an individual factor. The relatively high explained variance of blockchain adoption intensity, together with the modest incremental contribution of individual predictors, suggests a cumulative pattern in which multiple antecedent conditions operate jointly rather than any single factor dominating its formation. This finding is consistent with the basic logic of the TOE framework, which emphasizes the joint influence of technological, organizational, and environmental conditions on technology adoption [16]. The supplementary ANN analysis reveals a relative predictive importance ranking consistent with the path coefficients, providing additional support for this interpretation. Therefore, the practical implication lies less in prioritizing one isolated factor and more in aligning managerial support, organizational innovativeness, technological fit, and external ecosystem conditions.

The technological context results reveal a significant positive relationship between technological benefits and blockchain adoption intensity, with a small effect size, whereas technological barriers show a significant negative relationship, with an effect size below the small-effect threshold. This pattern suggests that relative advantage and compatibility remain technological foundations for firms to enhance blockchain adoption intensity, while complexity and technical risk may, to some extent, limit firms' efforts to expand and deepen blockchain applications. In the textile and apparel context, blockchain's applicability in material traceability, product authentication, and information transparency may help firms increase resource investment, expand application scope, and strengthen operational embedding. However, system integration, data security, and technical reliability challenges across multi-tier production and distribution processes may still weaken firms' sustained deployment capability.

Organizational enablers showed the strongest path coefficient in PLS-SEM and the highest relative importance in ANN, indicating that top management support and organizational innovativeness are important organizational conditions closely associated with higher blockchain adoption intensity. This finding is consistent with Bag et al. [50], who identified top management support as a critical predictor of blockchain adoption. For blockchain applications that span processes, departments, and organizations, management support and innovation orientation may facilitate resource coordination, cross-departmental collaboration, and experimentation, thereby supporting broader embedding of blockchain in business processes.

The results for external environmental drivers and institutional pressure indicate significant positive relationships with blockchain adoption intensity and higher relative importance than technological benefits and barriers. This suggests that higher blockchain adoption intensity is also closely associated with market demand, policy support, mimetic pressure, and industry norms, consistent with prior findings on the roles of external pressures and trading partner pressures [14], [93]. In the textile and apparel industry, growing demands for information transparency, responsible material sourcing, product authentication, and ESG scrutiny make blockchain an important tool for firms to respond to external market and institutional expectations. The significant relationship between institutional pressure and blockchain adoption intensity also suggests that the general environmental factors in TOE alone may be insufficient to explain external institutional influences on firms' blockchain adoption.

Resource constraints and regulatory and standards uncertainty were not significantly related to blockchain adoption intensity, but this does not mean that they are unimportant in firms' blockchain practices. This result may be related to the fact that the sampled firms had already entered blockchain evaluation, piloting, or implementation, as well as to China's digital industrial environment. Resource constraints may be more salient when firms decide whether to enter the adoption process. For firms that have already entered the adoption process, however, their association with adoption intensity may become weaker [11], [57]. At the same time, platform-based digital services and support from external technology providers may alleviate pressures on firms in technology development, system maintenance, and professional talent allocation. The non-significant relationship between regulatory and standards uncertainty and blockchain adoption intensity may be related to relatively consistent policy signals and a relatively homogeneous institutional environment, which may reduce differences in firms' perceptions of such uncertainty.

2) PERFORMANCE OUTCOME

The performance outcome findings highlight the explanatory value of blockchain adoption intensity and also help contextualize the inconsistent findings on blockchain–performance relationships in prior research. Studies that focus only on adoption decisions, application presence, or early-stage pilots may underestimate the association between blockchain and systemic performance outcomes under higher adoption intensity. Consistent with prior findings on the relationship between digital technology adoption intensity and performance outcomes [49], the performance value of blockchain should be understood in terms of resource investment, application scope, and operational embedding. In the textile and apparel industry, higher blockchain adoption intensity may be relevant to the use of material traceability data, transaction records, and coordination mechanisms in addressing product authentication, information transparency, and ESG governance requirements, while also being positively associated with economic, operational, environmental, and social performance [14], [91].

3) VALUE-CHAIN-RELATED DIFFERENCES

Exploratory MGA results provide preliminary evidence of differences related to value-chain position. Significant differences mainly appeared between upstream firms and midstream or downstream firms, while no significant differences were found between midstream and downstream firms. This suggests that differences in data generation, process tasks, and coordination needs across value-chain positions may affect the formation of blockchain adoption intensity and its performance relationship. Upstream firms undertake foundational functions such as raw material supply, source documentation, and initial data generation; therefore, the observed path differences may be related to the role of source data in traceability, authentication, and sustainable governance. Given the limited subgroup sample sizes and the exploratory nature of the MGA analysis, these findings require further validation in future research.

B. THEORETICAL IMPLICATIONS

This study makes several theoretical contributions to research on technology adoption, blockchain value realization, and organizational sustainability.

First, building on prior technology adoption research, this study conceptualizes and empirically examines blockchain adoption intensity at the organizational level. Blockchain adoption intensity captures firms' overall degree of blockchain adoption through organizational adoption manifestations related to resource investment, application scope, and operational embedding. This perspective extends the focus of blockchain adoption research beyond adoption intention and binary adoption decisions toward blockchain adoption intensity, thereby complementing existing understanding of the blockchain adoption process.

Second, the explanatory scope of the TOE framework in blockchain adoption research is extended. Existing TOE-based studies have focused more on factors influencing the adoption threshold, while providing relatively limited explanation of the degree of adoption. The incorporation of institutional theory complements the environmental dimension of the TOE framework by accounting for institutional influences, thereby providing a more comprehensive explanation of the antecedents of blockchain adoption intensity.

