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Digital Technologies Research and Applications

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Article

Digital Innovation and Supply Chain Performance: Investigating the Moderating Effect of Technology Usage on Risk Management-Resilience-Performance Linkages

Mingyu Lei [1,2,*], Norhayati Zakuan [1], Mohd Zulfabli Hasan [1], Muhamad Zameri Mat Saman [3] and Xin Chen [4]

[1] Faculty of Management, Universiti Teknologi Malaysia, Johor Bahru 81310, Malaysia

[2] College of Accounting and Finance, Jiangxi Tourism and Commerce Vocational College, Nanchang 330100, China

[3] Faculty of Mechanical, Universiti Teknologi Malaysia, Johor Bahru 81310, Malaysia

[4] Faculty of Management, Shanxi Vocational University of Engineering Science and Technology, Jinzhong 030619, China

[*] Correspondence: chenchuntie@mail.com

Received: 16 January 2026; **Revised:** 13 February 2026; **Accepted:** 5 March 2026; **Published:** 27 April 2026

Abstract: This study aims to investigate the interrelations among digital innovation, risk management, resilience, and performance in supply chain contexts, in which technology utilization is conceptualized as a moderator. Based on the concepts of dynamic capabilities and the resource-based view, the proposed model suggests risk management and resilience as sequential mediators between digital innovation and performance. The model is empirically validated using Partial Least Squares Structural Equation Modeling (PLS-SEM) with a sample of 256 manufacturing and service organizations selected from the World Bank Enterprise Surveys dataset. Findings show that digital innovation has both direct ($\beta = 0.218$) and indirect effects on supply chain performance through risk management and resilience. Digital innovation exhibits the strongest association with supply chain risk management ($\beta = 0.521$), followed by risk management's effect on resilience ($\beta = 0.489$) and resilience's effect on performance ($\beta = 0.372$). Technology usage strengthens both the risk management–resilience path ($\beta = 0.127$) and the resilience–performance path ($\beta = 0.143$). Sequential mediation accounts for 53.3% of the total effect, as measured by the Variance Accounted For (VAF) index, confirming partial mediation. This study also contributes to the supply chain management literature by providing empirical specification for the integrated paths in which digital innovation drives performance through risk management and resilience capabilities, and technology application as a boundary condition in these paths. The results indicate that supply chain managers should integrate digital innovation investments with risk management and resilience capabilities for the best performance in supply chain management.

Keywords: Digital Innovation; Supply Chain Resilience; Risk Management; Supply Chain Performance; Technology Usage

1. Introduction

The global supply chain has witnessed a series of disruptions caused by COVID-19, geopolitical conflicts, and climate change-related issues. These disruptions have highlighted the inherent weaknesses in traditional supply chain management methodologies [1, 2]. The rising scale and regularity of these disruptions have resulted in a phenomenon termed a "shortage economy" by Ivanov and Dolgui [3], wherein shortages emerge as a feature of the global economy. These developments have resulted in a re-evaluation of the position of digital technologies to improve supply chains [4].

The digital innovation, which is defined as the development or major enhancement of products, services, processes, or business models through digital technologies [5], has attracted more research attention in the field of supply chain management. While digital transformation implies all-around strategic and organizational changes in embracing enterprise technology adoption [6,7], digital innovation is more centered on the development of new outputs and innovations that transform supply chains. The technologies of big data analytics, artificial intelligence (AI), blockchain, and the Internet of Things (IoT) are considered the basic foundation for digital innovation in supply chains [8].

Although there has been a considerable increase in the research on the relationship between digital innovation and supply chain performance, there has not been an in-depth study on the processes that mediate this relationship [9]. Among the processes that have been identified as a mediator in this relationship is supply chain risk management, in which technology helps in managing it [10]. The other mediating process could be supply chain resilience, and it is defined as a firm's ability to anticipate, respond, and recover from supply chain disruptions [11]. Previous research proposed supply chain risk management as a precondition for supply chain resilience [12]. Another process that could mediate is the moderating effect of technology use, where information technology use enhances supply chain risk management and supply chain resilience process effectiveness [13]. However, so far, no study has investigated the mediating role of supply chain risk management, followed by supply chain resilience, with the moderating role of technology usage [14].

This study aims to conceptualize and test a sequential mediation model based on dynamic capabilities theory and resource-based theory. It extends the dominant focus on direct effects as highlighted in existing literature [1,15]. This study also responds to the need to investigate the channels through which digital capabilities lead to tangible supply chain outcomes, as discussed in past studies [16]. This study aims to address the following three research questions:

RQ1: To what extent does digital innovation directly and indirectly influence supply chain performance through supply chain risk management and supply chain resilience?

RQ2: Do supply chain risk management and supply chain resilience sequentially mediate the relationship between digital innovation and supply chain performance?

RQ3: Does technology usage moderate the relationships between supply chain risk management and resilience, and between supply chain resilience and performance?

2. Theoretical Background and Hypotheses Development

2.1. Theoretical Foundations

This study is based on two theories: the theory of dynamic capabilities (DCT), and the resource-based view (RBV). According to the RBV, gaining and sustaining competitive advantage is possible through the possession of resources that are considered valuable, scarce, difficult to imitate, and non-substitutable [17]. In supply chain management, digital innovation is a valuable resource, considering that it improves information flows, coordination between firms, and management decisions [9]. However, the process by which resources in a firm develop is not sufficiently explained by the RBV because the business environment is turbulent [18].

This is where the Dynamic Capabilities Theory (DCT) comes in, which explains how an organization is able to spot opportunities and threats, capitalize on new opportunities, and change its resource base to adapt to environmental changes [19]. Teece [19] proposed that dynamic capabilities have three major dimensions: sensing, seizing, and reconfiguring. All these elements have implications for supply chains because organizations in supply chains constantly face disruptions, demand fluctuations, and technology advancements [11]. Managing risks in supply chains relates to the sensing and seizing dimensions because it includes the identification of risks that can occur in the future and the adoption of proactive strategies to avoid risks. On the contrary, resilience is associated with the reconfiguration component, which is described as an organization's ability to alter its supply chain in order to adapt to disruptions [20]. This, in turn, explains the role of digital innovation as a strategic resource (RBV), which is increasingly converted into risk management competencies, resilience, and, therefore, enhanced supply chain performance (DCT).

