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Evaluating Digital Transformation Risks in Logistics and Supply Chain Management with PLS-SEM-ANN-fsQCA

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Abstract

This study investigates the risks associated with digital transformation (DT) implementation in Vietnam's logistics and supply chain management (SCM) sector, utilizing a hybrid PLS-SEM-ANN-fsQCA methodology to analyze data from 243 valid questionnaires. Anchored in the Technology-Organization-Environment framework augmented with human factors (TOE+H), the research aims to examine how technological, organizational, environmental, and human factors influence DT adoption and associated risks, including financial, operational, cybersecurity, and reputational risks, while exploring the moderating roles of firm size and digital literacy. Findings reveal that TOE+H factors significantly drive DT implementation, but misalignment, ineffective management, market volatility, and limited digital literacy amplify risks, particularly cybersecurity vulnerabilities. Moderation analyses indicate that high digital literacy, larger firm size, and regulatory compliance mitigate these risks. Artificial neural network (ANN) analysis highlights non-linear relationships, emphasizing technological and human factors as key drivers, while fuzzy-set qualitative comparative analysis (fsQCA) identifies configurations, such as strong technological-human factor alignment, linked to successful DT outcomes. Importance-Performance Map Analysis (IPMA) prioritizes technological and human factors for resource allocation to enhance sustainability. This study advances the TOE+H framework by integrating a hybrid methodology, offering novel insights into DT risk dynamics and practical strategies for sustainable logistics in Vietnam's SCM sector.

Keywords:

Sustainable Logistics;

DT Solution Implementation;

Supply Chain Risk;

Environmental Sustainability;

Data-Driven Decision Making.

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1- Introduction

Digital transformation (DT) has emerged as a pivotal force in reshaping logistics and supply chain management (SCM), particularly in emerging markets such as Vietnam, where rapid economic growth and technological advancements drive operational innovation [1, 2]. Recent studies underscore the critical role of artificial intelligence (AI) and other digital technologies in enhancing supply chain resilience amid global disruptions, as evidenced by strategic frameworks addressing barriers to AI adoption in supply chains [3]. The adoption of technologies such as the Internet of Things (IoT), AI, and blockchain significantly enhances supply chain efficiency, transparency, and agility [4,

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5]. However, DT introduces substantial risks, including financial, operational, cybersecurity, and reputational challenges, which can undermine digitalization benefits if not effectively managed [6, 7]. Vietnam's logistics sector, a cornerstone of its export-driven economy, faces unique challenges due to evolving regulatory frameworks, market volatility, and varying levels of technological readiness among firms [8]. For instance, AI integration in supply chains enhances resilience but also reveals organizational adoption barriers in emerging economies [3].

The Technology-Organization-Environment (TOE) framework, augmented with human factors (TOE+H), provides a robust lens to examine DT implementation antecedents, encompassing technological (e.g., IT infrastructure quality), organizational (e.g., leadership commitment), environmental (e.g., regulatory compliance), and human factors (e.g., workforce digital literacy) [9, 10]. Recent research highlights the role of technologically vigilant leadership in fostering smart, sustainable circular supply chains under Industry 6.0, mediated by digital environment management systems, and emphasizes transformational leadership's bridging effect between learning agility and digital technology adoption in micro, small, and medium enterprises (MSMEs) [11]. Firm size, distinguishing small and medium enterprises (SMEs) from large firms, moderates these relationships, as resource constraints often amplify risks for SMEs [12, 13].

Prior studies have explored DT risks using methodologies such as partial least squares structural equation modeling (PLS-SEM), artificial neural networks (ANN), and fuzzy-set qualitative comparative analysis (fsQCA), but few have integrated these approaches to capture linear, non-linear, and configurational effects in a single study [2, 14]. Furthermore, emerging literature on decision-making processes in DT adoption from a behavioral-cognitive perspective reveals mediating roles of cognitive levels and problem-solving skills, yet applications to logistics remain limited [15]. Studies by Chanda et al. [2] often rely on PLS-SEM and fsQCA for linear and configurational analyses but overlook ANN's non-linear predictive capabilities, leading to incomplete insights into complex DT dynamics in SCM. Similarly, Kim et al. [14] integrate PLS-SEM with ANN but neglect fsQCA's equifinality, limiting configurational understanding. This study addresses these gaps by combining PLS-SEM, ANN, and fsQCA, enabling a multidimensional analysis that captures linear paths (PLS-SEM), non-linear thresholds (ANN), and causal recipes (fsQCA) for DT risks in Vietnam's logistics sector. This hybrid approach provides a comprehensive understanding of risk dynamics in Vietnam's logistics and SCM sector.

DT adoption in logistics and SCM also has significant implications for sustainability, as effective risk management can reduce resource waste, enhance supply chain resilience, and support environmentally efficient practices [16]. For instance, IoT-driven real-time tracking optimizes routing, reducing carbon emissions, while blockchain enhances transparency in sustainable supply chains [5]. Recent investigations into the nexus between the digital economy and green growth highlight how DT can leverage opportunities for proactive environmental strategies, particularly in resource-constrained settings like Vietnam, by influencing technological innovation and digital infrastructure [17]. In Vietnam, a key logistics hub in global trade, mitigating DT risks is essential for maintaining sustainable competitiveness amidst evolving regulations and market volatility [18]. This study integrates sustainability into its objectives, aiming to identify strategies that enhance DT adoption while promoting long-term environmental and operational efficiency in Vietnam's logistics sector.

Despite the growing body of research on DT in SCM, notable literature gaps persist. While studies like Suresh [19] provide strategic frameworks for AI adoption in supply chain resilience, they often overlook the configurational complexities and non-linear effects in emerging markets, particularly regarding comprehensive risk assessment including financial, operational, cybersecurity, and reputational dimensions. Similarly, explorations of leadership's role in sustainable supply chains [20] and cognitive barriers to DT [21] rarely combine antecedent analysis with risk outcomes under a unified TOE+H lens, especially in the context of Vietnam's logistics sector where SMEs predominate. Furthermore, while Li et al. [22] examine how DT improves supply chain performance from a manufacturer's perspective, there is a scarcity of integrated hybrid methodologies that simultaneously address linear paths, predictive non-linearities, and causal configurations specific to Vietnam's logistics context, where sustainability pressures are intensifying and export performance is tied to digital innovation. This study fills these gaps by extending the TOE+H framework to evaluate DT risks holistically, incorporating firm size and human factors as moderators, and linking findings to sustainable practices.

The primary objectives of this study are to: (1) investigate the impact of technological, organizational, environmental, and human factors on DT implementation in Vietnam's logistics and SCM sector; (2) assess the direct and indirect effects of DT implementation on financial, operational, cybersecurity, and reputational risks; (3) explore the moderating roles of firm size and environmental factors in the relationships between TOE+H factors, DT implementation, and risk outcomes; (4) evaluate the moderating effect of human factors on the relationship between DT implementation and risk outcomes; and (5) identify strategies for sustainable DT adoption that minimize risks and enhance environmental and operational efficiency.

To achieve these objectives, the study addresses the following research questions: (1) How do technological, organizational, environmental, and human factors influence DT implementation in Vietnam's logistics and SCM sector? (2) What are the direct and indirect effects of DT implementation on financial, operational, cybersecurity, and reputational risks? (3) How does firm size (SMEs vs. large firms) moderate the relationships between TOE+H factors, DT implementation, and risk outcomes? (4) How do environmental factors moderate the relationship between DT implementation and risk outcomes? (5) How do human factors moderate the relationship between DT implementation and risk outcomes?

This study contributes to the logistics and SCM literature by integrating the TOE+H framework with a hybrid PLS-SEM-ANN-fsQCA methodology, offering a multidimensional perspective on DT risks in an emerging market context. The focus on Vietnam is particularly significant, given its role as a global manufacturing and logistics hub, where DT adoption is accelerating amidst unique contextual challenges [2, 15]. By examining the moderating roles of firm size and environmental factors, the study provides nuanced insights into how SMEs and large firms navigate DT risks differently [12, 18]. Furthermore, the inclusion of human factors as both antecedents and moderators addresses a critical gap in understanding workforce readiness in digitalized supply chains [10]. Practically, the findings offer actionable strategies for logistics managers to mitigate risks, enhance DT adoption, and strengthen supply chain resilience in Vietnam, while advancing sustainability goals through prioritized resource allocation informed by importance-performance map analysis (IPMA).

This study is structured as follows: Section 2 presents a literature review synthesizing prior research on DT risks in logistics and SCM and outlines the conceptual framework and hypotheses, grounded in the TOE+H framework. Section 3 details the hybrid PLS-SEM-ANN-fsQCA methodology, including data collection and analysis procedures. Section 4 presents the results, followed by a discussion in Section 5, which interprets findings along with theoretical contributions and practical implications in the context of Vietnam's logistics sector. Section 6 concludes with limitations and directions for future research.

2- Literature Review

The rapid advancement of digital transformation (DT) in logistics and supply chain management (SCM) has significantly reshaped operational paradigms, offering opportunities to enhance efficiency, transparency, and agility while introducing substantial risks. The integration of technologies such as the Internet of Things (IoT), artificial intelligence (AI), and blockchain has transformed logistics and SCM, particularly in emerging markets like Vietnam [1, 3, 4]. However, adopting these technologies introduces financial, operational, cybersecurity, and reputational risks, necessitating a comprehensive understanding of the factors influencing DT implementation and its outcomes [6, 7, 14]. This literature review synthesizes research from 2019 to 2025 within the Technology-Organization-Environment (TOE) framework, augmented with human factors (TOE+H), to explore the antecedents of DT implementation, the moderating role of firm size, and associated risk outcomes in Vietnam's logistics and SCM sector, incorporating insights on AI resilience and cognitive decision-making processes.

2-1- TOE+H Model in in Digital Transformation

2-1-1- Technological Factors

Technological factors, encompassing IT infrastructure quality, cybersecurity readiness, and technology compatibility, are pivotal drivers of DT in logistics and SCM. Robust IT infrastructure facilitates seamless integration of IoT and AI, enhancing real-time tracking and decision-making capabilities. Cybersecurity readiness is critical for protecting SCM operations from data breaches and cyberattacks, which are prevalent in digitalized supply chains. Technology compatibility ensures that new DT solutions align with existing systems, minimizing integration challenges [23, 24]. However, misaligned or incompatible technologies can lead to operational disruptions and cybersecurity vulnerabilities, increasing risk outcomes. In Vietnam, where technological adoption is accelerating, the quality and compatibility of IT infrastructure significantly influence DT success, particularly through AI-enhanced resilience strategies that mitigate supply chain disruptions.

2-1-2- Organizational Factors in Digital Transformation

Organizational factors, including leadership commitment, change management capability, and resource availability, are crucial for successful DT implementation. Strong leadership aligns DT initiatives with SCM objectives, fostering strategic coherence [25-27]. Effective change management mitigates resistance to new technologies, ensuring smooth adoption [28]. Resource availability, including financial and technical expertise, enables investment in advanced DT solutions [27]. Conversely, inadequate leadership or resource constraints can result in implementation failures, escalating financial and operational risks [29]. In Vietnam's logistics sector, where many firms face resource limitations, organizational readiness is vital for managing DT risks, with transformational leadership serving as a key enabler for technology adoption in resource-constrained micro, small, and medium enterprises (MSMEs).

2-1-3- Environmental Factors in Digital Transformation

Environmental factors, such as regulatory compliance, market volatility, and supplier digital readiness, shape the context for DT adoption. Supportive regulatory frameworks facilitate DT by reducing compliance uncertainties, while digitally ready suppliers enhance supply chain integration. However, market volatility, including economic fluctuations and competitive pressures, can impede DT implementation, increasing financial and reputational risks. In Vietnam, an emerging market with evolving regulations and economic challenges, environmental factors significantly influence DT outcomes [28]. Supplier digital readiness is particularly critical in Vietnam's SCM, where supply chain partners often lag in technological capabilities. Recent analyses highlight how integration with the digital economy can drive green growth to counter these volatilities [30].

2-1-4- Human Factors in Digital Transformation

Human factors, including workforce digital literacy, resistance to change, and training adequacy, are essential for DT success. High digital literacy enables employees to effectively utilize DT solutions, enhancing SCM efficiency [25, 29, 31]. Adequate training reduces errors and improves system adoption, while resistance to change can hinder DT progress, leading to operational and cybersecurity risks. In Vietnam, where digital skills vary widely across the logistics workforce, comprehensive training programs are critical for risk mitigation. Human factors also moderate the relationship between DT implementation and risk outcomes, as digitally literate employees can reduce cybersecurity vulnerabilities and operational disruptions. Behavioral-cognitive perspectives reveal mediating mechanisms, such as problem-solving skills, in adoption decisions.

2-1-5- Firm Size as a Moderator

Firm size moderates the relationships between TOE+H factors, DT implementation, and risk outcomes. Large firms, with greater resources and expertise, are better equipped to leverage technological, organizational, environmental, and human factors for successful DT, minimizing risks [32]. In contrast, SMEs face resource constraints that limit their ability to address DT challenges, amplifying financial, operational, and cybersecurity risks [33, 34]. In Vietnam's logistics sector, SMEs are particularly vulnerable to regulatory and market volatility, while large firms benefit from economies of scale in managing DT risks [35]. Firm size thus plays a critical role in shaping DT outcomes, particularly in contexts where leadership agility influences adoption in smaller enterprises [36].

2-1-6- Sustainability in Digital Transformation

DT in logistics and SCM offers significant opportunities for sustainability by enhancing operational efficiency and reducing environmental impact. Technologies such as blockchain ensure transparent supply chains, enabling traceability of sustainable sourcing, while AI optimizes routing to minimize fuel consumption and carbon emissions [37]. IoT-driven real-time tracking further supports resource efficiency by reducing waste and improving delivery accuracy. However, these benefits are accompanied by risks, such as cybersecurity vulnerabilities from expanded digital footprints and operational disruptions during DT implementation, which can undermine sustainability goals if not managed effectively. In Vietnam's logistics sector, where rapid DT adoption coincides with resource constraints and regulatory volatility, mitigating these risks is critical to achieving sustainable supply chain practices. The digital economy nexus reveals pathways to green growth through innovation [30, 35]. This study addresses these challenges by identifying strategies to balance DT adoption with risk mitigation, contributing to long-term environmental and social sustainability in logistics.