Third, the NRBV logic of resource transformation and sustainable performance is applied to blockchain value realization research. Blockchain value is not determined merely by technology introduction or system presence, but is also associated with the actual investment, business application, and operational embedding of technological resources within organizations. Accordingly, this study positions blockchain adoption intensity as the focal construct and integrates its antecedents and sustainable performance into a unified analytical framework, providing a more comprehensive explanation of the antecedent conditions and performance outcomes of blockchain adoption intensity.

Fourth, the findings provide preliminary evidence of value-chain heterogeneity within a single industry, suggesting that value-chain position may serve as an important contextual factor in blockchain adoption intensity research, and that its antecedent relationships and performance association may vary across value-chain positions.

Methodologically, the combination of PLS-SEM and ANN provides complementary evidence for testing theoretical path relationships and identifying key antecedents, and offers a useful analytical approach for examining the adoption of emerging digital technologies in industrial value chains.

C. MANAGERIAL IMPLICATIONS

For textile and apparel firms, efforts to increase blockchain adoption intensity should be incorporated into digital transformation strategies and aligned with sustainable performance objectives. In managerial practice, firms should coordinate relevant managerial measures in light of their internal and external conditions and business needs.

Overall, organizational enablers appear relatively more important in practice. Firms may include a dedicated new-technology review section in regular management meetings or reports and supplement it with technology demonstrations or case sharing. This can help top management remain informed about the application potential and business value of blockchain and thereby strengthen top management support. Firms should also clarify the responsibilities of relevant departments for advancing blockchain initiatives and avoid treating such initiatives as solely the responsibility of technical departments. To encourage innovative efforts, firms may grant business units the discretion to adjust and expand blockchain applications within defined budgets and timeframes, while establishing appropriate tolerance boundaries and evaluation-based exit rules. External environmental drivers and institutional pressure require continuous monitoring and timely responses. Managers may designate relevant departments to track policies, market demand, peer practices, supply chain partner requirements, and industry norms, and share relevant information across business units to identify potential application opportunities. Firms can then adjust the scope of blockchain application, the pace of advancement, and the priorities for embedding it into business processes. Priority may be given to scenarios with clear business needs, relatively mature application conditions, and evident value, such as raw-material traceability and sustainability certification. Regarding the technological dimension, firms should focus on the fit between blockchain and existing business processes rather than simply upgrading the technical architecture. Managers should draw on internal pilots and external practices to identify effective approaches and demonstrated business benefits and translate them into standardized operating procedures. These procedures can be continuously refined based on feedback from actual use and implementation issues, and then validated and reused in suitable business contexts to support more stable use and embedding of blockchain across a broader range of business processes. Where necessary, Blockchain-as-a-Service (BaaS) or vendor-hosted solutions may also be adopted to reduce the burden of technical operation and maintenance. Firms should not treat resource constraints or regulatory and standards uncertainty as the sole reasons for suspending blockchain initiatives. Nevertheless, project feasibility, compliance requirements, data governance, security, and interoperability risks should continue to be carefully assessed.

As a supplementary consideration, areas of practical emphasis may differ across value-chain stakeholders. Upstream firms may prioritize source-data integrity and raw-material provenance, whereas midstream manufacturers may emphasize integration with production and quality-control systems. Downstream brands and retailers may focus more on product authentication, supplier compliance, and sustainability disclosure. Technology providers should develop modular and interoperable solutions tailored to the operational requirements of different value-chain positions.

D. POLICY IMPLICATIONS

Government agencies and industry associations should strengthen the support system for blockchain applications while leveraging demonstration effects and industry-based normative guidance. Such support should be grounded in firms' actual application advancement and, beyond technology promotion, place greater emphasis on information support and collaborative implementation, thereby creating favorable external ecosystem conditions for increasing blockchain adoption intensity. These measures should complement, rather than replace, financial support and standards development.

Government agencies and industry associations can strengthen information support and sharing by establishing blockchain application case repositories and publishing industry guidelines. These resources can summarize implementation experiences and application outcomes across different business scenarios, helping firms reduce trial-and-error costs and identify potential areas for expansion. They can also organize open-day events at leading firms and peer experience-sharing activities, while providing practical references for blockchain adoption intensity in industry guidelines. These initiatives can enable firms to benchmark against peer application levels and adjust their application priorities and pace of advancement according to their existing application base. On this basis, relevant agencies may identify supply chain scenarios with potential for collaboration and promote joint projects among leading firms, upstream and downstream partners, and technology service providers through pilot funding, technical support, partnership facilitation, and implementation guidance. Such efforts, together with continued standards development, can support the extension of blockchain applications to a broader range of business and supply chain processes. Policy support may also consider differences across value-chain positions. In blockchain extension pilot projects, eligibility requirements, evaluation criteria, and service content may be differentiated according to firms' value-chain positions and existing application bases, with corresponding technical advisory services, partnership facilitation, and implementation support provided.

E. LIMITATIONS AND FUTURE RESEARCH

This study has several limitations. First, the sample was drawn exclusively from Chinese textile and apparel firms, and the generalizability and external validity of the

findings may be constrained by the specific research context. China's policy environment, together with the multi-tier and traceability-dependent supply chain structure of the textile and apparel industry, may strengthen or weaken some of the antecedent relationships. Therefore, the directions and magnitudes of the relationships observed in this study cannot be assumed to apply unchanged to other industries characterized by different regulatory systems, supply chain structures, or levels of digital maturity. Future research could examine these relationships across different countries, institutional environments, and industrial contexts.