2.2. Digital Innovation, Risk Management, and Resilience

Digital innovation contributes to supply chain performance via various channels. As one of the intangible resources, it helps firms improve information processing, minimize operational costs, and quickly adapt to environmental fluctuations [15]. Studies show that the digitalization of the supply chain has a positive influence on the performance of the supply chain through the following mechanisms: corporate governance, competitiveness, and integration of the supply chain [1,9,15]. The same has been found to be the case with the sustainability of the supply chain performance, especially in the manufacturing industry [21]. According to the DCT, organizations with higher digital innovation capability are more capable of perceiving the fluctuations in the environment and capitalizing on the opportunities that the fluctuations create [22].

The relationship between digital innovation and supply chain risk management could be analyzed through the sensing dimension of DCT. Digital innovation is helpful for responding to risks through analytical tools [23]. It has been argued that digitalization has a significant impact on risk management, where digital innovation can enable firms to detect disruptions and develop mitigation strategies to address these disruptions in a coordinated manner [24]. For example, big data analytics enables firms to analyze vast data in the supply chain, while IoT technology enables real-time tracking of inventories and suppliers' activities [8,25]. This is a significant shift from reactive to anticipatory risk management, which is in line with the sensing and seizing concept in DCT [19].

Moreover, digital innovation plays an essential role in improving supply chain resilience, especially through adaptive and recovery-oriented supply chain capabilities. For example, in the automotive industry of emerging economies, there are studies showing that digital innovation can improve responses to supply chain disruptions [26]. Additionally, digital empowerment can have a positive effect on supply chain resilience in the manufacturing supply chain, especially through innovation vitality and resource reconfiguration [14]. Based on the DCT, digital innovation was found to support the reconfiguration dimension through its contribution to adapting supply chain configurations, logistics rerouting, and resource reallocation in response to disruptions [22].

The relationship between risk management and resilience may be seen as an evolutionary sequence from sensing and seizing phases to the reconfiguration phase of dynamic capabilities. The key effective risk management practices provide a foundation for resilience to be built upon [4]. For instance, the COVID-19 pandemic has shown that the application of risk management techniques can significantly reduce the impact of disruption factors on the resilience and robustness of the supply chain [4]. Additionally, the application of efficient risk management techniques is considered vital for achieving resilience within the context of global uncertainty [27]. The supply chain resilience as a dynamic capability with both proactive and reactive elements [11], has been found to be underpinned by the systematic identification of risks and the organizational preparedness for swift response to disruptions [12].

Based on the above theoretical reasoning and empirical evidence, the following hypotheses are proposed:

H1. *Digital innovation positively influences supply chain performance.*

H2a. *Digital innovation positively influences supply chain risk management.*

H2b. *Digital innovation positively influences supply chain resilience.*

H3. *Supply chain risk management positively influences supply chain resilience.*

2.3. Risk Management, Resilience, and Supply Chain Performance

Firms that utilize effective risk management systems tend to experience fewer unexpected disruptions to their supply chain, lower recovery costs, and more reliable delivery times [10]. The application of enterprise risk management has been shown to significantly improve supply chain performance, and resilience acts as a mediator for this relationship [12]. Such capabilities are essential for maintaining a firm's resource base and sustaining a competitive advantage, even in unfavorable circumstances [17].

Resilient supply chains maintain and enhance their operational capacities during disruptive events by absorbing, adapting, and recovering from disruptions [11, 28]. Research on third-party logistics providers has demonstrated that resilience contributes positively to service performance [29], and that relational practices and network complexities can enhance the strength of the resilience–performance link [30]. Furthermore, the construct of supply chain agility has been shown to have a positive influence on operational performance [31], thus supporting the notion that adaptive supply chain capabilities are important to enhance performance.

Similarly, the DCT argues that dynamic capabilities are made possible by a sequential process. In this case, the activities of sensing and seizing, embodied in risk management, establish the foundations for reconfiguration, embodied in resilience, which in turn drives performance [19]. This shows that there is a sequential mediation process by which the benefits of digital innovation are channeled through risk management and resilience, rather than a direct path.

Based on the above discussion, the following hypotheses are proposed:

H4a. *Supply chain risk management positively influences supply chain performance.*

H4b. *Supply chain resilience positively influences supply chain performance.*

2.4. The Moderating Role of Technology Usage

Technology usage, which is defined as the extent to which firms use and integrate information technology (IT) in their daily activities [26], is hypothesized to moderate the links between risk management and resilience, and between resilience and performance. As a complementary enabler, technology usage provides the technological basis to enable the application of effective risk management and resilience strategies [32]. The high adoption of technology provides support for the effective implementation of risk management techniques geared towards improving resilience [13]. The contribution of Industry 4.0 technologies to supply chain improvement and resilience is evident [33]. This suggests that existing technology adoption conditions are favorable for the effective utilization of risk management techniques in improving resilience.

In addition, the application of technology will further increase the performance benefits derived from resilience by accelerating information processing and improving recovery coordination. Research findings show that the application of data analytics, along with flexibility, improves the performance of resilient supply chains [34], while AI-driven innovation strengthens the resilience–performance relationship under conditions of supply chain dynamism [35].

Based on the discussion of the foregoing paragraphs, the following hypotheses are proposed:

H5a. *Technology usage positively moderates the relationship between supply chain risk management and supply chain resilience.*

H5b. *Technology usage positively moderates the relationship between supply chain resilience and supply chain performance.*

Figure 1 depicts the conceptual model for the variables discussed above. The model suggests that digital innovation has a relationship with supply chain performance that is both direct and indirect, with risk management and resilience as sequential mediator variables. Technology usage also acts as a moderator in the risk management–resilience and resilience–performance relationships.