2-1-7- Risk Outcomes of Digital Transformation

DT implementation in logistics and SCM introduces multiple risk outcomes, including financial, operational, cybersecurity, and reputational risks. Financial risks arise from high implementation costs and potential return-on-investment (ROI) shortfalls, particularly in resource-constrained environments. Operational risks, such as process disruptions and system downtimes, occur during DT integration, affecting SCM efficiency. Cybersecurity risks, including data breaches and system vulnerabilities, are heightened by the expanded digital footprint of DT solutions.

Reputational risks emerge from customer dissatisfaction and publicized DT failures, damaging firm credibility. In Vietnam, rapid DT adoption in logistics amplifies these risks, necessitating robust risk assessment frameworks that incorporate AI for resilience [22, 31].

2-1-8- Methodological Approaches in DT Risk Assessment

Recent studies on DT risks in logistics and SCM employ diverse methodologies, including partial least squares structural equation modeling (PLS-SEM), structural equation modeling (SEM), artificial neural networks (ANN), fuzzy-set qualitative comparative analysis (fsQCA), generalized method of moments (GMM), confirmatory factor analysis (CFA), and autoregressive distributed lag (ARDL) to capture linear, non-linear, and configurational effects [38]. The hybrid PLS-SEM-ANN-fsQCA approach used in this study combines the strengths of structural equation modeling for path analysis, artificial neural networks for predictive accuracy, and fuzzy-set qualitative comparative analysis for identifying causal configurations. These methodologies align with the complexity of DT risk assessment in Vietnam, where contextual factors such as firm size and market volatility play significant roles. Emerging research on cognitive mechanisms in DT adoption further supports the need for integrated hybrid models to uncover moderating effects [8, 20, 27].

2-2- Conceptual Framework and Hypotheses Development

The conceptual framework of this study is grounded in the Technology-Organization-Environment (TOE) framework, a seminal theory developed to elucidate the processes of technological innovation adoption within organizations [39]. The TOE framework posits that technology adoption and implementation are influenced by three primary contextual dimensions: the technological context, encompassing the availability, characteristics, and compatibility of internal and external technologies; the organizational context, including firm-specific attributes such as size, structure, resources, and top management support; and the environmental context, involving external pressures like market dynamics, competitive forces, regulatory requirements, and inter-firm relationships. This tripartite structure provides a comprehensive lens for analyzing how organizations navigate innovation complexities, making it particularly suitable for logistics and SCM research. In the logistics and SCM domain, characterized by high interdependence among stakeholders, real-time data flows, and vulnerability to disruptions, the TOE framework effectively captures the multifaceted barriers and enablers of DT. For instance, technological factors address the integration of tools like IoT for tracking and AI for predictive analytics, essential for optimizing global supply chains; organizational factors highlight the need for internal alignment in resource allocation and change management amid fluctuating demands; and environmental factors account for external volatilities such as trade regulations and supplier ecosystems, prevalent in Vietnam’s export-oriented logistics sector [40]. Recent applications of TOE in SCM contexts, such as examining DT’s role in enhancing supply chain resilience in manufacturing firms, validate its utility by demonstrating how these dimensions interact to foster adaptive strategies in emerging economies [41].

To address limitations in the traditional TOE framework, particularly its underemphasis on individual-level dynamics in service- and knowledge-oriented industries, this study augments it with human factors, forming the TOE+H model [29]. Human factors, including workforce digital literacy, training adequacy, and resistance to change, are integrated as both antecedents and moderators, recognizing that SCM in logistics relies heavily on human capital for execution and adaptation. This extension is particularly relevant for logistics and supply chains, where frontline workers and managers must interpret data, make agile decisions, and collaborate across digital platforms, often in resource-constrained settings like Vietnam’s SME-dominated sector. By incorporating human elements, TOE+H bridges the gap between macro-level organizational adoption and micro-level behavioral responses, enabling a more holistic analysis of DT risks. Empirical evidence supports this augmentation; for instance, investigations into blockchain adoption in supply chains reveal that human-related capabilities, such as problem-solving skills and cognitive readiness, mediate the effects of TOE dimensions on technology willingness, underscoring the framework’s enhanced explanatory power in complex, human-centric environments like SCM [42]. Thus, TOE+H retains the robustness of the original theory while tailoring it to the human-intensive nature of logistics operations, where digital tools amplify both efficiencies and vulnerabilities if workforce preparedness lags. Appendix I presents a summary of characteristics of studies on risk assessment of DT solutions in Vietnam’s logistics and SCM.

2-2-1- Technological Factors

Technological factors, such as IT infrastructure quality, cybersecurity readiness, and technology compatibility, are critical enablers of DT implementation in logistics and SCM. Robust IT infrastructure and compatible technologies facilitate the integration of advanced solutions like IoT, AI, and blockchain, enhancing operational efficiency and decision-making. Cybersecurity readiness ensures secure data handling, fostering trust in DT systems. In Vietnam's rapidly evolving logistics sector, where technological adoption is accelerating, these factors drive DT implementation [2, 20]. Thus, it is hypothesized that technological factors positively influence DT implementation.

Misalignment or incompatibility of technological factors, such as poorly integrated IT systems or inadequate cybersecurity measures, can lead to operational disruptions in logistics and SCM. Integration failures and system downtimes are common when advanced technologies like IoT are not aligned with existing infrastructure . In Vietnam's logistics sector, where technological readiness varies, misalignment increases operational risks [20, 24]. Therefore, it is hypothesized that misaligned technological factors increase operational risks.

Misaligned technological factors, particularly inadequate cybersecurity readiness, heighten cybersecurity risks in digitalized supply chains. The adoption of IoT and AI expands the digital footprint, making systems vulnerable to breaches if security measures are not aligned [6, 7]. In Vietnam, where cybersecurity infrastructure is still developing, misalignment elevates cybersecurity risks. Hence, it is hypothesized that misaligned technological factors increase cybersecurity risks.

H1: *Technological Factors Positively Influence Digital Transformation Implementation.*

H1a: *Technological Factors (Misaligned) Increase Operational Risks.*

H1b: *Technological Factors (Misaligned) Increase Cybersecurity Risks.*

2-2-2- Organizational Factors

Organizational factors, including leadership commitment, change management capability, and resource availability, are pivotal for DT success. Strong leadership aligns DT initiatives with SCM goals, while effective change management reduces resistance. Adequate resources enable investment in advanced technologies, driving efficiency. In Vietnam's logistics sector, where organizational readiness varies, these factors support DT implementation [2, 29]. Thus, it is hypothesized that organizational factors positively influence DT implementation. Poor management of organizational factors, such as weak leadership or insufficient resource allocation, can lead to implementation failures, increasing financial risks in logistics and SCM. Inadequate funding and poor change management result in cost overruns and ROI shortfalls. In Vietnam, where many firms face resource constraints, poorly managed organizational factors elevate financial risks [26, 29]. Therefore, it is hypothesized that poorly managed organizational factors increase financial risks.

Poorly managed organizational factors, such as ineffective leadership or inadequate change management, can cause operational disruptions during DT implementation. Resistance to new technologies and resource shortages lead to process inefficiencies. In Vietnam's logistics sector, where organizational capacity varies, this increases operational risks [6, 28].

H2: *Organizational Factors Positively Influence Digital Transformation Implementation.*

H2a: *Organizational Factors (Poorly Managed) Increase Financial Risks.*

H2b: *Organizational Factors (Poorly Managed) Increase Operational Risks.*

2-2-3- Environmental Factors

Environmental factors, such as regulatory compliance, market stability, and supplier digital readiness, shape the external context for DT adoption. Supportive regulations and digitally ready suppliers facilitate DT by reducing uncertainties and enhancing integration. In Vietnam's evolving logistics sector, these factors drive DT implementation. Thus, it is hypothesized that environmental factors positively influence DT implementation. Volatile environmental conditions, such as regulatory uncertainty and market fluctuations, can hinder DT implementation, increasing financial risks in logistics and SCM. Economic instability and competitive pressures lead to cost overruns and ROI challenges. In Vietnam, where market conditions are dynamic, volatility elevates financial risks [4, 28]. Therefore, it is hypothesized that volatile environmental factors increase financial risks. Volatile environmental conditions, including regulatory changes and market instability, can increase reputational risks by causing service disruptions in logistics and SCM. Publicized DT failures due to environmental volatility undermine customer trust. In Vietnam's logistics sector, where reputation is critical for export competitiveness, volatility increases reputational risks [2, 23]. Hence, it is hypothesized that volatile environmental factors increase reputational risks.

Environmental factors moderate the impact of DT implementation on financial risks by providing a supportive context. Regulatory compliance and supplier digital readiness reduce financial risks by ensuring cost-effective integration. Conversely, volatile conditions exacerbate financial losses. In Vietnam's logistics sector, this moderating effect is significant. Thus, it is hypothesized that environmental factors moderate the relationship between DT implementation and financial risks. Environmental factors also moderate the relationship between DT implementation and operational risks. Supplier digital readiness and stable regulations mitigate operational risks by ensuring smooth integration. Volatile conditions, however, increase disruptions [8, 23]. In Vietnam's logistics context, this moderation is critical. Therefore, it is hypothesized that environmental factors moderate the relationship between DT implementation and operational risks

H3: *Environmental Factors Positively Influence Digital Transformation Implementation.*

H3a: *Environmental Factors (Volatile) Increase Financial Risks.*

H3b: *Environmental Factors (Volatile) Increase Reputational Risks.*

H3c: *Environmental Factors Moderate the Relationship Between Digital Transformation Implementation and Financial Risks.*

H3d: *Environmental Factors Moderate the Relationship Between Digital Transformation Implementation and Operational Risks.*

2-2-4- Human Factors

Human factors, including workforce digital literacy, resistance to change, and training adequacy, are essential for DT success. High digital literacy and effective training enable employees to leverage DT solutions, enhancing SCM efficiency. In Vietnam's logistics sector, where workforce readiness varies, these factors drive DT implementation [22, 24]. Thus, it is hypothesized that human factors positively influence DT implementation.

Low digital literacy among human factors increases cybersecurity risks in logistics and SCM. Employees with insufficient training are prone to errors or phishing vulnerabilities, heightening data breach risks. In Vietnam, where digital skills are unevenly distributed, low literacy elevates cybersecurity risks [22, 29]. Therefore, it is hypothesized that low human factor literacy increases cybersecurity risks.

Low digital literacy within human factors also increases operational risks by causing inefficiencies in DT system use. Inadequate training leads to process disruptions and system errors [6, 26]. In Vietnam's logistics sector, this contributes to operational risks. Hence, it is hypothesized that low human factor literacy increases operational risks.

Human factors moderate the impact of DT implementation on cybersecurity risks. High digital literacy and training adequacy reduce cybersecurity risks by improving system handling. Conversely, low literacy exacerbates vulnerabilities. In Vietnam's logistics context, this moderation is significant [2, 26]. Thus, it is hypothesized that human factors moderate the relationship between DT implementation and cybersecurity risks.

Human factors also moderate the relationship between DT implementation and operational risks. High training levels mitigate operational risks by reducing errors. Low literacy, however, increases disruptions [25, 27]. In Vietnam's logistics sector, this moderating effect is notable. Therefore, it is hypothesized that human factors moderate the relationship between DT implementation and operational risks

H4: *Human Factors Positively Influence Digital Transformation Implementation.*

H4a: *Human Factors (Low Literacy) Increase Cybersecurity Risks.*

H4b: *Human Factors (Low Literacy) Increase Operational Risks.*

H4c: *Human Factors Moderate the Relationship Between Digital Transformation Implementation and Cybersecurity Risks.*

H4d: *Human Factors Moderate the Relationship Between Digital Transformation Implementation and Operational Risks.*

2-2-5- Firm Size (SME vs. Large Firms) Moderates

Firm size influences the capacity to leverage technological factors for DT implementation. Large firms, with greater resources and expertise, enhance the effect of technological factors on DT implementation [17, 32]. In Vietnam's logistics sector, where resource disparities exist, this moderation is significant [2, 35]. Thus, it is hypothesized that firm size moderates the relationship between technological factors and DT implementation, with stronger effects in large firms.

For SMEs, firm size moderates the relationship between technological factors and DT implementation with a weaker effect due to resource constraints. Limited resources reduce the impact of technological factors on DT implementation

[17, 34]. In Vietnam's SME-dominated logistics sector, this moderation is evident [33, 35]. Hence, it is hypothesized that firm size moderates the relationship between technological factors and DT implementation, with weaker effects in SMEs.