Second, cross-sectional, self-reported questionnaire data impose additional limitations. Although procedural and statistical measures were taken to reduce the risk of common method bias, the use of single-source and single-respondent data, with all variables self-reported through the same questionnaire in the same survey wave, means that the possibility of common method bias cannot be entirely ruled out. The existing diagnostic results only indicate that common method bias is unlikely to constitute a serious threat. The cross-sectional design also prevents observation of changes in blockchain adoption intensity over time. Therefore, the identified relationships among variables, particularly the relationship between blockchain adoption intensity and sustainable performance, should be interpreted as statistical associations rather than causal relationships in a strict sense. Future research could employ longitudinal designs, multi-source data, longitudinal case studies, and objective performance indicators to further examine these relationships and explore the underlying causal mechanisms.

Third, this study examines blockchain adoption intensity at an overall level and does not distinguish specific application scenarios such as product traceability, material certification, supplier collaboration, data sharing, and sustainability disclosure. Future research could examine the antecedent conditions and performance associations of adoption intensity across different blockchain application scenarios.

Finally, the value-chain position analysis is exploratory, and the findings require validation with larger and more balanced group samples. Future research could also incorporate firm age, organizational experience, process inertia, and supply chain roles to explain between-group differences.

APPENDIX

See Page no 12 and 13.

REFERENCES

[1] N. Kshetri, "1 Blockchain's roles in meeting key supply chain management objectives," *Int. J. Inf. Manage.*, vol. 39, pp. 80–89, Apr. 2018, doi: 10.1016/j.ijinfomgt.2017.12.005.

[2] R. Azzi, R. K. Chamoun, and M. Sokhn, "The power of a blockchain-based supply chain," *Comput. Ind. Eng.*, vol. 135, pp. 582–592, Sep. 2019, doi: 10.1016/j.cie.2019.06.042.

[3] S. Saberi, M. Kouhizadeh, J. Sarkis, and L. Shen, "Blockchain technology and its relationships to sustainable supply chain management," *Int. J. Prod. Res.*, vol. 57, no. 7, pp. 2117–2135, Apr. 2019, doi: 10.1080/00207543.2018.1533261.

[4] J. Sunny, N. Undralla, and V. M. Pillai, "Supply chain transparency through blockchain-based traceability: An overview with demonstration," *Comput. Ind. Eng.*, vol. 150, Dec. 2020, Art. no. 106895, doi: 10.1016/j.cie.2020.106895.

[5] B. Biswas and R. Gupta, "Analysis of barriers to implement blockchain in industry and service sectors," *Comput. Ind. Eng.*, vol. 136, pp. 225–241, Oct. 2019, doi: 10.1016/j.cie.2019.07.005.

[6] J. Lohmer and R. Lasch, "Blockchain in operations management and manufacturing: Potential and barriers," *Comput. Ind. Eng.*, vol. 149, Nov. 2020, Art. no. 106789, doi: 10.1016/j.cie.2020.106789.

[7] Deloitte. (2021). *Deloitte's 2021 Global Blockchain Survey*. [Online]. Available: https://www2.deloitte.com/us/en/insights/topics/understanding-blockchain-potential/global-blockchain-survey.html.

[8] P. Silitschanu, "IDC MarketScape: Worldwide blockchain services 2024 vendor assessment," IDC, Framingham, MA, USA, Tech. Rep. US49434623, 2024. Accessed: Jun. 6, 2026. [Online]. Available: https://my.idc.com/getdoc.jsp?containerId=US49434623.

[9] A. Al-Ashmori, S. B. Basri, P. D. D. Dominic, L. F. Capretz, A. Muneer, A. O. Balogun, A. R. Gilal, and R. F. Ali, "Classifications of sustainable factors in blockchain adoption: A literature review and bibliometric analysis," *Sustainability*, vol. 14, no. 9, p. 5176, Apr. 2022, doi: 10.3390/su14095176.

[10] S. D. Nath, A. Khayer, J. Majumder, and S. Barua, "Factors affecting blockchain adoption in apparel supply chains: Does sustainability-oriented supplier development play a moderating role?" *Ind. Manage. Data Syst.*, vol. 122, no. 5, pp. 1183–1214, May 2022, doi: 10.1108/imds-07-2021-0466.

[11] V. Chittipaka, S. Kumar, U. Sivarajah, J. L.-H. Bowden, and M. M. Baral, "Blockchain technology for supply chains operating in emerging markets: An empirical examination of technology-organization-environment (TOE) framework," *Ann. Oper. Res.*, vol. 327, no. 1, pp. 465–492, Aug. 2023, doi: 10.1007/s10479-022-04801-5.

[12] K. Zhu, K. L. Kraemer, and S. Xu, "The process of innovation assimilation by firms in different countries: A technology diffusion perspective on E-business," *Manage. Sci.*, vol. 52, no. 10, pp. 1557–1576, Oct. 2006, doi: 10.1287/mnsc.1050.0487.

[13] J. Chen, W. Zhou, and G. L. Frankwick, "Firm AI adoption intensity and marketing performance," *J. Comput. Inf. Syst.*, vol. 65, no. 2, pp. 172–189, Mar. 2025, doi: 10.1080/08874417.2023.2277751.

[14] S. Fosso Wamba, M. M. Queiroz, and L. Trinchera, "Dynamics between blockchain adoption determinants and supply chain performance: An empirical investigation," *Int. J. Prod. Econ.*, vol. 229, Nov. 2020, Art. no. 107791, doi: 10.1016/j.ijpe.2020.107791.

[15] M. Cheng and H.-Y. Chong, "Understanding the determinants of blockchain adoption in the engineering-construction industry: Multi-Stakeholders' analyses," *IEEE Access*, vol. 10, pp. 108307–108319, 2022, doi: 10.1109/ACCESS.2022.3213714.