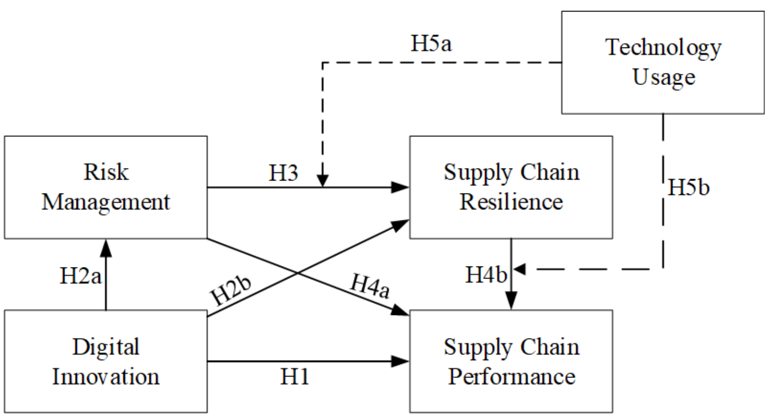

Figure 1. Research Model and Hypotheses.

3. Data and Methods

3.1. Research Design and Data Source

The main source of data is based on the World Bank Enterprise Surveys (WBES, http://www.enterprisesurveys.org), which is a nationally representative set of firm-level surveys conducted among owners and top managers of businesses covering more than 168 countries. The World Bank administers the WBES along with participating institutions across various global areas. The WBES are limited to non-agricultural, formal, and private sector businesses of various sizes, including small, medium, and large businesses. The WBES contains microdata covering more than 253,000 businesses across 168 countries and includes information on variables covering enterprise attributes, infrastructure, innovation, technology adoption, competition, and enterprise performance. The data were collected using face-to-face interviews with business owners and their top management. In light of the broad scope of enterprise data that has been collected, World Bank Enterprise Surveys have become the main source of information on the environment and performance of enterprises.

Data for testing hypotheses of the study were gathered through survey waves undertaken between 2019 and 2024, focusing on firms in the manufacturing and service sectors. The manufacturing sector involves production enterprises such as food, textiles, machinery, and electronics, while the service sector involves wholesale, retail, transportation, and information technology. The inclusion of the two sectors is significant, as they have been profoundly involved in supply chain management processes and digital innovation. Firms were selected according to the presence of innovation variables, technology variables, risk management variables, and performance variables. To ensure the accuracy of the data, cases with missing data in the variables of interest are deleted using the listwise deletion method, whereby cases containing missing data in any of the variables in the study are deleted.

The sample size was computed based on the conventional "10 times rule," which is commonly cited in the PLS-SEM literature [36]. This rule proposes that the sample size should be greater than ten times the highest number of indicators (arrows) pointing to any latent construct in the framework of structural equation modeling. The modeling framework consists of five latent constructs, as well as eight hypotheses addressing their relationships, of which at most four arrows point to the supply chain performance construct. Based on these requirements, at least 200 responses were considered adequate in order to attain 80% power at an alpha-level of 0.05 [36]. This serves as a guide within current PLS-SEM literature, suggesting that larger samples help PLS-SEM models provide more reliable parameter estimates while improving result generalization [37]. The application of PLS-SEM is further guided by its advantages in dealing with complicated structural modeling involving latent constructs, such as mediations and moderating relationships. The data extraction process is presented in **Figure 2**.

3.2. Variable Measurement

All the variables employed for the study have been operationally defined based on existing indicators available through the WBES database. The selection of proxy variables is based on conventions set forth in the extant literature on supply chain management and digital innovation research. **Table 1** below shows the constructs and their measurement indicators.

Digital Innovation (DI) is operationalized using four innovation-related items from the WBES, following the measurement approach outlined in the Oslo Manual [38]: (1) whether the firm has launched new or significantly improved products or services during the past three years (h1); (2) whether the enterprise has adopted a novel or enhanced method of producing or delivering the good or service (h5); (3) research and development expenditure as a proportion of total annual sales (h8); and (4) whether the enterprise uses technologies licensed from foreign enterprises (e6).

Supply Chain Risk Management (SCRM) is represented by four proxy variables reflecting organizational risk mitigation efforts [39]: (1) the possession of quality certification (b8); (2) the utilization of external auditing services (k21); (3) the ratio of inputs sourced from local suppliers relative to imported suppliers (d3); and (4) the number of suppliers of primary inputs (d3b).

Supply Chain Resilience (SCR) is measured through indicators that aim to reflect adaptability and recovery capabilities [30]. These are as follows: (1) capacity utilization ratio (f1); (2) level of key inputs in inventory (d12a); (3) days of key inputs in inventory (d12b); and (4) ability to expand production in case of an increase in demand (e1).

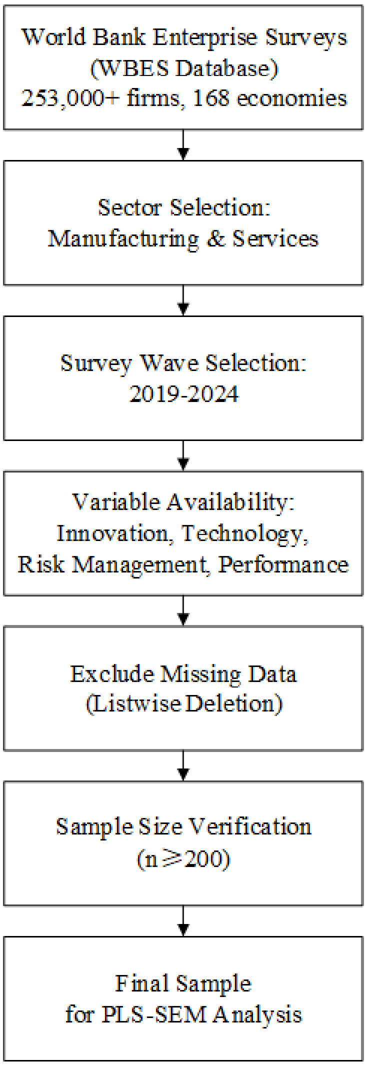

Figure 2. Research Design and Analytical Process.