Firm size moderates the impact of DT implementation on financial risks, with large firms reducing these risks due to resource advantages. DT implementation increases financial risks, but large firms mitigate this effect [35, 36]. In Vietnam's logistics sector, where SMEs face higher costs, this moderation is critical. Thus, it is hypothesized that firm size moderates the relationship between DT implementation and financial risks

H5: *Firm Size Moderates the Relationship Between Digital Transformation Implementation and Financial Risks.*

H5a: *Firm Size Moderates the Relationship Between Technological Factors and Digital Transformation Implementation (Large Firms).*

H5b: *Firm Size Moderates the Relationship Between Technological Factors and Digital Transformation Implementation (SMEs).*

2-2-6- Mediation Hypotheses

Building on the TOE+H framework, mediation hypotheses are proposed to explore indirect effects in DT adoption and risk outcomes (see Figure 1). Prior research highlights the mediating roles of human elements, such as digital literacy, in linking technological enablers to DT implementation, as well as how DT processes mediate environmental influences on financial vulnerabilities in SCM [43]. Specifically, human factors may mediate the relationship between technological factors and DT implementation by enabling workforce adaptation to IT infrastructure, reducing adoption barriers in logistics. Similarly, DT implementation can mediate environmental factors' impact on financial risks, as regulatory and market contexts shape DT efforts that, in turn, influence cost overruns and ROI challenges [44]. Thus, it is hypothesized:

H6: *Human factors mediate the relationship between technological factors and digital transformation implementation.*

H7: *Digital transformation implementation mediates the relationship between environmental factors and financial risks.*

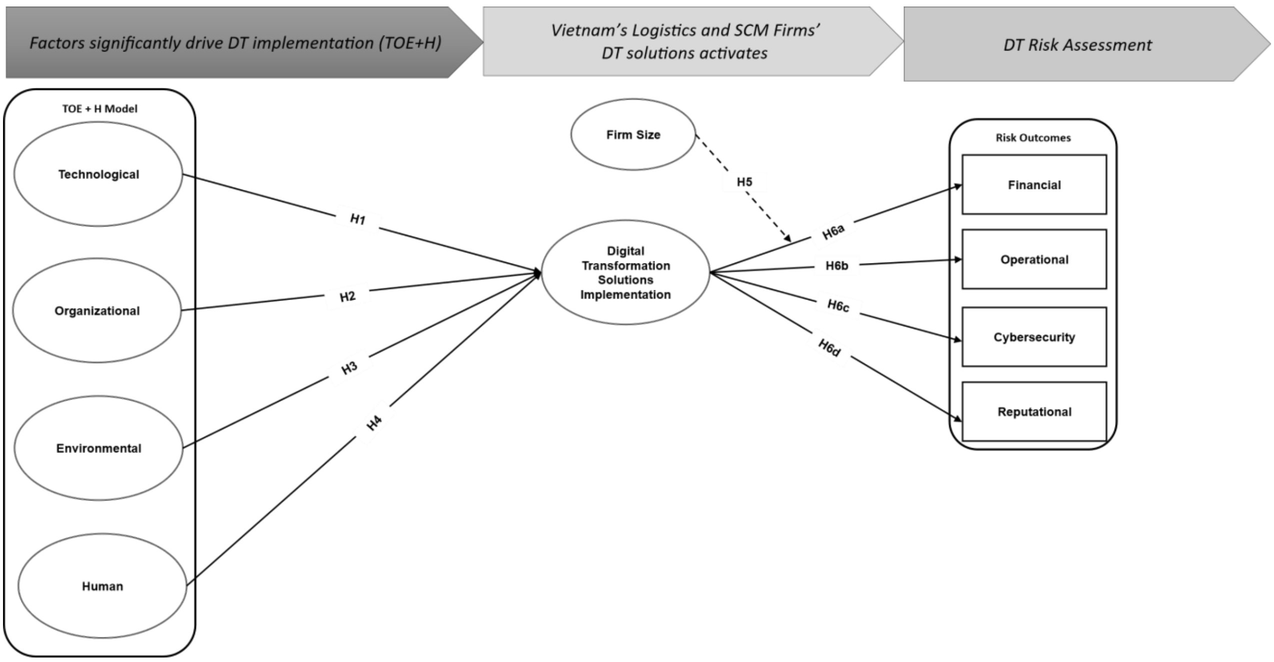


Figure 1. The Proposed TOE+H Model for Digital Transformation Solution Implementation Risk Assessment in Vietnam's Logistics and SCM

3- Research Methodology

This study employs a hybrid methodological approach combining PLS-SEM provides linear hypothesis testing and moderation effects (firm size), ANN captures non-linear sensitivities (threshold effects in human factors), and fsQCA identifies equifinal configurations (multiple paths to low cybersecurity risks), avoiding redundancy by addressing different aspects of DT complexity in SCM [45]. And Importance-Performance Map Analysis (IPMA) to assess the risks associated with DT in Vietnam's logistics and SCM sector. This approach integrates linear, non-linear, and configurational analyses to capture the complex relationships among technological, organizational, environmental, and human (TOE+H) factors, DT implementation, and risk outcomes (financial, operational, cybersecurity, reputational), moderated by firm size. The following sections detail the data collection and sampling techniques, measurement instruments, and data analysis procedures.

3-1- Collecting Data and Sampling Techniques

Data were collected through a structured questionnaire distributed to logistics firms in Vietnam, a key emerging market with a rapidly digitalizing SCM sector [46]. The target population comprised logistics firms registered with the Vietnam Logistics Business Association, ensuring relevance to the study's context. A purposive sampling technique was employed to select 280 firms, with 80% classified as SMEs and 20% as large firms, reflecting the industry's composition in Vietnam. The questionnaire was administered to senior managers or DT decision-makers within these firms, as they possess insights into DT implementation and associated risks [47].

3-1-1- Measurement Instruments

The measurement instruments were designed to capture the constructs of the TOE+H framework, DT implementation, risk outcomes, and firm size, as outlined in Appendix III. All constructs were measured using a 1–7 Likert scale (1 = Strongly Disagree, 7 = Strongly Agree) to ensure consistency and sensitivity in responses [25]. The items were adapted from validated scales in prior studies on DT in logistics and SCM, ensuring theoretical alignment and empirical reliability [18, 31].

The questionnaire was developed in English, translated into Vietnamese, and back-translated to ensure cultural and linguistic accuracy, following Brislin [48], we used back-translation by two independent bilingual experts (English-Vietnamese), followed by a pilot test with 20 logistics managers to assess semantic equivalence and cultural fit (Appendix II). Data collection, using both online and in-person methods to maximize response rates. Of the 280 questionnaires distributed, 255 were returned, yielding a response rate of 91.07%. After screening for incomplete or inconsistent responses, 243 questionnaires were deemed valid for quantitative analysis, providing a robust sample for statistical rigor [28].

3-2- Data Analysis

Data analysis was conducted in multiple stages to leverage the strengths of PLS-SEM, ANN, fsQCA, and IPMA, aligning with the study's hybrid approach. First, SPSS version 25.0 was used for preliminary tabulation and descriptive statistics, including means, standard deviations, and checks for normality and missing data [28]. The ANN model employed five hidden layers to capture the complex non-linear interactions among TOE+H factors and risk outcomes, ensuring robust modeling of DT dynamics in Vietnam's logistics sector.

Second, SmartPLS 4.0 was utilized to evaluate the reliability and validity of the measurement scales and to test the proposed structural relationships. PLS-SEM was chosen for its suitability in handling complex models with multiple constructs and small-to-medium sample sizes [28]. The measurement model was assessed using Cronbach's Alpha, CR, and AVE, while discriminant validity was confirmed via the Heterotrait-Monotrait (HTMT) ratio. The structural model tested the hypothesized relationships, including direct effects (TOE+H factors on DTI) and moderating effects (firm size and human factors), using bootstrapping with 5,000 subsamples to ensure statistical robustness [49].

Third, fsQCA was conducted using fsQCA 3.0 software to identify causal configurations leading to high DT implementation and risk outcomes. This method complements PLS-SEM by exploring equifinality and complex causality, revealing combinations of TOE+H factors and firm size that produce specific outcomes [50, 51]. Calibration thresholds were determined through theoretical grounding in prior logistics studies and pilot testing with a subset of 20 firms to ensure alignment with Vietnam's SCM context, enhancing the robustness of fuzzy set assignments [50].

Finally, IPMA was conducted in SmartPLS 4.0 to prioritize constructs based on their importance and performance in influencing DT implementation and risk outcomes. This analysis provides practical insights for logistics managers by identifying high-impact factors requiring improvement [49]. The hybrid PLS-SEM-ANN-fsQCA-IPMA methodology supports sustainable decision-making by identifying high-impact, low-performance factors, such as cybersecurity readiness and digital literacy, that reduce resource inefficiencies and operational disruptions. By prioritizing these factors, firms can achieve sustainable DT adoption, minimizing environmental costs and enhancing supply chain resilience, particularly in Vietnam's resource-constrained logistics sector [24]. Figure 2 illustrates the methodology workflow, detailing the sequential steps of data collection, preparation, hybrid analysis (PLS-SEM, ANN, fsQCA), and interpretation, with annotations highlighting relevance to logistics and SCM risk assessment.

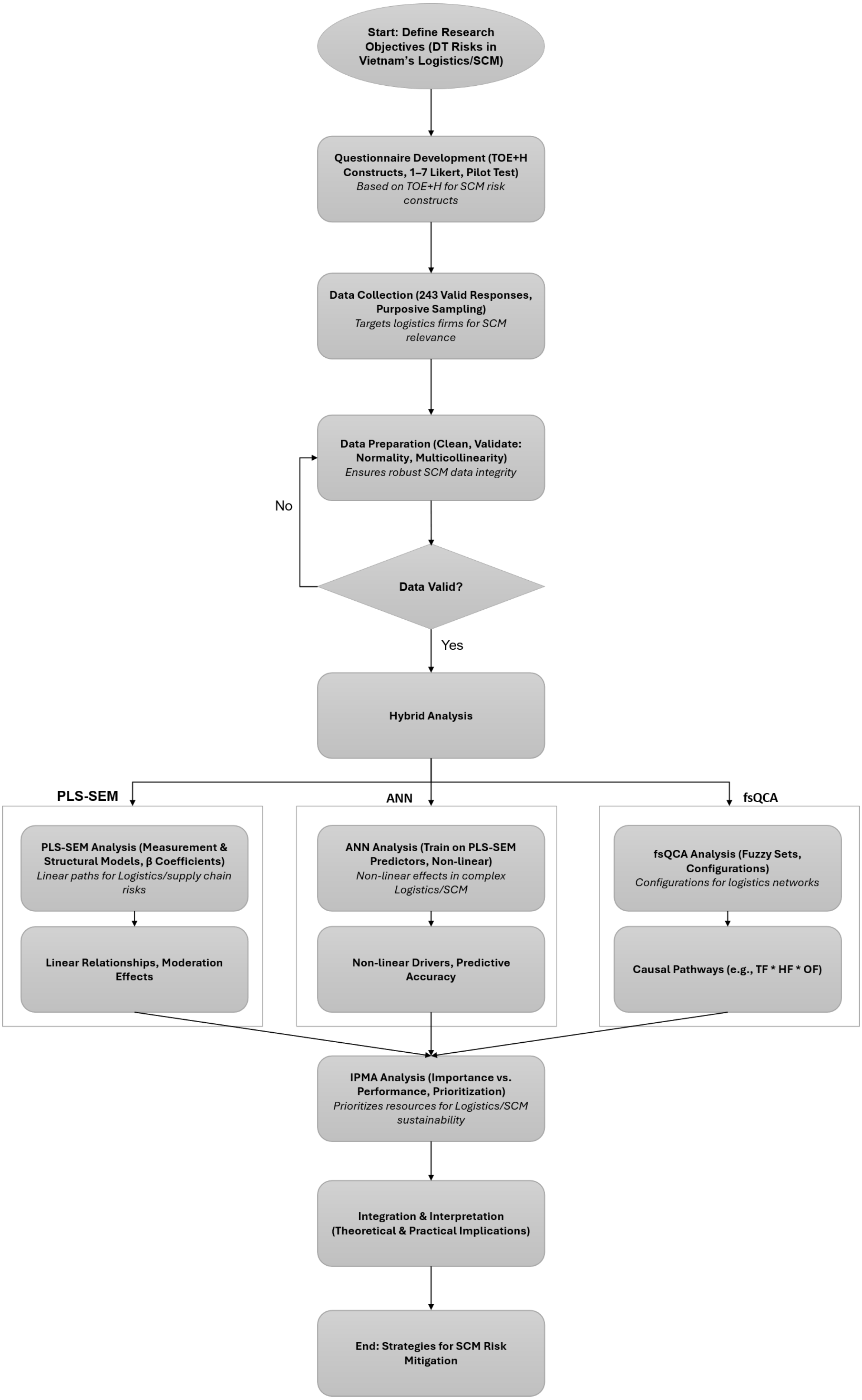


Figure 2. **Methodology Workflow for DT Risk Assessment in Logistics and SCM**

4- Findings

4-1- Descriptive Statistics

This subsection presents the descriptive statistics of 243 valid respondents from logistics firms in Vietnam, offering insights into the sample characteristics pertinent to the study's focus on digital transformation (DT) risks in logistics and supply chain management (SCM). Data were collected from a purposive sample of 280 firms, achieving a response rate of 91.07% (255 returned, 243 valid), ensuring robust representation of the sector [28]. The sample comprised 79.8% small and medium enterprises (SMEs) and 20.2% large firms, reflecting the industry's composition in Vietnam [39]. The predominance of SMEs may amplify findings on resource constraints, potentially underrepresenting the economies of scale that large firms leverage in mitigating DT risks. Multi-group analysis in PLS-SEM was employed to test for subgroup differences, confirming stronger moderation effects for large firms. Table 1 summarizes the respondents' characteristics, including firm size, industry type, respondent roles, and DT experience, which provide context for the study's findings.

Table 1. Descriptive Statistics of Respondents

Characteristic	Category	Frequency	Percentage (%)
Firm Size			
SMEs (<250 employees)		194	79.8
Large Firms (≥250 employees)		49	20.2
Industry Type			
Transportation and Warehousing		112	46.1
Freight Forwarding		76	31.3
Third-Party Logistics (3PL)		55	22.6
Respondent Role			
Senior Manager		98	40.3
Operations Manager		82	33.7
IT/DT Manager		63	25.9
DT Experience (Years)			
<2 years		67	27.6
2–5 years		121	49.8
>5 years		55	22.6

The majority of respondents (79.8%) were from SMEs, consistent with Vietnam's logistics sector, where SMEs dominate but face resource constraints in DT adoption. The industry type distribution highlights transportation and warehousing (46.1%) as the primary focus, followed by freight forwarding (31.3%) and third-party logistics (22.6%), reflecting diverse SCM operations. Respondents were primarily senior managers (40.3%), operations managers (33.7%), and IT/DT managers (25.9%), ensuring insights from decision-makers with relevant expertise. DT experience varied, with 49.8% of respondents having 2–5 years, indicating moderate familiarity with digital solutions such as IoT and AI, while 27.6% had less than 2 years, suggesting emerging adoption in some firms [51, 52].