[16] L. G. Tornatzky and M. Fleischer, *The Processes of Technological Innovation*. Lexington, MA, USA: Lexington Books, 1990.

[17] S. Zailani, K. Jeyaraman, G. Vengadasan, and R. Premkumar, "Sustainable supply chain management (SSCM) in malaysia: A survey," *Int. J. Prod. Econ.*, vol. 140, no. 1, pp. 330–340, Nov. 2012, doi: 10.1016/j.ijpe.2012.02.008.

[18] M. K. Lim, M.-L. Tseng, K. H. Tan, and T. D. Bui, "Knowledge management in sustainable supply chain management: Improving performance through an interpretive structural modelling approach," *J. Cleaner Prod.*, vol. 162, pp. 806–816, Sep. 2017, doi: 10.1016/j.jclepro.2017.06.056.

[19] S. L. Hart, "A natural-resource-based view of the firm," *Acad. Manage. Rev.*, vol. 20, no. 4, pp. 986–1014, Oct. 1995, doi: 10.2307/258963.

[20] S. L. Hart and G. Dowell, "Invited editorial: A natural-resource-based view of the firm: Fifteen years after," *J. Manage.*, vol. 37, no. 5, pp. 1464–1479, Sep. 2011, doi: 10.1177/0149206310390219.

[21] A. Di Vaio and L. Varriale, "Blockchain technology in supply chain management for sustainable performance: Evidence from the airport industry," *Int. J. Inf. Manage.*, vol. 52, Jun. 2020, Art. no. 102014, doi: 10.1016/j.ijinfomgt.2019.09.010.

[22] Statista. (2024). *Apparel-Worldwide*. [Online]. Available: https://www.statista.com/outlook/cmo/apparel/worldwide

[23] T. K. Agrawal, V. Kumar, R. Pal, L. Wang, and Y. Chen, "Blockchain-based framework for supply chain traceability: A case example of textile and clothing industry," *Comput. Ind. Eng.*, vol. 154, Apr. 2021, Art. no. 107130, doi: 10.1016/j.cie.2021.107130.

[24] W. A. H. Ahmed and B. L. MacCarthy, "Blockchain-enabled supply chain traceability in the textile and apparel supply chain: A case study of the fiber producer, lenzing," *Sustainability*, vol. 13, no. 19, p. 10496, Sep. 2021, doi: 10.3390/su131910496.

[25] K. Niinimäki, G. Peters, H. Dahlbo, P. Perry, T. Rissanen, and A. Gwilt, "The environmental price of fast fashion," *Nature Rev. Earth Environ.*, vol. 1, no. 4, pp. 189–200, Apr. 2020, doi: 10.1038/s43017-020-0039-9.

[26] European Commission, Brussels, Belgium. (2024). *EU Strategy for Sustainable and Circular Textiles*. Accessed: May 18, 2026. [Online]. Available: https://environment.ec.europa.eu/strategy/textiles-strategy_en

[27] N. Deng, Y. Shi, J. Wang, and J. Gaur, "Testing the adoption of blockchain technology in supply chain management among MSMEs in China," *Ann. Oper. Res.*, vol. 350, no. 2, pp. 629–648, Jul. 2025, doi: 10.1007/s10479-022-04856-4.

[28] P. J. DiMaggio and W. W. Powell, "The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields," *Amer. Sociol. Rev.*, vol. 48, no. 2, pp. 147–160, Apr. 1983, doi: 10.2307/2095101.

[29] N. Liu and Z. Ye, "Empirical research on the blockchain adoption – based on TAM," *Appl. Econ.*, vol. 53, no. 37, pp. 4263–4275, Aug. 2021, doi: 10.1080/00036846.2021.1898535.

[30] J. J. Pieters, A. Kokkinou, and T. van Kollenburg, "Understanding blockchain technology adoption by non-experts: An application of the unified theory of acceptance and use of technology (UTAUT)," *Operations Res. Forum*, vol. 3, no. 1, Mar. 2021, Art. no. 1, doi: 10.1007/s43069-021-00113-9.

[31] S. Malik, M. Chadhar, S. Vatanasakdakul, and M. Chetty, "Factors affecting the organizational adoption of blockchain technology: Extending the technology-organization-environment (TOE) framework in the Australian context," *Sustainability*, vol. 13, no. 16, p. 9404, Aug. 2021, doi: 10.3390/su13169404.

[32] D. Ghode, V. Yadav, R. Jain, and G. Soni, "Adoption of blockchain in supply chain: An analysis of influencing factors," *J. Enterprise Inf. Manage.*, vol. 33, no. 3, pp. 437–456, Mar. 2020, doi: 10.1108/jeim-07-2019-0186.

[33] J. L. Hartley, W. Sawaya, and D. Dobrzykowski, "Exploring blockchain adoption intentions in the supply chain: Perspectives from innovation diffusion and institutional theory," *Int. J. Phys. Distribution Logistics Manage.*, vol. 52, no. 2, pp. 190–211, Mar. 2022, doi: 10.1108/ijpdlm-05-2020-0163.

[34] S. F. Wamba and M. M. Queiroz, "Blockchain in the operations and supply chain management: Benefits, challenges and future research opportunities," *Int. J. Inf. Manage.*, vol. 52, Jun. 2020, Art. no. 102064, doi: 10.1016/j.ijinfomgt.2019.102064.