Table 1. Variable Measurement.

Variable	Proxy Indicators	WBES Code	Source
Digital Innovation	Product/process innovation, R&D, technology licensing	h1, h5, h8, e6	OECD [38]
Supply Chain Risk Management	Quality certification, auditing, supplier diversification	b8, k21, d3, d3b	Belhadi et al. [39]
Supply Chain Resilience	Capacity utilization, inventory management	f1, d12a, d12b, e1	Chowdhury et al. [30]
Supply Chain Performance	Sales growth, productivity, exports	d2, n3/l1, d3a	Panigrahi et al. [31]
Technology Usage	Website, email, computer use, online procurement	c22a, c22b, c21, c23a	Balakrishnan and Ramanathan [26]
Control Variables	Firm size, age, industry, export status	l1, b5, a4a, d3a	—

Supply Chain Performance (SCP) is measured using firm performance indicators [31]: (1) annual sales growth rate (d2); (2) labor productivity measured as sales per employee (n3/l1); and (3) percentage of sales that are exports (d3a).

Technology Usage (TU), the moderating variable, is measured by the following indicators [26]: (1) whether the firm has its own website (c22a); (2) whether the firm uses email to communicate with clients/suppliers (c22b); (3) percentage of workforce using computers (c21); and (4) whether the firm purchases inputs online (c23a).

The set of control variables comprises firm size (measured as the natural logarithm of total number of employees, l1), firm age (measured as years since establishment, b5), industry classification (manufacturing/servicing, a4a), and export status (d3a) [1].

3.3. Statistical Analysis

For the analysis, SPSS 26.0 and SmartPLS 4.0 software are used. SPSS 26.0 handles descriptive statistics and common method bias testing. SmartPLS 4.0 performs the PLS-SEM analysis, covering measurement model assessment (reliability and validity) and structural model estimation for hypothesis testing. Direct, mediating, and moderating effects are all examined [36]. Path coefficient significance is assessed via bootstrapping with 5,000 resamples [40]. Robustness checks are additionally conducted to verify the outcomes.

4. Results

4.1. Descriptive Statistics and Correlation Analysis

Descriptive statistics on all variables are provided in **Table 2**. The final sample represents 256 firms that are sourced from both manufacturing and service sectors. The study has full information on all variables of interest. In the field of Digital Innovation (DI), the mean is 3.42, and the standard deviation (SD) is 0.89, showing moderate practices of using digital innovation among firms. The range is broad, spanning from 1.25 to 5.00. Supply Chain Risk Management (SCRM) has an average score of 3.56 with a Standard Deviation (SD) of 0.82, which is slightly higher than DI but still reflects the effective implementation of risk management practices by firms. The SD is also relatively lower than that of DI; hence, a higher degree of homogeneity in risk management practices is observed across firms. Supply Chain Resilience (SCR) has a mean value of 3.38 (SD = 0.91), reflecting moderate resilience capabilities with a higher SD than the other constructs. Supply Chain Performance (SCP) has the highest mean value at 3.61 (SD = 0.85), reflecting favorable SCP for firms. Technology Usage (TU), which is the moderator for this study, has a mean value of 3.29 (SD = 0.94). Its standard deviation is the largest among all the constructs, suggesting that the adoption rate of digital technologies in the supply chain is moderate but varies significantly.

Table 2. Descriptive Statistics.

Variable	N	Min	Max	Mean	SD	Skewness	Kurtosis
Digital Innovation (DI)	256	1.25	5.00	3.42	0.89	−0.31	−0.42
Supply Chain Risk Management (SCRM)	256	1.50	5.00	3.56	0.82	−0.28	−0.35
Supply Chain Resilience (SCR)	256	1.00	5.00	3.38	0.91	−0.19	−0.51
Supply Chain Performance (SCP)	256	1.50	5.00	3.61	0.85	−0.36	−0.29
Technology Usage (TU)	256	1.00	5.00	3.29	0.94	−0.15	−0.58
Firm Size (ln)	256	1.61	8.52	4.21	1.35	0.42	−0.18
Firm Age (years)	256	2	48	15.80	9.42	0.85	0.23
Industry (1 = Manufacturing)	256	0	1	0.58	0.49	−0.33	−1.89
Export Ratio (%)	256	0	95	22.30	25.67	1.12	0.45

Moving on to control variables, on average, the size of firms in logarithmic form is 4.21 (with an SD of 1.35), which is equivalent to 67 employees. Firm size varies from 5 employees (log 1.61) to much higher than 5,000 employees (log 8.52). The average age of firms is 15.8 years (with an SD of 9.42), ranging from 2 to 48 years, suggesting that both quite new and quite established firms are included in this study. More than 58% of firms are in the manufacturing industry, and the average export-to-sales ratio stands at 22.3% (with an SD of 25.67), showing that both domestic and exporting-oriented firms are included in the study. For all variables, skewness and kurtosis are within acceptable levels (±2 and ±7, respectively), indicating that variables are close to being normally distributed and thus suitable for analysis. For all five constructs shown in **Figure 3**, a normal distribution has been approximated.

The industry and firm size composition of the sample is shown in **Figure 4**. The industry composition, shown in **Figure 4a**, indicates that 58% (n = 148) of the sample consists of manufacturing firms, and 42% (n = 108) consists of service sector firms. The composition is representative of the standard structure that the WBES database follows and also ensures adequate representation of both industry types that are actively involved in supply chain activities. The dominance of the manufacturing firms is also appropriate for the study that aims to explore supply chain activities, given that more complex supply chain structures are prevalent among manufacturing organizations. The firm size composition is represented by **Figure 4b** and indicates that small firms with 5–19 employees comprise 32% (n = 82) of the sample. Medium firms with 20–99 employees account for 45% (n = 115) of the total sample. Large firms with 100 or more employees represent 23% (n = 59) of the total sample. The balanced composition of the sample with respect to firm size is appropriate because it offers a basis for examining if the hypothesized associations also exist between the study variables at different scales. Additionally, it is appropriate for helping ensure that the findings are not dominated by a specific firm size.