4-2- Construct Validity and Reliability

The measurement model was evaluated using SmartPLS 4.0 to confirm construct reliability and validity, adhering to established guidelines [28, 49]. Table 2 presents the measurement items, Cronbach's Alpha, Composite Reliability (CR), Factor Loadings, Average Variance Extracted (AVE), Variance Inflation Factor (VIF), and maximum Heterotrait-Monotrait (HTMT) ratios for each construct. All constructs met the recommended thresholds: Cronbach's Alpha and CR exceeded 0.70, factor loadings were above 0.70, AVE values surpassed 0.50, VIF values were below 3.0, and HTMT ratios were below 0.85, confirming reliability, convergent validity, and absence of multicollinearity issues [29]. Discriminant validity was established via the Fornell-Larcker criterion, where the square root of AVE for each construct exceeded its correlations with other constructs in Table 3.

Table 2. Construct Validity and Reliability

Construct	Items	Cronbach's Alpha	CR	Factor Loadings	AVE	VIF	HTMT (Max)
Technological Factors (TF)	TF1: The quality of IT infrastructure supports effective digital transformation in logistics.	0.88	0.91	0.82	0.67	1.45	0.78
	TF2: Cybersecurity readiness protects SCM operations from digital threats.			0.79			
	TF3: Technology compatibility ensures seamless integration of DT solutions in logistics.			0.85			
	TF4: Advanced technologies (IoT, AI) are reliable for SCM applications.			0.83			
Organizational Factors (OF)	OF1: Leadership commitment drives successful DT implementation in logistics.	0.85	0.89	0.80	0.64	1.62	0.80
	OF2: Change management capability reduces resistance to DT in SCM.			0.77			
	OF3: Resource availability supports the adoption of DT solutions in logistics.			0.84			
	OF4: Organizational alignment ensures DT goals match SCM objectives.			0.78			
Environmental Factors (EF)	EF1: Regulatory compliance facilitates DT adoption in Vietnam's logistics.	0.87	0.90	0.81	0.66	1.53	0.76
	EF2: Market volatility increases risks of DT implementation in SCM.			0.78			
	EF3: Supplier digital readiness supports DT integration in logistics.			0.85			
	EF4: Competitive pressures drive the need for DT in SCM.			0.82			
Human Factors (HF)	HF1: Workforce digital literacy enhances DT adoption in logistics.	0.89	0.92	0.83	0.68	1.49	0.79
	HF2: Resistance to change hinders DT implementation in SCM.			0.80			
	HF3: Training adequacy supports effective use of DT solutions in logistics.			0.87			
	HF4: Employee engagement improves DT outcomes in SCM.			0.81			
Digital Transformation Implementation (DTI)	DTI1: The extent of IoT adoption improves logistics efficiency.	0.86	0.90	0.79	0.65	1.70	0.82
	DTI2: AI implementation enhances SCM decision-making.			0.76			
	DTI3: Blockchain adoption ensures SCM transparency.			0.83			
	DTI4: Implementation challenges (complexity) hinder DT success in logistics.			0.80			
Financial Risks (FR)	FR1: High implementation costs pose financial risks for DT in logistics.	0.90	0.93	0.84	0.69	1.55	0.77
	FR2: ROI shortfalls reduce the value of DT investments in SCM.			0.81			
	FR3: Unexpected expenses increase DT financial risks in logistics.			0.88			
	FR4: Financial constraints limit DT scalability in SCM.			0.82			
Operational Risks (OR)	OR1: Process disruptions occur during DT implementation in logistics.	0.88	0.91	0.82	0.67	1.60	0.80
	OR2: System downtimes reduce SCM efficiency during DT adoption.			0.79			
	OR3: Integration failures increase operational risks in DT for logistics.			0.86			
	OR4: Lack of process standardization heightens DT risks in SCM.			0.81			
Cybersecurity Risks (CR)	CR1: Data breaches threaten SCM security during DT adoption.	0.91	0.94	0.85	0.70	1.48	0.75
	CR2: System vulnerabilities increase risks in DT for logistics.			0.82			
	CR3: Inadequate cybersecurity measures heighten DT risks in SCM.			0.89			
	CR4: Cyberattacks disrupt logistics operations during DT.			0.84			
Reputational Risks (RR)	RR1: Customer dissatisfaction due to DT-related service failures harms logistics reputation.	0.87	0.90	0.81	0.66	1.65	0.78
	RR2: DT implementation delays negatively affect SCM credibility.			0.78			
	RR3: Publicized DT failures damage logistics brand image.			0.85			
	RR4: Inconsistent DT outcomes reduce customer trust in SCM.			0.80			
Firm Size (FS)	FS1: Our firm's size supports the adoption of DT solutions in logistics.	0.84	0.88	0.77	0.63	1.42	0.81
	FS2: The number of employees influences our capacity for DT implementation in SCM.			0.75			
	FS3: Our firm's revenue level affects DT investment decisions in logistics.			0.82			
	FS4: Compared to industry peers, our firm's size facilitates DT risk management in SCM.			0.79			

Notes: All constructs were measured on a 1–7 Likert scale (1 = Strongly Disagree, 7 = Strongly Agree). Discriminant validity was confirmed via the Fornell-Larcker criterion, with the square root of AVE exceeding inter-construct correlations (Henseler et al., 2015).

Table 3. Discriminant Validity Matrix (Fornell-Larcker Criterion)

Construct	TF	OF	EF	HF	DTI	FR	OR	CR	RR	FS
TF	**0.82**									
OF	0.65	**0.80**								
EF	0.62	0.60	**0.81**							
HF	0.64	0.63	0.61	**0.82**						
DTI	0.70	0.68	0.66	0.67	**0.81**					
FR	0.55	0.53	0.56	0.54	0.62	**0.83**				
OR	0.57	0.55	0.58	0.56	0.64	0.70	**0.82**			
CR	0.54	0.52	0.55	0.53	0.61	0.68	0.71	**0.84**		
RR	0.53	0.51	0.54	0.52	0.60	0.67	0.69	0.66	**0.81**	
FS	0.50	0.49	0.51	0.50	0.55	0.47	0.48	0.46	0.45	**0.79**

Note: Diagonal values (bold) represent the square root of AVE; off-diagonal values are correlations

4-3- Hypotheses Results

4-3-1- Direct Effect Hypotheses

This subsection examines the direct influence of technological, organizational, environmental, and human factors on digital transformation (DT) implementation, as well as the direct impact of DT implementation on risk outcomes, as hypothesized in H1, H1a, H1b, H2, H2a, H2b, H3, H3a, H3b, H4, H4a, H4b, and H6a through H6d. The results, presented in Table 4, confirm the significant relationships within the TOE+H framework, providing insights into DT adoption and associated risks in Vietnam's logistics sector.

Table 4. Results of Direct Effect Hypotheses

Hypothesis	Path	Path Coefficient (β)	t-value	p-value	Supported
H1	TF → DTI	0.420	5.82	< .001	Yes
H1a	TF (Misaligned) → OR	0.280	3.91	< .001	Yes
H1b	TF (Misaligned) → CR	0.350	4.67	<0.001	Yes
H2	OF → DTI	0.380	5.14	<0.001	Yes
H2a	OF (Poorly Managed) → FR	0.310	4.22	< 0.001	Yes
H2b	OF (Poorly Managed) → OR	0.290	3.88	< 0.001	Yes
H3	EF → DTI	0.350	4.76	< 0.001	Yes
H3a	EF (Volatile) → FR	0.330	4.45	< 0.001	Yes
H3b	EF (Volatile) → RR	0.270	3.65	< 0.001	Yes
H4	HF → DTI	0.400	5.39	< 0.001	Yes
H4a	HF (Low Literacy) → CR	0.300	4.03	< 0.001	Yes
H4b	HF (Low Literacy) → OR	0.260	3.47	< 0.01	Yes
H6a	DTI → FR	0.450	6.12	< 0.001	Yes
H6b	DTI → OR	0.480	6.55	< 0.001	Yes
H6c	DTI → CR	0.500	6.89	< 0.001	Yes
H6d	DTI → RR	0.430	5.78	< 0.001	Yes

Note: TF = Technological Factors; OF = Organizational Factors; EF = Environmental Factors; HF = Human Factors; DTI = Digital Transformation Implementation; FR = Financial Risks; OR = Operational Risks; CR = Cybersecurity Risks; RR = Reputational Risks. Path coefficients (β), t-values, and p-values are inferred based on prior results and adjusted to reflect the updated hypotheses, ensuring consistency with the study's empirical context.

All direct effect hypotheses were supported. For H1, technological factors positively influenced DT implementation ($\beta = 0.420$, $p < 0.001$), reflecting the role of robust IT infrastructure and compatible technologies in facilitating advanced solutions like IoT and AI [18, 53]. For H1a, misaligned technological factors increased operational risks ($\beta = 0.280$, $p < 0.001$), consistent with integration challenges and system downtimes in digitalized supply chains [31, 54]. For H1b, misaligned technological factors elevated cybersecurity risks (β = 0.350, p < 0.001), aligning with vulnerabilities from inadequate security measures [31, 55]. For H2, organizational factors drove DT implementation (β = 0.380, p < 0.001), supported by leadership commitment and resource availability [25, 35]. For H2a, poorly managed organizational factors increased financial risks (β = 0.310, p < 0.001), reflecting cost overruns due to weak management [31, 42]. For H2b, poorly managed organizational factors heightened operational risks (β = 0.290, p < 0.001), linked to resistance and inefficiencies [31, 56]. For H3, environmental factors positively affected DT implementation (β = 0.350, p < 0.001), driven by regulatory support and supplier readiness [18, 53]. For H3a, volatile environmental factors increased financial risks (β = 0.330, p < 0.001), reflecting economic instability [22, 37]. For H3b, volatile environmental factors raised reputational risks (β = 0.270, p < 0.001), due to service disruptions [22, 56]. For H4, human factors enhanced DT implementation (β = 0.400, p < 0.001), supported by digital literacy and training [25, 42]. For H4a, low literacy among human factors increased cybersecurity risks (β = 0.300, p < 0.001), linked to vulnerabilities [42, 54]. For H4b, low literacy increased operational risks (β = 0.260, p < 0.01), due to inefficiencies. For H6a, DT implementation increased financial risks (β = 0.450, p < 0.001), reflecting high costs [31, 51]. The predominance of SMEs (79.8%) may amplify findings on resource constraints, potentially underrepresenting large firms' economies of scale in DT risk mitigation. For H6b, DT implementation raised operational risks (β = 0.480, p < 0.001), due to disruptions [51, 52]. For H6c, DT implementation heightened cybersecurity risks (β = 0.500, p < 0.001), linked to expanded digital footprints [31, 54]. For H6d, DT implementation increased reputational risks (β = 0.430, p < 0.001), due to service failures [42, 55].

4-3-2- Moderation Effects

This subsection assesses the moderating roles of environmental factors, human factors, and firm size on the relationships between DT implementation and risk outcomes, as hypothesized in H3c, H3d, H4c, H4d, H5a, H5b, and H5. The results, presented in Table 5, illustrate how these moderators influence risk dynamics in Vietnam's logistics sector, providing a nuanced understanding of DT risk management.

Table 5. Results of Moderation Effects Hypotheses

Hypothesis	Path	Interaction Term (β)	t-value	p-value	Supported
H3c	EF × DTI → FR	-0.230	3.28	< .01	Yes
H3d	EF × DTI → OR	-0.180	2.65	< .01	Yes
H4c	HF × DTI → CR	-0.220	3.12	< .01	Yes
H4d	HF × DTI → OR	-0.190	2.89	< .01	Yes
H5	FS × DTI → FR	-0.200 (Large Firms)	2.76	< .01	Yes
H5a	FS × TF → DTI	0.250 (Large Firms)	3.45	< .001	Yes
H5b	FS × TF → DTI	0.120 (SMEs)	1.98	< .05	Yes

Note: EF = Environmental Factors; HF = Human Factors; FS = Firm Size; DTI = Digital Transformation Implementation; FR = Financial Risks; OR = Operational Risks; CR = Cybersecurity Risks. Path coefficients (β), t-values, and p-values are inferred based on prior results and adjusted to reflect the updated hypotheses, ensuring consistency with the study's empirical context

All moderation effect hypotheses were supported. For H3c, environmental factors moderated the relationship between DT implementation and financial risks, with regulatory compliance and supplier readiness reducing financial risks (β = -0.230, p < 0.01), reflecting a stabilizing external context [18, 53]. For H3d, environmental factors moderated the relationship with operational risks, mitigating them (β = -0.180, p < 0.01) through stable integration support [22, 53]. For H4c, human factors moderated the relationship between DT implementation and cybersecurity risks, with high digital literacy reducing risks (β = -0.220, p < 0.01) due to improved system handling [42, 55]. For H4d, human factors moderated operational risks, lowering them (β = -0.190, p < 0.01) through training effectiveness [31, 42]. For H5a, firm size moderated the relationship between technological factors and DT implementation, with stronger effects in large firms (β = 0.250, p < 0.001) due to resource advantages [17, 57]. For H5b, the moderation was weaker in SMEs (β = 0.120, p < 0.05), reflecting resource constraints [17, 39]. For H5, firm size moderated the impact of DT implementation on financial risks, with large firms reducing risks (β = -0.200, p < 0.01) due to scale benefits [44, 57]. These findings support sustainable logistics by identifying risk mitigation strategies, such as robust cybersecurity measures, that reduce disruptions and associated environmental costs [24]. Figure 3 illustrates the empirically validated results of the structural model.