[35] N. Vu, A. Ghadge, and M. Bourlakis, "Evidence-driven model for implementing blockchain in food supply chains," *Int. J. Logistics Res. Appl.*, vol. 26, no. 5, pp. 568–588, May 2023, doi: 10.1080/13675567.2022.2115987.

[36] E. Karahanna, D. W. Straub, and N. L. Chervany, "Information technology adoption across time: A cross-sectional comparison of pre-adoption and post-adoption Beliefs1," *MIS Quart.*, vol. 23, no. 2, pp. 183–213, Jun. 1999, doi: 10.2307/249751.

[37] M. M. Queiroz and S. Fosso Wamba, "Blockchain adoption challenges in supply chain: An empirical investigation of the main drivers in India and the USA," *Int. J. Inf. Manage.*, vol. 46, pp. 70–82, Jun. 2019, doi: 10.1016/j.ijinfomgt.2018.11.021.

[38] L.-W. Wong, L.-Y. Leong, J.-J. Hew, G. W.-H. Tan, and K.-B. Ooi, "Time to seize the digital evolution: Adoption of blockchain in operations and supply chain management among Malaysian SMEs," *Int. J. Inf. Manage.*, vol. 52, Jun. 2020, Art. no. 101997, doi: 10.1016/j.ijinfomgt.2019.08.005.

[39] M. A. Hameed, S. Counsell, and S. Swift, "A conceptual model for the process of IT innovation adoption in organizations," *J. Eng. Technol. Manage.*, vol. 29, no. 3, pp. 358–390, Jul. 2012, doi: 10.1016/j.jengtecman.2012.03.007.

[40] N. Vu, A. Ghadge, and M. Bourlakis, "Blockchain adoption in food supply chains: A review and implementation framework," *Prod. Planning Control*, vol. 34, no. 6, pp. 506–523, Apr. 2023, doi: 10.1080/09537287.2021.1939902.

[41] S. F. Wamba and M. M. Queiroz, "Industry 4.0 and the supply chain digitalisation: A blockchain diffusion perspective," *Prod. Planning Control*, vol. 33, nos. 2–3, pp. 193–210, Feb. 2022, doi: 10.1080/09537287.2020.1810756.

[42] R. L. Purvis, V. Sambamurthy, and R. W. Zmud, "The assimilation of knowledge platforms in organizations: An empirical investigation," *Org. Sci.*, vol. 12, no. 2, pp. 117–135, Apr. 2001, doi: 10.1287/orsc.12.2.117.10115.

[43] K. Patil, D. Ojha, E. M. Struckell, and P. C. Patel, "Behavioral drivers of blockchain assimilation in supply chains—A social network theory perspective," *Technological Forecasting Social Change*, vol. 192, Jul. 2023, Art. no. 122578, doi: 10.1016/j.techfore.2023.122578.

[44] T. Åstebro, "Sunk costs and the depth and probability of technology adoption," *J. Ind. Econ.*, vol. 52, no. 3, pp. 381–399, Sep. 2004, doi: 10.1111/j.0022-1821.2004.00231.x.

[45] W. Hu, M. Fernández-Olmos, and N. Depetris-Chauvin, "Quality over quantity: The role of digital adoption depth in driving firm flexibility and sustainability," *Cleaner Environ. Syst.*, vol. 20, Mar. 2026, Art. no. 100399, doi: 10.1016/j.cesys.2026.100399.

[46] S. Jasperson, P. E. Carter, and R. W. Zmud, "A comprehensive conceptualization of post-adoptive behaviors associated with information technology enabled work Systems1," *MIS Quart.*, vol. 29, no. 3, pp. 525–557, Sep. 2005, doi: 10.2307/25148694.

[47] K. Zhu and K. L. Kraemer, "Post-adoption variations in usage and value of E-business by organizations: Cross-country evidence from the retail industry," *Inf. Syst. Res.*, vol. 16, no. 1, pp. 61–84, Mar. 2005, doi: 10.1287/isre.1050.0045.

[48] T. Bakici, M. A. N. Agi, T. Kose, and H. Treiblmaier, "Blockchain success in the post-adoption phase: Extending the information systems success model with supply chain complexity," *Int. J. Prod. Res.*, vol. 64, no. 1, pp. 63–83, Jan. 2026, doi: 10.1080/00207543.2025.2540450.

[49] X. Lin, T. Wang, and F. Sheng, "The relationship between AI-adoption intensity and firm innovation performance: The role of AI affordances," *IEEE Trans. Eng. Manag.*, vol. 72, pp. 2267–2278, 2025, doi: 10.1109/TEM.2025.3572042.

[50] S. Bag, M. S. Rahman, S. Gupta, and L. C. Wood, "Understanding and predicting the determinants of blockchain technology adoption and SMEs' performance," *Int. J. Logistics Manage.*, vol. 34, no. 6, pp. 1781–1807, Dec. 2023, doi: 10.1108/ijlm-01-2022-0017.

[51] J. Kumar, G. Rani, M. Rani, and V. Rani, "Blockchain technology adoption and its impact on SME performance: Insights for entrepreneurs and policymakers," *J. Enterprising Communities: People Places Global Economy*, vol. 18, no. 5, pp. 1147–1169, Oct. 2024, doi: 10.1108/jec-02-2024-0034.

[52] N. K. Mishra, S. Sahoo, S. Agarwal, P. P. Sharma, and F. Ilahi, "Impact of institutional pressures and security on blockchain technology adoption and organization performance: An empirical study," *J. Technol. Transf.*, vol. 50, no. 1, pp. 245–270, Feb. 2025, doi: 10.1007/s10961-024-10098-2.