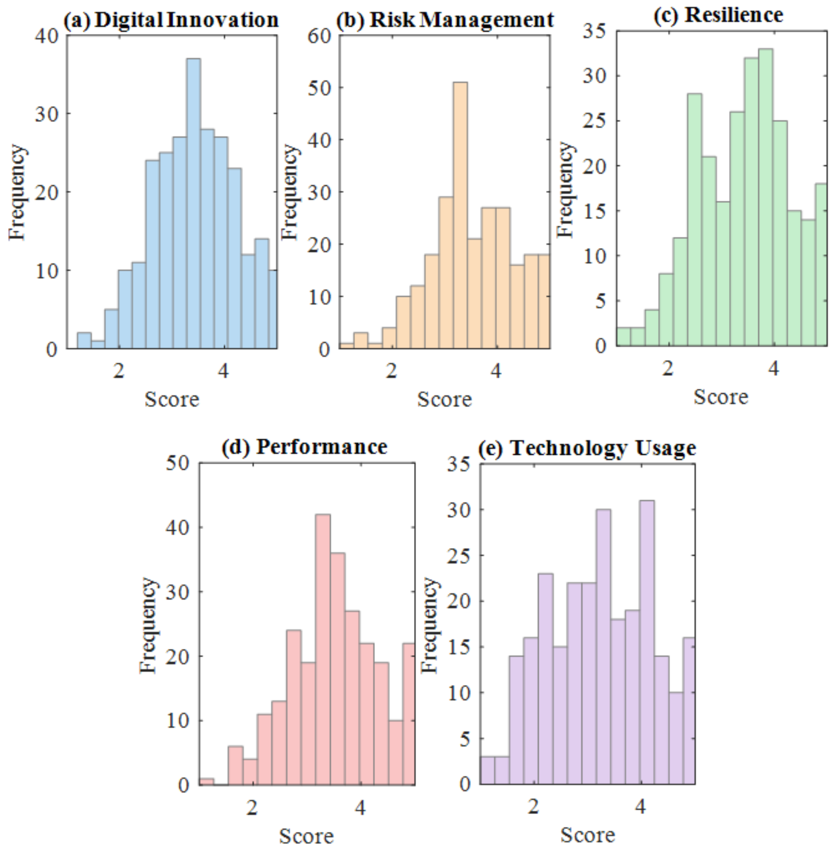

Figure 3. Distribution of Main Variables.

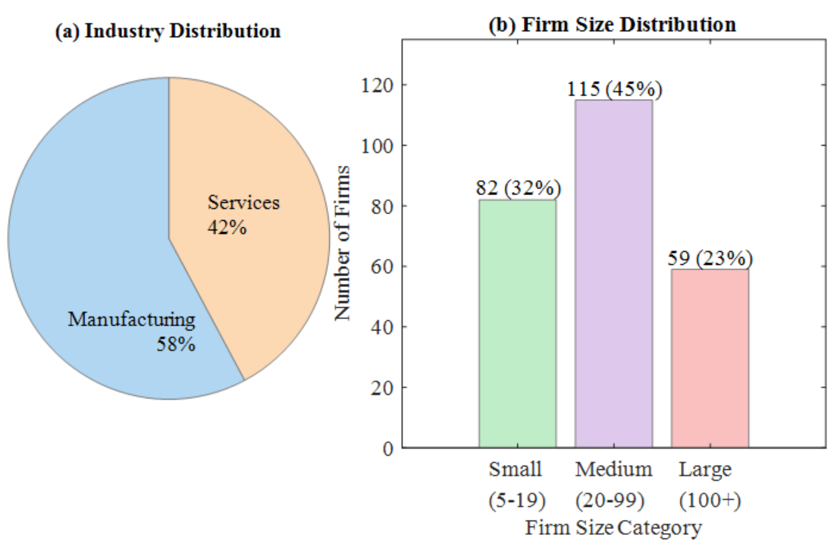

Figure 4. Sample Composition.

Table 3 shows the intercorrelations of the primary constructs. It indicates that all the primary constructs are positively intercorrelated, which offers preliminary evidence in support of the hypotheses. The relationship between digital innovation and supply chain risk management is positive (r = 0.52, $p < 0.01$), suggesting that organizations that are more digitally innovative tend to have a wider scope of supply chain risk management. Moreover, digital innovation is positively correlated with supply chain resilience (r = 0.48, $p < 0.01$) and supply chain performance (r = 0.55, $p < 0.01$), suggesting that more digitally innovative supply chains are more resilient and perform better compared to less digitally innovative supply chains. The positive association between supply chain risk management and supply chain resilience (r = 0.61, $p < 0.01$) is the highest of the remaining associations; it shows a high relation between the two. The positive association of supply chain risk management with supply chain performance (r = 0.49, $p < 0.01$) indicates a better performance in companies that are well-risk-managed. There is a positive association (r = 0.58, $p < 0.01$) between supply chain resilience and supply chain performance; thus, more resilient companies tend to perform better. There are positive associations between technology usage and the remaining primary constructs ranging between 0.41 and 0.53, which show that the adoption of technology usage has positively affected the remaining constructs. The values of the intercorrelation are less than 0.85; therefore, the problem of multicollinearity among the primary constructs is not a major issue, and the constructs represent distinct concepts suitable for structural equation modeling analysis.

Table 3. Correlation Matrix.

Variable	DI	SCRM	SCR	SCP	TU
Digital Innovation (DI)	1				
Supply Chain Risk Management (SCRM)	0.52**	1			
Supply Chain Resilience (SCR)	0.48**	0.61**	1		
Supply Chain Performance (SCP)	0.55**	0.49**	0.58**	1	
Technology Usage (TU)	0.53**	0.45**	0.41**	0.47**	1

Note: ** $p < 0.01$.