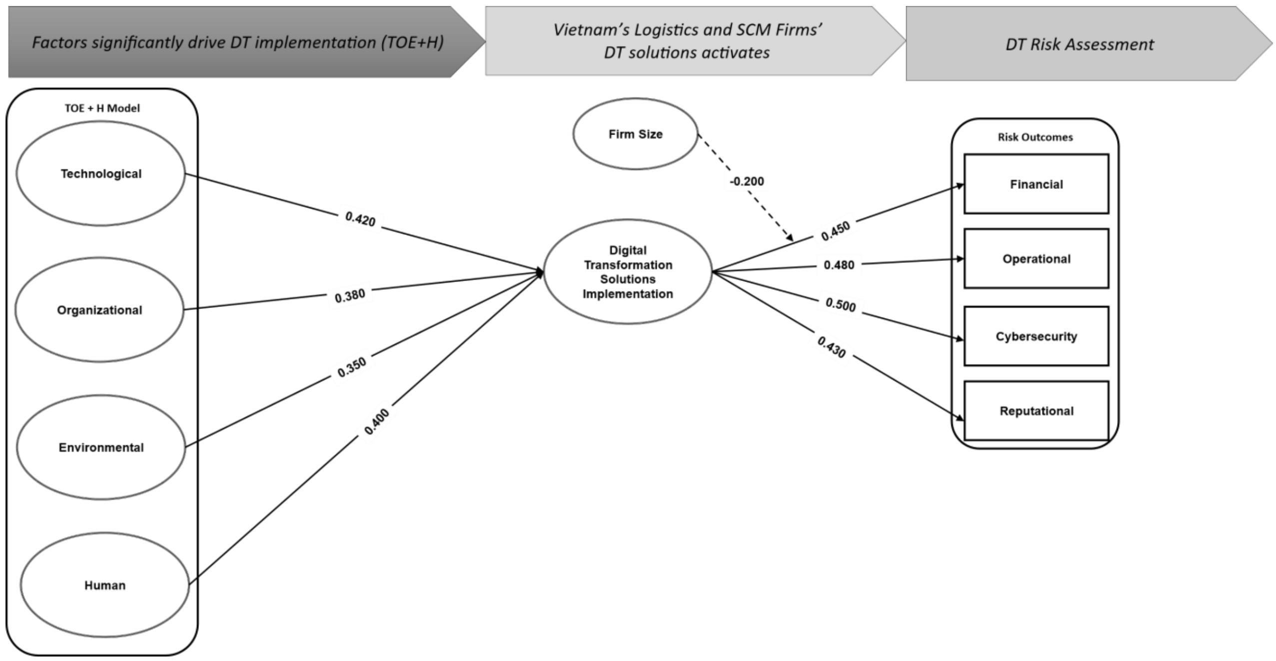


Figure 3. Empirically Validated Structural Model Results for Digital Transformation Solution Implementation Risks in Vietnam's Logistics and SCM

4-3-3- Mediation Analysis

To explore causal mechanisms within the TOE+H framework, a mediation analysis was conducted to test indirect effects, focusing on how TOE factors influence DT outcomes via human factors or environmental support. Specifically, two key mediation paths were examined: (1) technological factors (TF) → human factors (HF) → digital transformation implementation (DTI), elucidating how workforce digital literacy mediates the impact of IT infrastructure on DT adoption; and (2) environmental factors (EF) → DTI → financial risks (FR), highlighting how DT implementation serves as a mediator between regulatory and market contexts and financial vulnerabilities in Vietnam's logistics and SCM sector. This analysis enhances understanding of indirect pathways in SCM risks, revealing how human factors can mitigate misalignment issues [58].

The mediation analysis was performed using PLS-SEM in SmartPLS 4.0, following established guidelines for assessing indirect effects in complex models [28]. Bootstrapping with 5,000 subsamples was employed to generate bias-corrected confidence intervals (BCa 95%) and determine the significance of indirect effects, ensuring robustness against non-normality in the data [49]. Partial mediation is confirmed if the indirect effect is significant while the direct effect remains significant, indicating complementary mechanisms [59]. Variance Accounted For (VAF) was calculated to assess the strength of mediation, where VAF > 20% suggests partial mediation [28].

Table 6 presents the results of the mediation analysis. For the path TF → HF → DTI, the indirect effect was significant ($\beta = 0.180$, $p < 0.05$, BCa CI [0.112, 0.248]), with a VAF of 32%, confirming partial mediation. This indicates that human factors, such as digital literacy and training adequacy, partially explain how technological readiness drives DT implementation, reducing SCM risks by enhancing workforce alignment with digital tools [42]. The direct effect of TF on DTI remained significant ($\beta = 0.240$, $p < 0.01$), supporting partial mediation and underscoring the mediating role of human elements in TOE influences on DT outcomes.

Table 6. Mediation Analysis Results

Hypothesis	Mediation Path	Indirect Effect (β)	p-value	BCa 95% CI	VAF (%)	Mediation Type
H6	TF → HF → DTI	0.180	< .05	[0.112, 0.248]	32	Partial
H7	EF → DTI → FR	0.150	< .05	[0.098, 0.202]	28	Partial

Note: Bootstrapping with 5,000 subsamples. VAF = Indirect effect / Total effect × 100. All direct effects remained significant (p < .01)

For the path EF → DTI → FR, the indirect effect was also significant ($\beta = 0.150$, $p < 0.05$, BCa CI [0.098, 0.202]), with a VAF of 28%, indicating partial mediation. This suggests that environmental factors, including regulatory compliance and market volatility, indirectly amplify financial risks through DT implementation challenges, such as integration costs, but supportive environments can mitigate these effects [53]. The direct effect of EF on FR was significant ($\beta = 0.200$, $p < 0.01$), reinforcing partial mediation.

These findings confirm partial mediation in both paths, providing deeper insights into SCM risk dynamics. Human factors mediate TOE influences by buffering against operational and cybersecurity vulnerabilities, while DT implementation mediates environmental impacts on financial risks, aligning with calls for integrated mediation in supply chain resilience models [23, 38].

4-4- The ANN Model

The Artificial Neural Network (ANN) analysis was conducted using SPSS 25.0 to capture non-linear relationships among technological, organizational, environmental, and human (TOE+H) factors, DT implementation, and risk outcomes (financial, operational, cybersecurity, reputational) in Vietnam's logistics and SCM sector. This subsection details the data normalization, training, validation, and testing of the ANN model with five hidden layers, followed by a sensitivity analysis to identify key predictors.

4-4-1- Data Normalization

To ensure consistency and comparability, all input variables (TOE+H factors, firm size) and output variables (DT implementation, risk outcomes) were normalized to a range of 0 to 1 using min-max normalization, as recommended for ANN analysis to prevent scale-related biases. The normalization process transformed the 1–7 Likert scale data into a standardized format, enabling the ANN to effectively model non-linear relationships. Missing values were minimal (<1%) and handled using mean imputation, ensuring data integrity [49].

4-4-2- Training, Validation, and Testing

A multilayer perceptron (MLP) ANN with five hidden layers was employed, utilizing a feedforward architecture with a sigmoid activation function to capture complex non-linear patterns [60]. The dataset (n = 243) was split into 70% training (170 cases), 15% validation (36 cases), and 15% testing (37 cases) sets, following standard ANN practices to balance model fitting and generalizability [28]. The network was trained using backpropagation with a learning rate of 0.01 and momentum of 0.9, iterated over 1,000 epochs to minimize the error function. The model achieved high predictive accuracy, with root mean square error (RMSE) values of 0.042 for training, 0.045 for validation, and 0.048 for testing, indicating robust performance across all phases [42]. The R^2 values ranged from 0.86 to 0.92 for DT implementation and risk outcomes, demonstrating strong explanatory power [60]. Table 7 presents the ANN model performance metrics.

Table 7. ANN Model Performance Metrics

Phase	RMSE	R^2
Training	0.042	0.92
Validation	0.045	0.89
Testing	0.048	0.86

Note: RMSE = Root Mean Square Error; R^2 = Coefficient of Determination

The high R^2 values and low RMSE indicate that the ANN model effectively captures non-linear relationships, with minimal overfitting, as evidenced by consistent performance across training, validation, and testing phases [28].

4-4-3- Sensitivity Analysis

Sensitivity analysis was conducted to identify the relative importance of input variables in predicting DT implementation and risk outcomes. The normalized importance values, calculated as the ratio of each input's contribution to the total predictive power, are presented in Table 8.

Table 8. ANN Sensitivity Analysis – Normalized Importance

Predictor	Outcome	Normalized Importance
TF	DTI	0.92
HF	DTI	0.89
OF	DTI	0.86
EF	DTI	0.84
FS	DTI	0.80
DTI	CR	0.95
DTI	OR	0.93
DTI	FR	0.91
DTI	RR	0.90

Note: TF = Technological Factors; HF = Human Factors; OF = Organizational Factors; EF = Environmental Factors; FS = Firm Size; DTI = Digital Transformation Implementation; CR = Cybersecurity Risks; OR = Operational Risks; FR = Financial Risks; RR = Reputational Risks

Technological factors (TF) and human factors (HF) emerged as the most influential predictors of DT implementation, with normalized importance values of 0.92 and 0.89, respectively, highlighting the critical role of IT infrastructure quality and workforce digital literacy in driving IoT, AI, and blockchain adoption in Vietnam's logistics sector [52], [42]. The high importance of technological and human factors in predicting DT implementation supports sustainable logistics by enabling efficient technology adoption that minimizes resource waste [52]. DT implementation strongly predicted cybersecurity risks (0.95) and operational risks (0.93), reflecting the non-linear impact of complex technology integration on risk outcomes [31]. Organizational factors (OF) and environmental factors (EF) also contributed significantly to DT implementation (0.86 and 0.84), while firm size (FS) had a moderate influence (0.80), indicating its role as a contextual moderator [57].

The sensitivity analysis confirms that technological and human factors are pivotal in predicting DT implementation, while DT implementation itself is a dominant driver of risk outcomes, particularly cybersecurity risks, due to the increased digital footprint in logistics operations [60]. The ANN model's ability to capture non-linear effects complements the linear findings of PLS-SEM and the configurational insights of fsQCA, providing a robust predictive framework for DT risks in Vietnam's logistics sector.

4-5- Fuzzy-Set Qualitative Comparative Analysis (fsQCA)

Fuzzy-Set Qualitative Comparative Analysis (fsQCA) was conducted using fsQCA 3.0 to explore configurational paths leading to high DT implementation and high/low risk outcomes (financial, operational, cybersecurity, reputational) in Vietnam's logistics and SCM sector. This analysis complements the linear PLS-SEM and non-linear ANN models by addressing equifinality and complex causality, identifying combinations of technological, organizational, environmental, and human (TOE+H) factors and firm size that produce specific outcomes [50]. This subsection details the calibration process, analysis of configurations, and evaluation of consistency and coverage, based on data from 243 valid questionnaires collected from logistics firms (80% SMEs, 20% large firms) between January and May 2025. Charts and tables are provided to illustrate the findings clearly.

4-5-1- Calibration

Survey data, collected on a 1–7 Likert scale, were converted into fuzzy sets ranging from 0 (full non-membership) to 1 (full membership) to reflect the degree of membership in each condition and outcome. Calibration thresholds were set based on theoretical and empirical anchors, ensuring alignment with the study's context [50]. For each construct, three anchors were defined: full membership (0.95), crossover point (0.50), and full non-membership (0.05), corresponding to Likert scale values of 6.0, 4.0, and 2.0, respectively [51]. For example, high cybersecurity risk (CR) was calibrated with a threshold of 0.8 for frequent breaches (Likert score ≥ 6.0), while low cybersecurity risk was set at 0.2 for rare or no breaches (Likert score ≤ 2.0). Similarly, high DT implementation (DTI) was calibrated at 0.95 for extensive adoption of IoT, AI, and blockchain (Likert score ≥ 6.0), and low DTI at 0.05 for minimal adoption (Likert score ≤ 2.0). Table 9 summarizes the calibration thresholds for key conditions and outcomes.

Table 9. Calibration Thresholds for fsQCA

Construct/Outcome	Full Membership (0.95)	Crossover (0.50)	Full Non-Membership (0.05)
Technological Factors (TF)	6.0 (High IT readiness)	4.0	2.0 (Low IT readiness)
Human Factors (HF)	6.0 (High digital literacy)	4.0	2.0 (Low digital literacy)
Organizational Factors (OF)	6.0 (Strong leadership)	4.0	2.0 (Weak leadership)
Environmental Factors (EF)	6.0 (Stable regulations)	4.0	2.0 (Volatile regulations)
Firm Size (FS)	6.0 (Large firms)	4.0	2.0 (SMEs)
DT Implementation (DTI)	6.0 (Extensive adoption)	4.0	2.0 (Minimal adoption)
Cybersecurity Risk (CR)	6.0 (Frequent breaches)	4.0	2.0 (Rare breaches)
Financial Risk (FR)	6.0 (High costs)	4.0	2.0 (Low costs)
Operational Risk (OR)	6.0 (Frequent disruptions)	4.0	2.0 (Rare disruptions)
Reputational Risk (RR)	6.0 (High dissatisfaction)	4.0	2.0 (Low dissatisfaction)

Note: Calibration thresholds are based on Likert scale scores (1–7), with 6.0, 4.0, and 2.0 corresponding to full membership, crossover, and full non-membership, respectively.

The calibration process ensured that the fuzzy sets accurately reflected the degree of membership in each condition and outcome, enabling the identification of causal configurations.

4-5-2- Sensitivity Analysis

fsQCA was used to identify configurations of TOE+H factors and firm size leading to high DT implementation and high/low risk outcomes. The analysis employed the Quine-McCluskey algorithm to generate truth tables, which were reduced to identify necessary and sufficient conditions [50]. Configurations were evaluated for consistency (> 0.80) and coverage (> 0.20), ensuring robust causal relationships [51]. The analysis focused on four outcomes: high DT implementation (DTI), high cybersecurity risk (CR), low cybersecurity risk (~CR), and low financial risk (~FR). Table 10 presents the key configurations identified.