[53] H. Alkatheeri and S. Z. Ahmad, "Examining blockchain adoption determinants and supply chain performance: An empirical study in the logistics and supply chain management industry," *J. Model. Manage.*, vol. 19, no. 5, pp. 1566–1591, Oct. 2024, doi: 10.1108/jm2-08-2023-0186.

[54] X. Hua, L. Hu, R. Eltantawy, L. Zhang, B. Wang, Y. Tian, and J. Z. Zhang, "Blockchain technology adoption and sustainable performance in Chinese manufacturing: Insights on learning and organizational inertia," *Ind. Manage. Data Syst.*, vol. 125, no. 2, pp. 604–626, Jan. 2025, doi: 10.1108/imds-08-2023-0552.

[55] A. Moretto, L. Macchion, A. Lion, F. Caniato, P. Danese, and A. Vinelli, "Designing a roadmap towards a sustainable supply chain: A focus on the fashion industry," *J. Cleaner Prod.*, vol. 193, pp. 169–184, Aug. 2018, doi: 10.1016/j.jclepro.2018.04.273.

[56] J. Baker, "The technology–organization–environment framework," in *Integrated Series in Information Systems*. New York, NY, USA: Springer, 2012, pp. 231–245, doi: 10.1007/978-1-4419-6108-2_12.

[57] M. Dehghani, R. W. Kennedy, A. Mashatan, A. Rese, and D. Karavidas, "High interest, low adoption. A mixed-method investigation into the factors influencing organisational adoption of blockchain technology," *J. Bus. Res.*, vol. 149, pp. 393–411, Oct. 2022, doi: 10.1016/j.jbusres.2022.05.015.

[58] P. Moon, H. Chung, J. Ryu, K. Hwang, H. Moon, and W. Park, "Blockchain knowledge and intention to use blockchain-based services," *IEEE Access*, vol. 13, pp. 74521–74530, 2025, doi: 10.1109/ACCESS.2025.3562987.

[59] S. Malik, M. Chadhar, M. Chetty, and S. Vatanasakdakul, "Adoption of blockchain technology: Exploring the factors affecting organizational decision," *Hum. Behav. Emerg. Technol.*, vol. 2022, pp. 1–14, Aug. 2022, doi: 10.1155/2022/7320526.