4.2. Reliability and Validity Testing

To assess the structural model, the measurement model was tested for reliability and validity. The reliability of the indicators was tested by assessing the outer loadings of the items on each of the respective constructs. As shown in **Table 4**, it is evident that all loadings are between 0.817 and 0.872, significantly higher than 0.708, which means each item represents more than 50% of its construct's variance. To check the internal consistency reliability, Cronbach's Alpha and composite reliability (CR) were used. Cronbach's Alpha ranged from 0.836 (SCP) to 0.867 (DI), while composite reliability ranged from 0.899 (SCRM) to 0.909 (DI). To check convergent validity, average variance extracted (AVE) was employed, and values ranged from 0.691 (SCRM) to 0.752 (SCP), which are greater than 0.50. A visual representation of these reliability and validity indicators is presented in **Figure 5**.

Table 4. Measurement Model Results.

Construct	Item	Loading	Cronbach's α	CR	AVE
Digital Innovation (DI)	DI1 DI2 DI3 DI4	0.842 0.856 0.831 0.849	0.867	0.909	0.714
Supply Chain Risk Management (SCRM)	SCRM1 SCRM2 SCRM3 SCRM4	0.825 0.863 0.819 0.817	0.851	0.899	0.691
Supply Chain Resilience (SCR)	SCR1 SCR2 SCR3 SCR4	0.837 0.851 0.829 0.846	0.862	0.906	0.707
Supply Chain Performance (SCP)	SCP1 SCP2 SCP3	0.871 0.859 0.872	0.836	0.901	0.752
Technology Usage (TU)	TU1 TU2 TU3 TU4	0.833 0.847 0.821 0.845	0.858	0.903	0.700

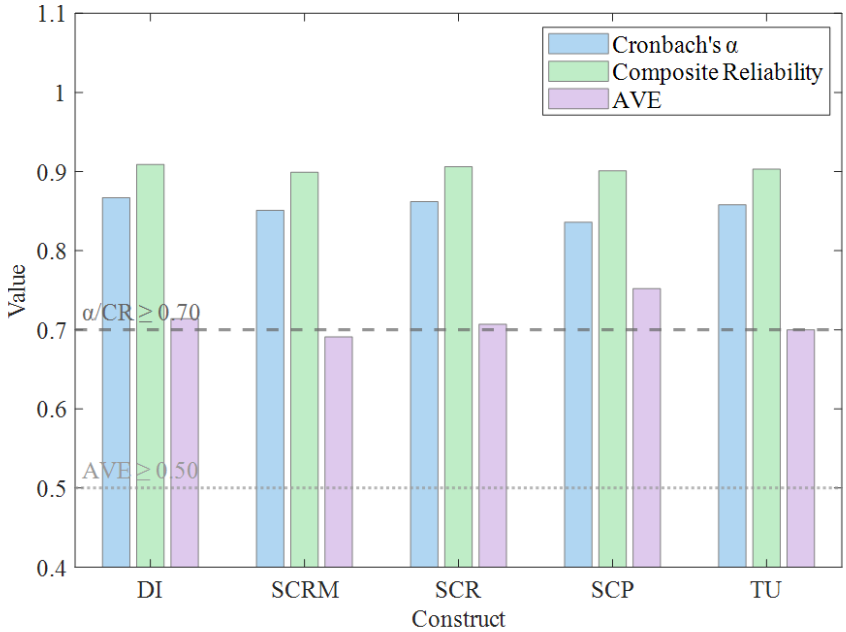

Figure 5. Reliability and Validity Assessment.

For assessing discriminant validity, the Heterotrait Monotrait (HTMT) ratio and the Fornell-Larcker Criterion were employed. As presented in **Table 5**, all the constructs' HTMT ratios range from 0.463 to 0.689, which is significantly lower than 0.85. The highest HTMT ratio is between supply chain risk management and supply chain resilience (0.689). This implies that there is a significant relationship between these variables while keeping it within acceptable limits. The Fornell-Larcker Criterion was also fulfilled since the square root of each construct's AVE was higher than its correlations with all other constructs.

Table 5. Discriminant Validity.

Construct	DI	SCRM	SCR	SCP	TU
Digital Innovation (DI)	0.845	0.582	0.537	0.612	0.593
Supply Chain Risk Management (SCRM)	0.520	0.831	0.689	0.548	0.502
Supply Chain Resilience (SCR)	0.480	0.610	0.841	0.651	0.463
Supply Chain Performance (SCP)	0.550	0.490	0.580	0.867	0.524
Technology Usage (TU)	0.530	0.450	0.410	0.470	0.837

Note: Diagonal values = √AVE; below diagonal = correlations; above diagonal = HTMT values.

Overall, the measurement model meets all the essential criteria for establishing construct reliability and validity, as all indicator loadings are well above 0.708, while Cronbach's alpha and composite reliability are all well above 0.70 for all constructs. The Average Variance Extracted (AVE) is also well above 0.50 for all constructs, while the HTMT and Fornell-Larcker tests also show that construct distinctiveness is adequately established, making the measurement model robust enough for estimation of the structural model.

4.3. Hypothesis Testing

The structural model is used to test the suggested relationships among digital innovation, risk management, resilience, performance, and the moderating effect of technology usage. To check for multicollinearity, the variance inflation factor (VIF) values are checked, which range from 1.42 to 2.18, all below 5.0, indicating no problem of multicollinearity. The explanatory relevance is measured by the coefficient of determination, which is defined as R^2. The values of R^2 for SCRM, SCR, and SCP are 0.271, 0.456, and 0.583, respectively. The values indicate that the model explains 27.1%, 45.6%, and 58.3% of the variance for SCRM, SCR, and SCP, respectively. The predictive relevance is checked, and all the Q^2 values are positive, which confirms the predictive relevance with the blindfolding results for SCRM = 0.182, SCR = 0.318, and SCP = 0.421. The significance of the path coefficients is checked using the bootstrapping method with 5,000 resamples, and the results are presented in **Table 6**.

Table 6. Hypothesis Testing Results.