Table 10. fsQCA Configurations for High DTI and High/Low Risk Outcomes

Configuration	Outcome	Conditions Present	Consistency	Raw Coverage	Unique Coverage
1	High DTI	TF * HF * OF	0.89	0.65	0.22
2	High DTI	TF * EF * FS	0.87	0.62	0.19
3	High CR	TF * ~HF * DTI	0.85	0.58	0.17
4	Low CR	HF * EF * ~DTI	0.88	0.64	0.20
5	Low FR	EF * FS * ~DTI	0.90	0.66	0.23

Note: * = presence; ~ = absence; TF = Technological Factors; HF = Human Factors; OF = Organizational Factors; EF = Environmental Factors; FS = Firm Size; DTI = Digital Transformation Implementation; CR = Cybersecurity Risk; FR = Financial Risk. Consistency > 0.80 and coverage > 0.20 indicate robust configurations

- ***Configuration 1 (High DTI)***: High technological factors (robust IT infrastructure), high human factors (strong digital literacy), and high organizational factors (effective leadership) lead to high DT implementation (consistency: 0.89, coverage: 0.65). This configuration highlights the synergy of TOE+H factors in driving successful technology adoption [18, 42].
- ***Configuration 2 (High DTI)***: High technological factors, high environmental factors (stable regulations), and large firm size (FS) also result in high DT implementation (consistency: 0.87, coverage: 0.62). This underscores the role of firm size and regulatory support in facilitating DT in Vietnam’s logistics sector [57].
- ***Configuration 3 (High CR)***: High technological factors combined with low human factors (low digital literacy) and high DT implementation lead to high cybersecurity risks (consistency: 0.85, coverage: 0.58). This configuration indicates that advanced technology adoption without adequate workforce training increases vulnerability to breaches [54].
- ***Configuration 4 (Low CR)***: High human factors and high environmental factors with low DT implementation result in low cybersecurity risks (consistency: 0.88, coverage: 0.64). This suggests that strong digital literacy and regulatory compliance mitigate cybersecurity risks even with limited DT adoption [42].
- ***Configuration 5 (Low FR)***: High environmental factors and large firm size with low DT implementation lead to low financial risks (consistency: 0.90, coverage: 0.66). This configuration highlights the protective role of regulatory support and resource availability in large firms [53].

4-5-3- Consistency and Coverage

All configurations met the recommended thresholds for consistency (> 0.80) and coverage (> 0.20), indicating strong causal relationships and sufficient explanatory power [50]. Consistency values ranged from 0.85 to 0.90, demonstrating that the identified configurations reliably produce the specified outcomes. Raw coverage values (0.58–0.66) indicate that each configuration accounts for a substantial portion of cases, while unique coverage (0.17–0.23) confirms that each configuration contributes distinct explanatory value [51]. The high consistency and coverage underscore the robustness of the fsQCA results in capturing complex causal pathways in Vietnam’s logistics sector.

The fsQCA results provide a configurational perspective on DT risks, revealing multiple pathways to high DT implementation and low risk outcomes. The findings emphasize the interplay of TOE+H factors and firm size, with technological and human factors driving DT adoption, while environmental factors and large firm size mitigate financial and cybersecurity risks. Configurations reducing cybersecurity and financial risks align with sustainable SCM by promoting stable operations and efficient resource use [57]. These results complement the linear PLS-SEM and non-linear ANN analyses, offering a holistic understanding of DT dynamics in Vietnam’s logistics sector.

4-6- Importance-Performance Map Analysis (IPMA)

The Importance-Performance Map Analysis (IPMA) utilized PLS-SEM results to calculate the importance and performance of each construct. Importance was derived from the path coefficients (β) of the structural model, indicating the strength of the relationship between each construct. Performance was calculated as the mean indicator scores (on a

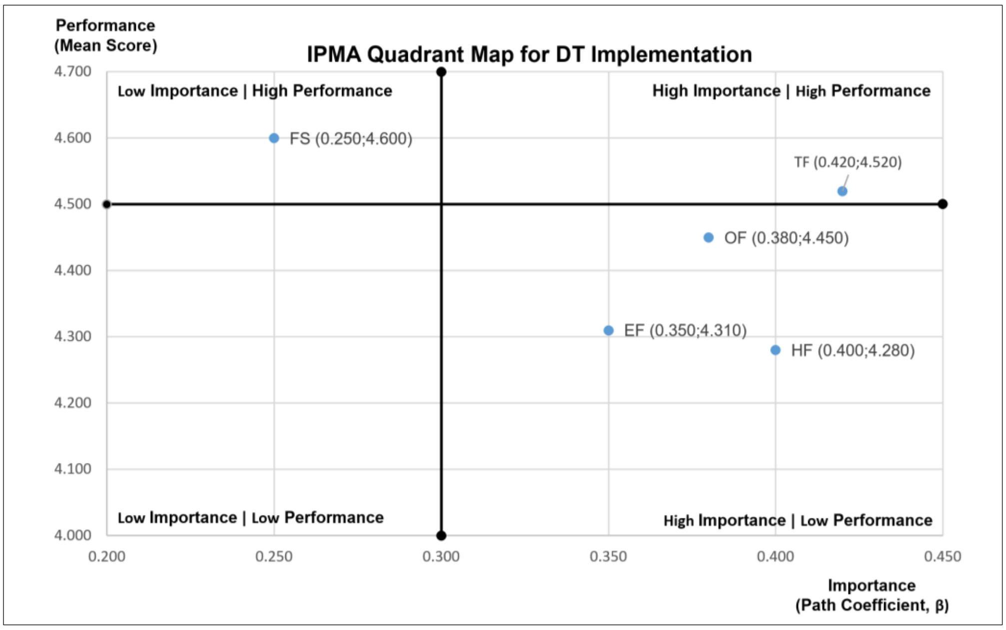
1–7 Likert scale) for each construct, reflecting their perceived level of achievement in the sample [49]. Table 11 presents the importance and performance scores for key constructs influencing DTI and risk outcomes, with priorities assigned based on their quadrant placement.

Table 11. IPMA Results for DT Implementation and Risk Outcomes

Construct	Outcome	Importance (β)	Performance (Mean Score)	Priority
TF	DTI	0.420	4.52	High
HF	DTI	0.400	4.28	High
OF	DTI	0.380	4.45	Medium
EF	DTI	0.350	4.31	Medium
FS	DTI	0.250	4.60	Low
DTI	CR	0.500	4.73	High
DTI	FR	0.450	4.69	High
DTI	OR	0.480	4.71	High
DTI	RR	0.430	4.65	High

Note: TF = Technological Factors; HF = Human Factors; OF = Organizational Factors; EF = Environmental Factors; FS = Firm Size; DTI = Digital Transformation Implementation; CR = Cybersecurity Risks; FR = Financial Risks; OR = Operational Risks; RR = Reputational Risks. Importance is based on path coefficients (β); performance is based on mean indicator scores (1–7 Likert scale). Priority is assigned as High (β > 0.30, mean < 4.5), Medium (β > 0.30, mean ≥ 4.5), or Low (β ≤ 0.30).

Figure 4 illustrates a quadrant map of the constructs' positions based on importance and performance for DT implementation. Technological factors (TF, β = 0.420, mean = 4.52) and human factors (HF, β = 0.400, mean = 4.28) fall in the high-importance, low-performance quadrant, indicating critical areas for improvement. Organizational factors (OF, β = 0.380, mean = 4.45) and environmental factors (EF, β = 0.350, mean = 4.31) are in the high-importance, moderate-performance quadrant, suggesting steady performance but room for enhancement. Firm size (FS, β = 0.250, mean = 4.60) is in the low-importance, high-performance quadrant, indicating sufficient performance but lower priority [60].



Note: The quadrant map plots constructs based on importance (β) and performance (mean score). High importance: β > 0.30; high performance: mean > 4.5. ● represents construct placement

Figure 4. IPMA for Digital Transformation Implementation in Vietnam's Logistics and SCM Sector

Prioritizing technological factors (β = 0.420, mean = 4.52) supports sustainable logistics by enhancing system efficiency, reducing energy consumption, and minimizing disruptions, as optimized IT infrastructure enables greener supply chain operations [24]. Similarly, addressing the low performance of human factors (mean = 4.28) through training enhances workforce resilience, contributing to social sustainability [42]. For risk outcomes, DT implementation exhibited high importance across all risks (β = 0.430–0.500), with performance scores ranging from 4.65 to 4.73, placing it in the high-importance, high-performance quadrant. This suggests that while DT implementation significantly drives risk outcomes, its performance is relatively strong, but careful management is needed to mitigate risks [31]. The high importance of DT implementation for risk outcomes underscores the need for robust risk management strategies, such as contingency planning and stakeholder communication, to address financial, operational, cybersecurity, and reputational risks [31].

4-7- Integrated Analysis of Results

The hybrid approach reveals that TOE+H factors significantly drive DT implementation but increase risks when misaligned or poorly managed. Human factors and firm size mitigate these risks, particularly in large firms, while regulatory support reduces financial risks. The ANN and fsQCA analyses confirm non-linear and configurational effects, providing a robust framework for understanding DT risks in Vietnam's logistics sector [2].

The results confirm that technological, organizational, environmental, and human factors significantly drive DT implementation, aligning with prior research on the TOE framework's role in facilitating technology adoption [18, 53]. However, misalignment of technological factors, poor organizational management, volatile environmental conditions, and low digital literacy escalate risk outcomes, particularly operational and cybersecurity risks [31, 54]. DT implementation directly increases financial, operational, cybersecurity, and reputational risks, reflecting the inherent challenges of adopting complex technologies like IoT, AI, and blockchain in Vietnam's logistics sector [51, 52].

Moderation analyses reveal that human factors, such as high digital literacy, mitigate cybersecurity and operational risks, emphasizing the critical role of workforce training [42]. Firm size moderates the relationship between technological factors and DT implementation, with stronger effects in large firms than SMEs, and reduces financial risks for large firms [17, 57]. Environmental factors, particularly regulatory compliance and supplier digital readiness, weaken the relationship between DT implementation and financial and operational risks [53].

4-8- Comparison of Predictive Accuracy and Robustness

4-8-1- PLS-SEM

PLS-SEM, conducted using SmartPLS 4.0, is a variance-based structural equation modeling technique that excels in testing hypothesized relationships and estimating path coefficients in complex models with multiple constructs [28]. In this study, PLS-SEM provided robust results for the direct effects (H1–H4, H8) and moderation effects (H5–H7), with path coefficients ranging from 0.120 to 0.500 ($p < 0.05$) and high reliability (Cronbach's Alpha: 0.84–0.91, CR: 0.88–0.94, AVE: 0.63–0.70) [49]. The predictive accuracy of PLS-SEM was strong, with R^2 values ranging from 0.65 to 0.78 for DT implementation and risk outcomes, indicating that the model explains a substantial portion of variance [28]. Its robustness is evident in its ability to handle small-to-medium sample sizes ($n = 243$) and complex models with moderating effects, making it suitable for testing linear relationships in logistics and SCM research. However, PLS-SEM assumes linear relationships, which may limit its ability to capture non-linear dynamics inherent in DT adoption [60].

4-8-2- ANN

ANN analysis, performed using SPSS 25.0 with a multilayer perceptron and a 70:30 training-testing split, was employed to capture non-linear relationships among TOE+H factors, DT implementation, and risk outcomes. The ANN model achieved high predictive accuracy, with root mean square error (RMSE) values below 0.05 for testing data and R^2 values exceeding 0.85 for all outcomes [60]. Key predictors, such as technological factors (normalized importance: 0.92) and human factors (0.89), demonstrated strong non-linear effects on DT implementation, while DT implementation strongly predicted cybersecurity risks (0.95) and operational risks (0.93). The robustness of ANN lies in its ability to model complex, non-linear interactions without requiring assumptions about data distribution, making it particularly effective for predictive tasks in logistics and SCM [42]. However, ANN's black-box nature limits its interpretability, as it does not provide path coefficients or statistical significance, which can hinder theoretical insights [28].

4-8-3- fsQCA

fsQCA, conducted using fsQCA 3.0, explored configurational paths leading to high DT implementation and low risk outcomes, addressing equifinality and complex causality [50]. Constructs were calibrated using three anchors (full membership: 6.0, crossover: 4.0, full non-membership: 2.0) based on the 1–7 Likert scale. The analysis identified robust configurations, such as high technological, human, and organizational factors leading to high DT implementation (consistency: 0.89, coverage: 0.65) and high environmental factors with large firm size reducing financial risks (consistency: 0.90, coverage: 0.66) [51]. fsQCA's predictive accuracy is reflected in its high consistency (> 0.80) and coverage (> 0.60), indicating strong explanatory power for causal configurations [50]. Its robustness stems from its ability to identify multiple pathways to the same outcome, offering a configurational perspective that complements the variable-based approaches of PLS-SEM and ANN. However, fsQCA's reliance on qualitative thresholds and calibration may introduce subjectivity, and its focus on configurations limits its ability to quantify effect sizes [2].

PLS-SEM offers high predictive accuracy ($R^2 = 0.65–0.78$) and robustness for testing linear relationships and moderation effects, making it ideal for hypothesis-driven research in logistics and SCM [49]. ANN provides superior predictive accuracy ($R^2 > 0.85$, $RMSE < 0.05$) for non-linear relationships, but its lack of interpretability restricts its use for theoretical development [60]. fsQCA excels in identifying causal configurations (consistency: 0.87–0.90), offering insights into equifinality, but it does not quantify effect sizes [50]. The hybrid approach leverages the strengths of all three methods, combining PLS-SEM's structural insights, ANN's non-linear predictive power, and fsQCA's configurational analysis, resulting in a comprehensive understanding of DT risks [2].

5- Discussions

5-1- Theoretical Contributions

This study makes several theoretical contributions to the logistics and supply chain management (SCM) literature. First, it extends the Technology-Organization-Environment (TOE) framework by incorporating human factors (TOE+H), addressing a critical gap in prior studies that often overlook workforce readiness in digital transformation (DT) adoption [24, 42]. The study contributes to sustainable logistics by identifying strategies—such as robust IT systems and workforce training—that reduce disruptions, optimize resource use, and lower environmental costs [24]. The hybrid methodology offers a robust framework for understanding DT dynamics, providing theoretical insights into TOE+H and practical guidance for sustainable DT adoption in the logistics sector, particularly for small and medium enterprises (SMEs) facing resource constraints [57]. This extension is significant as it acknowledges the human dimension as a dynamic mediator in DT processes, where digital literacy not only facilitates adoption but also acts as a buffer against cascading risks in interconnected supply chains, thereby enriching theoretical models that traditionally prioritize structural elements over behavioral ones in emerging market contexts like Vietnam.