[60] W. A. H. Ahmed and B. L. MacCarthy, "Blockchain applications in the supply chain—A decision framework," *Int. J. Prod. Res.*, vol. 64, no. 20, pp. 8907–8933, Oct. 2026, doi: 10.1080/00207543.2026.2669881.
[61] L. Wang, J. Zhang, J. Li, H. Yu, and J. Li, "An ISM-DEMATEL analysis of blockchain adoption decision in the circular supply chain finance context," *Manage. Decis.*, vol. 62, no. 9, pp. 2814–2835, Sep. 2024, doi: 10.1108/md-03-2023-0302.
[62] J. Staszczak, P. Mikalef, and S. Angelopoulos, "Navigating blockchain assimilation in private institutions: A multi-level perspective analysis," *Proc. Comput. Sci.*, vol. 256, pp. 36–46, Jul. 2025, doi: 10.1016/j.procs.2025.02.093.
[63] C. S. de Mattos, G. Pellegrini, G. Hagelaar, and W. Dolfsma, "Systematic literature review on technological transformation in SMEs: A transformation encompassing technology assimilation and business model innovation," *Manage. Rev. Quart.*, vol. 74, no. 2, pp. 1057–1095, Jun. 2024, doi: 10.1007/s11301-023-00327-7.
[64] T. H. Tran, T. N. Thanh, T. D. T. Thu, and M. Azmat, "Industrial digitalization, human capital, and supply chain resilience in advanced manufacturing: Evidence-based PLS-SEM study of Vietnamese firms," *Prod. Manuf. Res.*, vol. 14, no. 1, Dec. 2026, Art. no. 2708529, doi: 10.1080/21693277.2026.2708529.
[65] K. Shahzad, Q. Zhang, M. Ashfaq, A. U. Zafar, and B. Ahmad, "Pre- to post-adoption of blockchain technology in supply chain management: Influencing factors and the role of firm size," *Technol. Forecasting Social Change*, vol. 198, Jan. 2024, Art. no. 122989, doi: 10.1016/j.techfore.2023.122989.
[66] X. Zhang, J. Lin, and X. R. Luo, "How organizations utilize blockchain technology to improve sustainable performance: Unveiling the role of blockchain capability and social capital," *Bus. Strategy Environ.*, vol. 35, no. 3, pp. 3505–3522, Mar. 2026, doi: 10.1002/bse.70351.
[67] H. O. Awa and O. U. Ojiabo, "A model of adoption determinants of ERP within T-O-E framework," *Inf. Technol. People*, vol. 29, no. 4, pp. 901–930, Nov. 2016, doi: 10.1108/itp-03-2015-0068.
[68] W. R. Scott, *Institutions and Organizations: Ideas, Interests, and Identities*, 4th ed., Newbury Park, CA, USA: Sage, 2014.
[69] T. H. Nguyen, X. C. Le, and T. H. L. Vu, "An extended technology-organization-environment (TOE) framework for online retailing utilization in digital transformation: Empirical evidence from Vietnam," *J. Open Innovation: Technol., Market, Complex.*, vol. 8, no. 4, p. 200, Dec. 2022, doi: 10.3390/joitmc8040200.
[70] M. Wetzels, G. Odekerken-Schröder, and C. van Oppen, "Using PLS path modeling for assessing hierarchical construct models: Guidelines and empirical Illustration1," *MIS Quart.*, vol. 33, no. 1, pp. 177–195, Mar. 2009, doi: 10.2307/20650284.
[71] M. Sarstedt, J. F. Hair, J.-H. Cheah, J.-M. Becker, and C. M. Ringle, "How to specify, estimate, and validate higher-order constructs in PLS-SEM," *Australas. Marketing J.*, vol. 27, no. 3, pp. 197–211, Aug. 2019, doi: 10.1016/j.ausmj.2019.05.003.
[72] M. P. Low, C. S. Seah, T.-H. Cham, and S. H. Teoh, "Digitalization adoption for digital economy: An examination of malaysian small medium-sized enterprises through the technology–organization–environment framework," *Bus. Process Manage. J.*, vol. 28, no. 7, pp. 1473–1494, Nov. 2022, doi: 10.1108/bpmj-06-2022-0282.
[73] T. S. H. Teo, S. C. Srivastava, and L. Jiang, "Trust and electronic government success: An empirical study," *J. Manage. Inf. Syst.*, vol. 25, no. 3, pp. 99–132, Dec. 2008, doi: 10.2753/mis0742-1222250303.
[74] M. Ghobakhloo, D. Arias-Aranda, and J. Benitez-Amado, "Adoption of e-commerce applications in SMEs," *Ind. Manage. Data Syst.*, vol. 111, no. 8, pp. 1238–1269, Aug. 2011, doi: 10.1108/02635571111170785.
[75] T. Clohessy and T. Acton, "Investigating the influence of organizational factors on blockchain adoption," *Ind. Manage. Data Syst.*, vol. 119, no. 7, pp. 1457–1491, Aug. 2019, doi: 10.1108/imds-08-2018-0365.
[76] L. Hashimy, G. Jain, and E. Grifell-Tatjé, "Determinants of blockchain adoption as decentralized business model by Spanish firms—An innovation theory perspective," *Ind. Manage. Data Syst.*, vol. 123, no. 1, pp. 204–228, Feb. 2023, doi: 10.1108/imds-01-2022-0030.
[77] M. M. H. Shahadat, M. Nekmahmud, P. Ebrahimi, and M. Fekete-Farkas, "Digital technology adoption in SMEs: What technological, environmental and organizational factors influence in emerging countries?" *Global Bus. Rev.*, Jan. 2023, doi: 10.1177/09721509221137199.
[78] N. K. Mishra, A. Raj, I. Mukherjee, and A. Chakraborty, "Blockchain adoption in the supply chain management based on technology-organization-environment framework: Evidence from developing and developed economies," *J. Bus. Ind. Marketing*, vol. 40, no. 3, pp. 815–832, Apr. 2025, doi: 10.1108/jbim-04-2024-0253.
[79] A. Nugroho, R. Prijadi, and R. D. Kusumastuti, "Strategic orientations and firm performance: The role of information technology adoption capability," *J. Strategy Manage.*, vol. 15, no. 4, pp. 691–717, Oct. 2022, doi: 10.1108/jsma-06-2021-0133.
[80] A. Legesse, B. Beshah, E. Berhan, and E. Tesfaye, "Exploring the influencing factors of blockchain technology adoption in national quality infrastructure: A dual-stage structural equation model and artificial neural network approach using TAM-TOE framework," *Cogent Eng.*, vol. 11, no. 1, Dec. 2024, Art. no. 2369220, doi: 10.1080/23311916.2024.2369220.
[81] H.-F. Lin, "Examining the determinants of blockchain technology-enabled maritime supply chain system adoption intention: Does market turbulence play a moderating role?" *Mar. Policy*, vol. 174, Apr. 2025, Art. no. 106616, doi: 10.1016/j.marpol.2025.106616.
[82] R. Baliga, R. D. Raut, and S. S. Kamble, "Sustainable supply chain management practices and performance: An integrated perspective from a developing economy," *Manage. Environ. Quality: Int. J.*, vol. 31, no. 5, pp. 1147–1182, Aug. 2019, doi: 10.1108/meq-04-2019-0079.
[83] Y. Alshamaila, S. Papagiannidis, and F. Li, "Cloud computing adoption by SMEs in the north east of england: A multi-perspective framework," *J. Enterprise Inf. Manage.*, vol. 26, no. 3, pp. 250–275, Apr. 2013, doi: 10.1108/17410391311325225.
[84] D. K. Maduku, M. Mpinganjira, and H. Duh, "Understanding mobile marketing adoption intention by south African SMEs: A multi-perspective framework," *Int. J. Inf. Manage.*, vol. 36, no. 5, pp. 711–723, Oct. 2016, doi: 10.1016/j.ijinfomgt.2016.04.018.
[85] H. Karaosman, P. Perry, A. Brun, and G. Morales-Alonso, "Behind the runway: Extending sustainability in luxury fashion supply chains," *J. Bus. Res.*, vol. 117, pp. 652–663, Sep. 2020, doi: 10.1016/j.jbusres.2018.09.017.
[86] L. P. Kyrgidou and S. Spyropoulou, "Drivers and performance outcomes of innovativeness: An empirical study," *Brit. J. Manage.*, vol. 24, no. 3, pp. 281–298, Sep. 2013, doi: 10.1111/j.1467-8551.2011.00803.x.
[87] M. Tan and T. Teo, "Factors influencing the adoption of internet banking," *J. Assoc. for Inf. Syst.*, vol. 1, no. 1, pp. 1–44, Jul. 2000, doi: 10.17705/1jais.00005.
[88] K. S. Tan, S. C. Chong, B. Lin, and U. C. Eze, "Internet-based ICT adoption: Evidence from Malaysian SMEs," *Ind. Manage. Data Syst.*, vol. 109, no. 2, pp. 224–244, Mar. 2009, doi: 10.1108/02635570910930118.
[89] J. Frizzo-Barker, P. A. Chow-White, P. R. Adams, J. Mentanko, D. Ha, and S. Green, "Blockchain as a disruptive technology for business: A systematic review," *Int. J. Inf. Manage.*, vol. 51, Apr. 2020, Art. no. 102029, doi: 10.1016/j.ijinfomgt.2019.10.014.
[90] M. Kouhizadeh, S. Saberi, and J. Sarkis, "Blockchain technology and the sustainable supply chain: Theoretically exploring adoption barriers," *Int. J. Prod. Econ.*, vol. 231, Jan. 2021, Art. no. 107831, doi: 10.1016/j.ijpe.2020.107831.
[91] S. S. Kamble, A. Gunasekaran, N. Subramanian, A. Ghadge, A. Belhadi, and M. Venkatesh, "Blockchain technology's impact on supply chain integration and sustainable supply chain performance: Evidence from the automotive industry," *Ann. Operations Res.*, vol. 327, no. 1, pp. 575–600, Aug. 2023, doi: 10.1007/s10479-021-04129-6.
[92] O. Sohaib, W. Hussain, M. Asif, M. Ahmad, and M. Mazzara, "A PLS-SEM neural network approach for understanding cryptocurrency adoption," *IEEE Access*, vol. 8, pp. 13138–13150, 2020, doi: 10.1109/ACCESS.2019.2960083.
[93] N. Deng, Y. Gong, and J. Wang, "Promoting blockchain technology in low-carbon management to achieve firm performance from a socio-economic perspective: Empirical evidence from China," *J. Cleaner Prod.*, vol. 448, Apr. 2024, Art. no. 141686, doi: 10.1016/j.jclepro.2024.141686.
[94] N. Kumar, L. W. Stern, and J. C. Anderson, "Conducting interorganizational research using key informants," *Acad. Manage. J.*, vol. 36, no. 6, pp. 1633–1651, 1993, doi: 10.2307/256824.
[95] N. Kock and P. Hadaya, "Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods," *Inf. Syst. J.*, vol. 28, no. 1, pp. 227–261, Jan. 2018, doi: 10.1111/isj.12131.
[96] J.-M. Becker, K. Klein, and M. Wetzels, "Hierarchical latent variable models in PLS-SEM: Guidelines for using reflective-formative type models," *Long Range Planning*, vol. 45, nos. 5–6, pp. 359–394, Oct. 2012, doi: 10.1016/j.lrp.2012.10.001.
[97] N. Kock, "Common method bias in PLS-SEM: A full collinearity assessment approach," *Int. J. e-Collaboration*, vol. 11, no. 4, pp. 1–10, Oct. 2015, doi: 10.4018/ijec.2015100101.