Hypothesis	Path	β	SE	*t*-Value	*p*-Value	95% CI	Result
Direct Effects							
H1	DI → SCP	0.218	0.062	3.516	0.001	[0.098, 0.342]	Supported
H2a	DI → SCRM	0.521	0.054	9.648	0.000	[0.417, 0.628]	Supported
H2b	DI → SCR	0.197	0.068	2.897	0.004	[0.065, 0.331]	Supported
H3	SCRM → SCR	0.489	0.059	8.288	0.000	[0.375, 0.606]	Supported
H4a	SCRM → SCP	0.156	0.065	2.400	0.017	[0.030, 0.285]	Supported
H4b	SCR → SCP	0.372	0.058	6.414	0.000	[0.259, 0.487]	Supported
Moderating Effects							
H5a	TU × SCRM → SCR	0.127	0.052	2.442	0.015	[0.026, 0.230]	Supported
H5b	TU × SCR → SCP	0.143	0.049	2.918	0.004	[0.048, 0.241]	Supported
Indirect Effects							
	DI → SCRM → SCR	0.255	0.041	6.220	0.000	[0.178, 0.339]	Significant
	DI → SCRM → SCP	0.081	0.032	2.531	0.012	[0.024, 0.152]	Significant
	DI → SCR → SCP	0.073	0.029	2.517	0.015	[0.019, 0.138]	Significant
	DI → SCRM → SCR → SCP	0.095	0.025	3.800	0.002	[0.051, 0.149]	Significant
	Total Indirect Effect	0.249	0.045	5.533	0.000	[0.165, 0.341]	Significant

Note: β = standardized path coefficient; SE = standard error; CI = confidence interval; VAF = 53.3% (partial mediation).

In terms of direct effects, digital innovation has a positive and significant influence on supply chain performance (β = 0.218, $p < 0.01$), thus confirming H1. It also has a strong positive influence on supply chain risk management (β = 0.521, $p < 0.001$), thus validating H2a. Furthermore, a positive and significant relationship is found between digital innovation and supply chain resilience (β = 0.197, $p < 0.01$), thus validating H2b. Supply chain risk management also shows a substantial predictive relationship with supply chain resilience (β = 0.489, $p < 0.001$), thus corroborating H3. Furthermore, risk management is found to positively affect supply chain performance (β = 0.156, $p < 0.05$), thus confirming H4a. Moreover, a positive and significant impact of resilience on supply chain performance is apparent (β = 0.372, $p < 0.001$), thereby supporting H4b.

For assessing the moderating effects, the product indicator method was applied. The relationship between technology usage and risk management and resilience is positive (β = 0.127, $p < 0.05$), which supports H5a. This means that higher technology adoption enables firms to translate risk management efforts into resilience more effectively. Similarly, technology usage can strengthen the relationship between resilience and performance (β = 0.143, $p < 0.01$), which supports H5b. This suggests that the performance gains from resilience are amplified at higher levels of technology adoption. The moderating effects are presented in **Figure 6**.

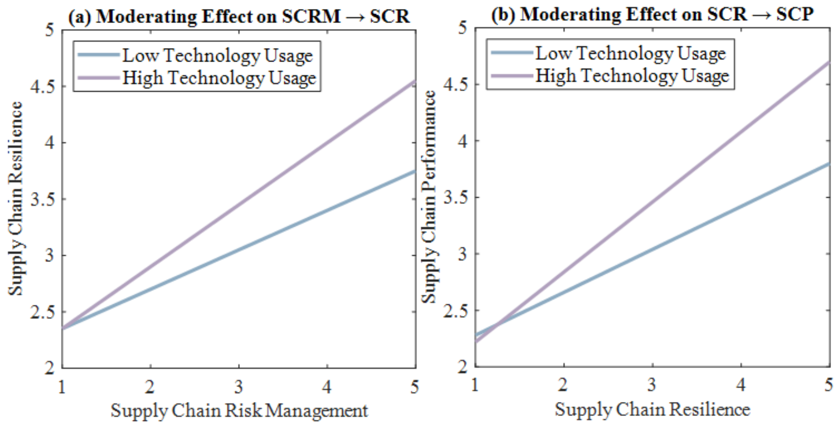

Figure 6. Moderating Effects of Technology Usage.

The mediation model was further tested using bootstrapping methods. As shown in **Table 6**, the indirect effect of digital innovation on resilience through risk management was statistically significant (β = 0.255, $p < 0.001$). This indicates that there is partial mediation between the variables. Moreover, the indirect effect of digital innovation on SCP through risk management (β = 0.081, $p < 0.05$), resilience (β = 0.073, $p < 0.05$), and the sequential path through both risk management and resilience (β = 0.095, $p < 0.01$) was also statistically significant. Moreover, the total indirect effect was statistically significant (β = 0.249, $p < 0.001$). Combined with the direct effect of 0.218, the total effect of digital innovation on SCP is 0.467. The VAF reaches 53.3%, confirming partial mediation.

The empirical results confirm all the hypotheses presented in this study. The digital innovation impacts the performance in the supply chain through both direct and indirect paths, and risk management and resilience are intervening variables. The technology application enhances the links between risk management and resilience, and between resilience and performance. The results validate the proposed framework and reiterate the significance of digital innovation as a facilitator for improving risk management and, in turn, supply chain performance, especially for those businesses with higher levels of technology application.

4.4. Robustness Tests

For the purpose of robustness checks, a series of tests was conducted to validate the findings. The results of the robustness checks are presented in **Table 7**. To check for common method bias (CMB), the single factor test as proposed by Harman was employed. The results showed that the first factor explained only 38.6% of the variance, which is less than 50%. Therefore, CMB is not a potential concern for this study. To check for CMB, as an additional test, the full collinearity VIF method was employed. The results showed that all VIF values were between 1.35 and 2.24, which is less than 3.3, confirming the absence of CMB.

Table 7. Robustness Test Results.