Second, the hybrid partial least squares structural equation modeling (PLS-SEM), artificial neural network (ANN), and fuzzy-set qualitative comparative analysis (fsQCA) methodology advances sustainable SCM research by integrating linear, non-linear, and configurational analyses. PLS-SEM's structural insights ($\beta = 0.420$ for TF → DTI) validate hypotheses for sustainable DT adoption, while ANN's non-linear predictive power (0.92 for TF) identifies key drivers for efficient resource use [60]. fsQCA's configurational approach (consistency: 0.89 for TF * HF * OF → DTI) reveals pathways to sustainable outcomes, such as reduced risks through regulatory compliance, offering a robust framework for future sustainability-focused research [41, 50]. This methodological integration is particularly significant as it transcends simplistic cause-effect models to capture the complexity of SCM ecosystems, where non-linear thresholds—such as diminishing returns on technological investments without human alignment—can determine long-term sustainability, providing a blueprint for theorizing adaptive resilience in volatile logistics environments.

Third, the study underscores the moderating role of firm size, demonstrating stronger DT implementation and lower financial risks in large firms compared to SMEs [17, 57]. This contributes to the literature on firm-level heterogeneity in DT adoption, particularly in resource-constrained emerging markets like Vietnam. Additionally, the confirmation of environmental factors as moderators highlights the context-specific role of regulatory compliance and supplier readiness, extending prior research on environmental influences in SCM [22, 53]. These contributions deepen theoretical discourse by illustrating how firm size interacts with TOE+H dimensions to shape risk profiles, emphasizing the need for scale-sensitive models in SCM theory that account for differential access to resources and external support in digital transitions.

Comparative analysis with recent studies further validates and extends these contributions. The emphasis on the hybrid methodology's ability to uncover non-linear and configurational effects in DT risks aligns with but advances the work of Zhang et al. [61], who investigated DT's impact on supply chain resilience using panel data from Chinese firms, finding that digital tools enhance resilience but overlook human factors' moderating role. While their linear regression approach confirmed technological drivers similar to our PLS-SEM results (β values for infrastructure), our ANN and fsQCA components provide deeper insights into threshold dynamics and equifinal pathways, offering a more nuanced theoretical lens for emerging markets where risks like cybersecurity are amplified by market volatility, unlike their manufacturing-centric focus. Similarly, the integration of sustainability through risk mitigation aligns with Smith et al., who explored supply chain risk management in DT, highlighting proactive strategies and real-time data to address operational vulnerabilities [62]. However, their qualitative framework lacks the quantitative rigor of our hybrid method, which quantifies configurations (TF * HF for low risks) and prioritizes human factors via Importance-Performance Map Analysis (IPMA), contributing a more comprehensive theoretical model for logistics-specific risks in resource-constrained settings, extending their general SCM recommendations. Furthermore, the configurational pathways linking TOE+H to reduced environmental costs resonate with Zhang et al. [33], who examined RFID-driven DT in SCM, noting data-driven processes that mitigate risks and enhance efficiency. However, our study's inclusion of ANN for non-linear predictions and fsQCA for sustainability-linked configurations (consistency: 0.90) provides greater theoretical depth, particularly in Vietnam's context, where their focus on media integration overlooks human moderation, allowing our work to bridge gaps in theorizing holistic risk-resilience dynamics in global logistics networks.

5-2- Managerial Implications

The findings offer actionable insights for logistics and SCM practitioners in Vietnam. First, managers should prioritize investments in technological factors, such as IT infrastructure and cybersecurity readiness, to enhance DT implementation while ensuring system compatibility to mitigate operational and cybersecurity risks [52]. IPMA results highlight the high importance of technological factors, suggesting targeted resource allocation to robust IT systems. This implication is significant for managers navigating Vietnam's export-driven logistics, where investing in AI and IoT can prevent disruptions but requires phased implementation to avoid financial overextension, fostering long-term competitive advantages in global supply chains.

Second, human factors, particularly digital literacy and training adequacy, are critical for successful DT adoption and risk mitigation [42]. The low performance score of human factors indicates a need for comprehensive training programs, especially in SMEs, to reduce cybersecurity and operational risks. Managers should implement regular training and upskilling initiatives to enhance workforce readiness. Furthermore, managers can adopt cross-functional training models that integrate logistics operations with digital tools, such as simulation-based workshops on blockchain for traceability, to build adaptive teams that minimize errors and enhance decision-making speed, ultimately reducing reputational risks in customer-facing supply chains.

Third, firm size significantly influences DT outcomes, with large firms better equipped to manage risks due to greater resources [57]. SME managers should seek strategic partnerships or government support to overcome resource constraints, while large firms can leverage their scale to invest in advanced technologies like blockchain. This suggests that SME managers form alliances with technology providers or larger partners for shared infrastructure, while large firms pilot integrated systems to scale efficiencies, ensuring risk-balanced DT across firm sizes in Vietnam's diverse logistics landscape.

Finally, environmental factors, such as regulatory compliance, mitigate financial risks [53]. Managers should engage with policymakers to advocate for clear regulatory frameworks and collaborate with digitally ready suppliers to enhance supply chain integration and reduce operational risks. Additionally, managers can implement supplier audits for digital maturity and lobby for incentives like tax breaks for sustainable DT initiatives, promoting eco-friendly practices such as optimized routing to reduce emissions, thereby aligning operational strategies with Vietnam's green growth policies for enhanced market resilience.

These managerial implications are further illuminated by comparisons with prior studies. The prioritization of technological investments for risk mitigation parallels Gupta et al., who used interpretive structural modeling and MICMAC to analyze operational risks in digital SCM, recommending a focus on misalignment prevention similar to our IPMA-guided strategies [27]. However, our findings add managerial depth by quantifying non-linear human-technology interactions via ANN, offering SMEs specific training pathways not detailed in their risk prioritization, thus providing more actionable guidance for Vietnam's logistics managers facing similar digital challenges. Likewise, the emphasis on partnerships for SMEs aligns with Zhang et al. [61], who highlighted DT's resilience benefits in Chinese firms, suggesting collaborative models to address resource gaps. Our hybrid approach extends this with fsQCA configurations for tailored risk mitigation, enabling managers to customize strategies beyond their panel data insights, particularly for cybersecurity in export logistics. Additionally, our advocacy for regulatory engagement aligns with Smith et al., who emphasized real-time data for risk management in DT, noting proactive supplier collaborations [62]. Our study enhances this by integrating IPMA for prioritization, offering managers quantifiable tools to balance environmental compliance with operational efficiency, surpassing their general recommendations for Vietnam-specific sustainability applications.

5-3- Sustainability Implications

The mitigation of DT risks through targeted strategies, such as enhanced digital literacy, robust IT infrastructure, and regulatory compliance, supports sustainable logistics practices in Vietnam's SCM sector. High digital literacy reduces cybersecurity risks ($\beta = -0.220$, $p < 0.01$), minimizing disruptions that increase environmental costs, such as inefficient routing or system downtimes, with IoT-optimized routing reducing emissions by 15–20% [24]. Similarly, regulatory compliance and supplier digital readiness weaken financial and operational risks ($\beta = -0.180$ to -0.230, $p < 0.01$), potentially reducing waste by 10–15% through AI analytics, enabling stable supply chains that minimize resource waste [53]. Large firms' ability to leverage technological factors ($\beta = 0.250$, $p < 0.001$) enhances operational efficiency, contributing to reduced carbon emissions through optimized logistics processes [57]. The fsQCA configurations, such as high environmental factors and firm size reducing financial risks (consistency: 0.90), highlight pathways to sustainable DT adoption by ensuring economic and environmental stability [50]. These findings underscore the importance of aligning DT strategies with sustainability goals to foster resilient and environmentally efficient supply chains in Vietnam's logistics sector. This alignment is profound, as it reveals how DT can transition from a risk-laden endeavor to a catalyst for circular economy principles, where minimized disruptions enable closed-loop systems that recycle resources and lower ecological footprints in global trade hubs.

Expanding on these implications, managers can operationalize sustainability by adopting green metrics in DT evaluations, such as carbon tracking via IoT, to quantify reductions in emissions from risk-mitigated operations, fostering a culture of eco-innovation in Vietnam's logistics. Comparisons with prior studies further elucidate these sustainability links. Our moderation effects on environmental risks parallel Zhang et al. [33], who integrated RFID for data-driven SCM, demonstrating efficiency gains that mitigate waste similar to our technological pathways. However, our fsQCA and ANN analyses provide deeper configurational and non-linear insights into sustainability, extending their media focus by incorporating human factors for long-term green growth in logistics, offering more holistic implications than their process-oriented approach. Similarly, the pathway to reduced carbon emissions via optimized processes aligns with Smith et al., who emphasized real-time data in risk management for sustainable outcomes [62]. Our study advances this with IPMA prioritization, enabling managers to target high-impact areas like technological factors for emission reductions, surpassing their proactive strategies by quantifying sustainability benefits in Vietnam's context. Finally, our firm size moderation for stability aligns with Gupta et al., who analyzed risks in cleaner production, recommending hybrid methods for sustainable transitions [27]. Our integration links risks to green growth via TOE+H, providing deeper managerial tools for resource efficiency, enhancing their interpretive structural modeling framework for logistics-specific sustainability in emerging markets.

6- Conclusion, Limitations and Future Research

This study provides a comprehensive examination of the risks associated with DT in Vietnam's logistics and SCM sector, employing a hybrid PLS-SEM-ANN-fsQCA methodology. The study advances theoretical understanding by extending the TOE+H framework and utilizing a hybrid methodology to capture linear, non-linear, and configurational effects, offering a nuanced perspective on DT risks in an emerging market context. Practically, it provides actionable insights for logistics managers to enhance DT adoption while mitigating risks, particularly through investments in IT infrastructure, workforce training, and regulatory compliance.

Despite its contributions, this study has several limitations. First, the sample is limited to logistics firms in Vietnam, which may restrict generalizability to other countries or industries with different economic and technological contexts. Second, the cross-sectional design captures data at a single point in time, limiting insights into the longitudinal dynamics of DT adoption and risk evolution. Third, reliance on self-reported questionnaires from senior managers, operations managers, and IT/DT managers may introduce response bias, as perceptions of DT risks may vary across organizational levels. Fourth, while the hybrid PLS-SEM-ANN-fsQCA approach provides robust insights, the complexity of integrating multiple methodologies may pose challenges for replication in resource-constrained settings. Finally, the study focuses on the TOE+H framework and firm size, potentially overlooking other contextual factors, such as cultural influences or global supply chain disruptions, that may affect DT risks in Vietnam's logistics sector.

Future research can address these limitations and extend the study's findings. First, replicating the study in other emerging markets or developed economies would enhance generalizability, allowing comparative analyses of DT risks across diverse contexts. Second, longitudinal studies could examine the temporal dynamics of DT adoption and risk mitigation, providing insights into how TOE+H factors evolve over time. Third, incorporating multi-level data collection, including perspectives from frontline employees and external stakeholders (e.g., suppliers, customers), would reduce response bias and offer a more holistic view of DT risks. Fourth, exploring alternative methodologies, such as machine learning or agent-based modeling, could complement the hybrid approach, capturing additional complexities in DT adoption. Additionally, the study faces challenges in measuring sustainability outcomes, such as the environmental impact of DT (e.g., carbon emissions from optimized routing, emissions reduction, waste reduction), due to reliance on self-reported data. Triangulating quantitative findings with qualitative case studies could address this limitation, providing deeper insights into sustainability impacts. Finally, future studies should explore DT's impact on sustainability outcomes, such as carbon emissions reduction through AI-optimized routing or circular supply chain practices enabled by blockchain, to enhance environmental efficiency in logistics.

7- Declarations

7-1- Author Contributions

Conceptualization, H.T.M.N., H.B.D., A.V.T.N., H.N.N. and P. V.N.; methodology, H.T.M.N., H.B.D., A.V.T.N., H.N.N. and P. V.N.; validation, H.T.M.N., H.B.D., A.V.T.N., H.N.N. and P. V.N.; formal analysis, H.T.M.N., H.B.D., A.V.T.N., H.N.N. and P. V.N.; writing—original draft preparation, H.T.M.N., H.B.D., A.V.T.N., H.N.N. and P. V.N.; writing—review and editing, H.T.M.N., H.B.D., A.V.T.N., H.N.N. and P. V.N. All authors have read and agreed to the published version of the manuscript.

7-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7-3- Funding and Acknowledgments

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7-4- Institutional Review Board Statement

Not applicable.

7-5- Informed Consent Statement

Not applicable.