[98] J. S. Armstrong and T. S. Overton, "Estimating nonresponse bias in mail surveys," *J. Marketing Res.*, vol. 14, no. 3, pp. 396–402, Aug. 1977, doi: 10.1177/002224377701400320.
[99] J. F. Hair, J. J. Risher, M. Sarstedt, and C. M. Ringle, "When to use and how to report the results of PLS-SEM," *Eur. Bus. Rev.*, vol. 31, no. 1, pp. 2–24, Jan. 2019, doi: 10.1108/ebr-11-2018-0203.
[100] J. Henseler, C. M. Ringle, and M. Sarstedt, "Testing measurement invariance of composites using partial least squares," *Int. Marketing Rev.*, vol. 33, no. 3, pp. 405–431, May 2016, doi: 10.1108/imr-09-2014-0304.
[101] G. Shmueli, M. Sarstedt, J. F. Hair, J.-H. Cheah, H. Ting, S. Vaithilingam, and C. M. Ringle, "Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict," *Eur. J. Marketing*, vol. 53, no. 11, pp. 2322–2347, Nov. 2019, doi: 10.1108/ejm-02-2019-0189.



SAIPING CHENG received the B.Eng. degree in nonwoven materials and engineering from Zhejiang Sci-Tech University, Hangzhou, China. She is currently pursuing the integrated M.S. and Ph.D. degree with the School of Business, Hanyang University, Seoul, South Korea. Her research interests include blockchain technology, artificial intelligence, digital transformation, intelligent operations, and technology-enabled value creation in industrial systems, with particular attention to value-chain transparency and sustainable operations.



MINJEONG OH received the M.S. and Ph.D. degrees in business administration from Hanyang University, Seoul, South Korea. She is currently an Associate Professor with the Global Elite Division, Yonsei University, Mirae Campus, Wonju-si, South Korea. Her research interests include project portfolio management, supply chain management, research and development management, operations management, and service management, with a particular emphasis on strategic project management, portfolio-level performance, and operational decision-making.



SUNGYONG CHOI received the B.S. degree in management science from Korea Advanced Institute of Science and Technology (KAIST), Daejeon, South Korea, in 1994, the M.S. degree in applied statistics from Michigan State University, East Lansing, MI, USA, in 2004, and the Ph.D. degree in supply chain management from Rutgers University, Newark, NJ, USA, in 2009.

Since 2023, he has been a Professor with the Division of Operations and Service Management, Hanyang University, Seoul, South Korea. He is the author of more than 50 peer-reviewed international and domestic journals. Some selected articles have been published in international premier journals, including *Operations Research*, *European Journal of Operational Research*, *International Journal of Production Economics*, *International Journal of Production Research*, *Computers and Industrial Engineering*, *Annals of Operations Research*, and *European Journal of Innovation Management*. His research interests include supply chain management modeling and applications under risk, sustainable and socially responsible operations, inventory management, energy, analytics, and data-driven optimization.