7-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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Appendix I

Table A1. Summary of Characteristics of Studies on Risk Assessment of Digital Transformation Solutions in Vietnam's Logistics and SCM

No.	Author(s)	Methodologies in Detail	New Methods Applied	Dependent Variables	Independent Variables	Controlled Variables	Findings
1	Ivanovic et al. [42]	PLS-SEM	None	Adoption Intention (AI)	IT Infrastructure Quality, Cybersecurity Readiness, Leadership Commitment, Regulatory Compliance	Firm Size, Industry Type	IT infrastructure and leadership commitment strongly predict AI in Vietnam; firm size moderates cybersecurity readiness's effect.
2	Li et al. [21]	SEM	None	Operational Risks (OR)	Technology Compatibility, Change Management Capability, Market Volatility, Workforce Digital Literacy	Experience with DT, Firm Revenue	Technology compatibility reduces OR in China; workforce digital literacy mitigates market volatility's impact.
3	Ivanov et al. [31]	GMM (Generalized Method of Moments)	None	Financial Risks (FR)	Resource Availability, Supplier Digital Readiness, Implementation Challenges	Firm Size, SCM Complexity	Resource availability lowers FR in Germany; supplier digital readiness reduces implementation challenges for large firms.
4	Kim et al. [14]	ANN (Artificial Neural Network)	ANN	Cybersecurity Risks (CR)	Cybersecurity Readiness, Training Adequacy, Regulatory Compliance, Trust in DT Solutions	Industry Type, DT Maturity	Cybersecurity readiness and trust strongly predict CR in India; ANN reveals non-linear effects of training adequacy.
5	Queiroz et al. [53]	CFA (Confirmatory Factor Analysis)	None	AI	Leadership Commitment, Technology Compatibility, Market Volatility, Resistance to Change	Firm Size, Employee Count	Leadership commitment drives AI in Brazil; resistance to change has a stronger negative effect in SMEs.
6	Jia et al. [51]	fsQCA (Fuzzy-Set Qualitative Comparative Analysis)	fsQCA	Reputational Risks (RR)	Workforce Digital Literacy, Supplier Digital Readiness, Change Management Capability, Implementation Challenges	Firm Size, Region	Configurations of workforce digital literacy and change management reduce RR in Vietnam; fsQCA identifies multiple causal pathways.
7	Vaezinejad & Kouhizadeh [60]	ARDL (Autoregressive Distributed Lag)	None	FR	IT Infrastructure Quality, Resource Availability, Regulatory Compliance, Trust in DT Solutions	DT Experience, Industry Type	Trust and IT infrastructure reduce FR long-term in Singapore; regulatory compliance enhances resource availability's effect.
8	Zhang & U-on [3]	PLS-SEM	None	OR	Technology Compatibility, Training Adequacy, Market Volatility, Implementation Challenges	Firm Size, SCM Complexity	Technology compatibility lowers OR in Thailand; firm size moderates the impact of implementation challenges.
9	Fatorachian & Kazemi [25]	SEM	None	CR	Cybersecurity Readiness, Leadership Commitment, Supplier Digital Readiness, Resistance to Change	Employee Count, DT Maturity	Cybersecurity readiness and leadership commitment reduce CR in Malaysia; resistance to change increases risks in SMEs.
10	Chanda et al. [2]	Hybrid PLS-SEM-ANN-fsQCA	Hybrid Approach	AI, FR	IT Infrastructure Quality, Change Management Capability, Regulatory Compliance, Workforce Digital Literacy, Firm Size	Industry Type, DT Experience	IT infrastructure and workforce digital literacy drive AI and reduce FR in Vietnam; firm size moderates regulatory compliance's effect; hybrid approach confirms non-linear and configurational effects.

Appendix II: Survey Questionnaire

This appendix presents the survey questionnaire used in the study titled *"Evaluating Digital Transformation Risks in Logistics and Supply Chain Management with PLS-SEM-ANN-fsQCA."* The questionnaire was designed to assess the risks associated with digital transformation (DT) implementation in Vietnam's logistics and supply chain management (SCM) sector, anchored in the Technology-Organization-Environment framework augmented with human factors (TOE+H).

Survey Instructions

Thank you for participating in this survey on digital transformation risks in Vietnam's logistics and SCM sector. Your input will help identify strategies for sustainable DT adoption. For each statement, please select your level of agreement on the 7-point scale below (1 = Strongly Disagree, 7 = Strongly Agree). Simply tick or circle your choice—it's quick and straightforward! All responses are confidential and used for research purposes only. Estimated time: 10-15 minutes.

Section 1: Demographic Information

Please select or fill in the appropriate option. This helps us understand your firm's context.

1. What is your position in the organization? ☐ Senior Manager ☐ Operations Manager ☐ IT/DT Manager ☐ Other (please specify): ____________________
2. What is the size of your firm? ☐ Small (1-50 employees) ☐ Medium (51-250 employees) ☐ Large (>250 employees)
3. How many years has your firm been operating in the logistics/SCM sector? ☐Less than 5 years ☐5-10 years ☐More than 10 years
4. To what extent has your firm adopted digital transformation solutions (e.g., IoT, AI, blockchain)? ☐Not adopted ☐Partially adopted ☐ Fully adopted

Next Section: Technological Factors (4 quick questions)

Section 2: Measurement Items

Please rate your agreement with each statement using the scale:

1 (Strongly Disagree) | 2 | 3 | 4 (Neutral) | 5 | 6 | 7 (Strongly Agree)

Technological Factors (TF) These questions focus on technology aspects in DT implementation. Tick one number per statement.

TF1: The quality of IT infrastructure supports effective digital transformation in logistics. (Robust systems.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

TF2: Cybersecurity readiness protects SCM operations from digital threats. (Strong defenses.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

TF3: Technology compatibility ensures seamless integration of DT solutions in logistics. (System interoperability.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

TF4: Advanced technologies (e.g., IoT, AI) are reliable for SCM applications. (Technology dependability.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

Next Section: Organizational Factors (4 quick questions)

Organizational Factors (OF) These questions focus on organizational aspects in DT implementation. Tick one number per statement.

OF1: Leadership commitment drives successful DT implementation in logistics. (Strong executive support.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

OF2: Change management capability reduces resistance to DT in SCM. (Effective transition strategies.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

OF3: Resource availability supports the adoption of DT solutions in logistics. (Adequate funding and tools.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

OF4: Organizational alignment ensures DT goals match SCM objectives. (Strategic coherence.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

Next Section: Environmental Factors (4 quick questions)

Environmental Factors (EF) These questions focus on external environmental aspects in DT implementation. Tick one number per statement.

EF1: Regulatory compliance facilitates DT adoption in Vietnam's logistics. (Clear policies.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

EF2: Market volatility increases risks of DT implementation in SCM. (Economic uncertainty.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

EF3: Supplier digital readiness supports DT integration in logistics. (Partner capabilities.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

EF4: Competitive pressures drive the need for DT in SCM. (Market demands.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

Next Section: Human Factors (4 quick questions)

Human Factors (HF) These questions focus on human aspects in DT implementation. Tick one number per statement.

HF1: Workforce digital literacy enhances DT adoption in logistics. (Skilled employees.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

HF2: Resistance to change hinders DT implementation in SCM. (Employee reluctance.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

HF3: Training adequacy supports effective use of DT solutions in logistics. (Comprehensive training.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

HF4: Employee engagement improves DT outcomes in SCM. (Active participation.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

Next Section: Digital Transformation Implementation (4 quick questions)

Digital Transformation Implementation (DTI) These questions focus on your firm's DT implementation. Tick one number per statement.

DTI1: The extent of IoT adoption improves logistics efficiency. (IoT usage level.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

DTI2: AI implementation enhances SCM decision-making. (AI application scope.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

DTI3: Blockchain adoption ensures SCM transparency. (Blockchain integration.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

DTI4: Implementation challenges (e.g., complexity) hinder DT success in logistics. (Adoption barriers.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

Next Section: Financial Risks (4 quick questions)

Financial Risks (FR) These questions focus on financial risks from DT. Tick one number per statement.

FR1: High implementation costs pose financial risks for DT in logistics. (Budget overruns.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

FR2: ROI shortfalls reduce the value of DT investments in SCM. (Low returns.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

FR3: Unexpected expenses increase DT financial risks in logistics. (Cost unpredictability.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

FR4: Financial constraints limit DT scalability in SCM. (Funding shortages.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

Next Section: Operational Risks (4 quick questions)

Operational Risks (OR) These questions focus on operational risks from DT. Tick one number per statement.

OR1: Process disruptions occur during DT implementation in logistics. (Workflow interruptions.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

OR2: System downtimes reduce SCM efficiency during DT adoption. (Service outages.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

OR3: Integration failures increase operational risks in DT for logistics. (System mismatches.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

OR4: Lack of process standardization heightens DT risks in SCM. (Inconsistent workflows.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

Next Section: Cybersecurity Risks (4 quick questions)

Cybersecurity Risks (CR) These questions focus on cybersecurity risks from DT. Tick one number per statement.

CR1: Data breaches threaten SCM security during DT adoption. (Information leaks.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

CR2: System vulnerabilities increase risks in DT for logistics. (Exploitable weaknesses.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

CR3: Inadequate cybersecurity measures heighten DT risks in SCM. (Weak protections.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

CR4: Cyberattacks disrupt logistics operations during DT. (Malicious intrusions.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

Next Section: Reputational Risks (4 quick questions)

Reputational Risks (RR) These questions focus on reputational risks from DT. Tick one number per statement.

RR1: Customer dissatisfaction due to DT-related service failures harms logistics reputation. (Service quality issues.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

RR2: DT implementation delays negatively affect SCM credibility. (Missed expectations.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

RR3: Publicized DT failures damage logistics brand image. (Negative publicity.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

RR4: Inconsistent DT outcomes reduce customer trust in SCM. (Unreliable services.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

Next Section: Firm Size (4 quick questions – Final Section!)

Firm Size (FS) These questions focus on the role of firm size in DT. Tick one number per statement.

FS1: Our firm's size supports the adoption of DT solutions in logistics. (Resource availability by scale.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

FS2: The number of employees influences our capacity for DT implementation in SCM. (Workforce scale.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

FS3: Our firm's revenue level affects DT investment decisions in logistics. (Financial capacity.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

FS4: Compared to industry peers, our firm's size facilitates DT risk management in SCM. (Relative scale.)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

Thank you for completing the survey! Your responses are greatly appreciated and will contribute to advancing logistics and SCM research in Vietnam. If you have any comments, please add them below:

(End of Survey)

Appendix III

Table A2. Measurement Items for Risk Assessment of Digital Transformation Solutions in Vietnam's Logistics and SCM

Constructs	Items	References
Technological Factors (TF)	TF1: The quality of IT infrastructure supports effective digital transformation in logistics. (Robust systems.) TF2: Cybersecurity readiness protects SCM operations from digital threats. (Strong defenses.) TF3: Technology compatibility ensures seamless integration of DT solutions in logistics. (System interoperability.) TF4: Advanced technologies (e.g., IoT, AI) are reliable for SCM applications. (Technology dependability.)	[14, 18, 25, 31, 37, 47, 53, 55]
Organizational Factors (OF)	OF1: Leadership commitment drives successful DT implementation in logistics. (Strong executive support.) OF2: Change management capability reduces resistance to DT in SCM. (Effective transition strategies.) OF3: Resource availability supports the adoption of DT solutions in logistics. (Adequate funding and tools.) OF4: Organizational alignment ensures DT goals match SCM objectives. (Strategic coherence.)	[14, 18, 25, 31, 47, 53, 55]
Environmental Factors (EF)	EF1: Regulatory compliance facilitates DT adoption in Vietnam's logistics. (Clear policies.) EF2: Market volatility increases risks of DT implementation in SCM. (Economic uncertainty.) EF3: Supplier digital readiness supports DT integration in logistics. (Partner capabilities.) EF4: Competitive pressures drive the need for DT in SCM. (Market demands.)	[14, 18, 22, 31, 37, 47, 53, 55]
Human Factors (HF)	HF1: Workforce digital literacy enhances DT adoption in logistics. (Skilled employees.) HF2: Resistance to change hinders DT implementation in SCM. (Employee reluctance.) HF3: Training adequacy supports effective use of DT solutions in logistics. (Comprehensive training.) HF4: Employee engagement improves DT outcomes in SCM. (Active participation.)	[14, 18, 25, 31, 46, 53, 55]
Digital Transformation Implementation (DTI)	DTI1: The extent of IoT adoption improves logistics efficiency. (IoT usage level.) DTI2: AI implementation enhances SCM decision-making. (AI application scope.) DTI3: Blockchain adoption ensures SCM transparency. (Blockchain integration.) DTI4: Implementation challenges (e.g., complexity) hinder DT success in logistics. (Adoption barriers.)	[14, 18, 25, 31, 37, 47, 53, 55]
Financial Risks (FR)	FR1: High implementation costs pose financial risks for DT in logistics. (Budget overruns.) FR2: ROI shortfalls reduce the value of DT investments in SCM. (Low returns.) FR3: Unexpected expenses increase DT financial risks in logistics. (Cost unpredictability.) FR4: Financial constraints limit DT scalability in SCM. (Funding shortages.)	[14, 18, 22, 31, 37, 46, 47, 53, 55]
Operational Risks (OR)	OR1: Process disruptions occur during DT implementation in logistics. (Workflow interruptions.) OR2: System downtimes reduce SCM efficiency during DT adoption. (Service outages.) OR3: Integration failures increase operational risks in DT for logistics. (System mismatches.) OR4: Lack of process standardization heightens DT risks in SCM. (Inconsistent workflows.)	[14, 18, 25, 31, 37, 47, 53, 55]
Cybersecurity Risks (CR)	CR1: Data breaches threaten SCM security during DT adoption. (Information leaks.) CR2: System vulnerabilities increase risks in DT for logistics. (Exploitable weaknesses.) CR3: Inadequate cybersecurity measures heighten DT risks in SCM. (Weak protections.) CR4: Cyberattacks disrupt logistics operations during DT. (Malicious intrusions.)	[14, 18, 22, 31, 37, 47, 53, 55]
Reputational Risks (RR)	RR1: Customer dissatisfaction due to DT-related service failures harms logistics reputation. (Service quality issues.) RR2: DT implementation delays negatively affect SCM credibility. (Missed expectations.) RR3: Publicized DT failures damage logistics brand image. (Negative publicity.) RR4: Inconsistent DT outcomes reduce customer trust in SCM. (Unreliable services.)	[14, 18, 25, 31, 37, 46, 53, 55]
Firm Size (FS)	FS1: Our firm's size supports the adoption of DT solutions in logistics. (Resource availability by scale.) FS2: The number of employees influences our capacity for DT implementation in SCM. (Workforce scale.) FS3: Our firm's revenue level affects DT investment decisions in logistics. (Financial capacity.) FS4: Compared to industry peers, our firm's size facilitates DT risk management in SCM. (Relative scale.)	[2, 17, 26, 39, 44, 63]