Test	**Criterion**	**Result**	**Conclusion**
Common Method Bias			
Harman's single-factor test	First factor < 50%	38.6%	No CMB
Full collinearity VIF	VIF < 3.3	1.35–2.24	No CMB
Alternative Model			
Model without control variables	Path significance	All paths significant	Robust
Model with additional control (region)	Path significance	All paths significant	Robust

Alternative model specifications are tested for the robustness of the results. The structural model is then estimated without control variables, and it is found that the significance and effect sizes for all hypothesized paths are intact, suggesting that the robustness of the results is not affected by the inclusion of control variables. An additional control variable (region) is then introduced in the model, and the results reveal the same significance and effect size for the paths as in the base model specification. Overall, the alternative model tests confirm the robustness of the hypothesized paths.

5. Discussion

This study aims to explore the relationships between digital innovation, supply chain risk management, resilience, and performance, including assessing the moderating role of technology usage. The results reveal that all eight hypotheses developed in the conceptual framework are empirically supported.

The study shows a direct positive impact of digital innovation on supply chain performance, and this is consistent with the findings of Zhao et al. [1], who showed that supply chain digitalization affects organizational performance through multiple channels. He et al.'s [15] study also revealed that digital innovation is a key factor for efficiency development in supply chains, especially for Chinese enterprises. Enterprises with digital innovation capabilities are those that exhibit the potential for more efficient information processing, cost reduction, and faster adaptation to dynamic market environments. These findings are supported by the resource-based view (RBV), where digital innovation is considered a valuable intangible resource.

Among the structural pathways, the relationship between digital innovation and supply chain risk management is the most significant (β = 0.521). This is in line with the findings of Türkeş [24], who reported that digitalization improves supply chain efficiency while at the same time improving the risk management function in the supply chain. Iftikhar et al. [23] argued that digital innovation and data analysis significantly increase supply chain resilience. Digitalization, which includes big data analysis and real-time monitoring systems, improves organizational capacity to detect risks before they occur in the operations of the organization. The robustness of the relationship between digital innovation and risk management implies that organizations should focus on developing the digital infrastructure.

Furthermore, the significant relationship between risk management and resilience (β = 0.489) highlights the importance of risk management. El Baz and Ruel [4] found that the application of risk management practices minimized the impact of the disruption on developing resilience and robustness during the COVID-19 pandemic. Han and Um [27] found similar evidence, emphasizing that the application of risk management practices is a prerequisite for developing resilience under global uncertainty. Chowdhury and Quaddus [11] conceptualized supply chain resilience as a dynamic capability of the supply chain, which includes both proactive and responsive aspects. The present findings support the conceptual model proposed by the authors, which emphasizes the importance of risk management for the development of supply chain resilience.

The sequential mediation chain of digital innovation → risk management → resilience → performance (β = 0.095) specifies the process by which the benefits of digital innovation are delivered. The result provides a VAF of 53.3%, implying that the total effect of digital innovation on performance is explained by more than half of the total process. This study extends the findings conducted by Oubrahim et al. [21], which examined the influence of digital innovation on sustainable supply chain performance. Furthermore, the study corroborates the findings conducted by Jidda Jidda et al. [12], which established that the positive mediation effect between enterprise risk management and supply chain performance is attributed to firm resilience.

The moderating coefficient of the association between the application of technology and the risk management-resilience relationship is β = 0.127, showing that the application of technology increases the effectiveness of risk management on resilience. Consistent with the research of Wu et al. [13], who found the positive impact of digital technology on supply chain resilience within the resource-action-performance framework, this research extends this research stream by examining the role of technology usage as a boundary condition. Huang et al. [33] found the significant impact of Industry 4.0 technologies on supply chain capabilities and resilience through the dynamic resource paradigm, which is consistent with the current research.

The moderating impact on the resilience-performance association (β = 0.143) indicates that the performance outcomes for resilient supply chains increase with the adoption of technology. Data analytics competency and organizational flexibility were recognized by Dubey et al. [34] as enablers of resilient supply chains, and the current study extends this to the performance domain. Similarly, Belhadi et al. [35] discovered that the relationship between AI innovation and resilience-performance is strengthened as supply chain dynamism increases. This also verifies the amplifying form of this relationship.

The study contributes to the SCM literature by empirically specifying the linkages among digital innovation, risk management, resilience, and performance in an integrative model. It addresses Ning and Yao's [16] call for a deeper and more rigorous investigation of the relationship among digital innovation, supply chain capabilities and competitive performance. The results suggest that digital innovation should be conceived not only as a driver of efficiency but also as a facilitator of SCM competence in general.

6. Conclusion

This study explores the relationships among digital innovation, supply chain risk management, resilience, and performance using a sample of 256 firms obtained from the database of the World Bank Enterprise Surveys (WBES). It adopts the method of partial least squares structural equation modeling (PLS-SEM), which shows that there is a partially mediated relationship between digital innovation and supply chain performance through risk management and resilience, with the total effect of digital innovation on supply chain performance explained by risk management and resilience to the tune of 53.3%. The application of technology enhances the positive relationship between risk management and resilience and between resilience and performance, thus implying that firms that have higher levels of technology adoption benefit from supply chain capabilities. The findings are of theoretical significance as they add to the body of knowledge on dynamic capabilities and their mediating role among digital innovation, risk management, and supply chain performance. They are relevant for managers as well, and they suggest that risk management should not be forgotten in corporate investments in digital innovation. As is often mentioned, the limited capacity for controlling variables because of secondary data use and difficulties in establishing causality between variables because of cross-sectional data are important issues. Additionally, since industries outside the manufacturing and service sectors are not included, the aforementioned support may not be applicable in other industries. Longitudinal studies should replace cross-sectional studies, and new variables should be explored, including industries and uncertainty.

Author Contributions

Conceptualization, M.L.; methodology, M.L.; software, M.L.; validation, M.L., N.Z., M.Z.H., M.Z.M.S. and X.C.; formal analysis, M.L.; investigation, M.L.; resources, M.L.; data curation, M.L.; writing—original draft preparation, M.L.; writing—review and editing, M.L.; visualization, M.L.; supervision, N.Z., M.Z.H., and M.Z.M.S.; project administration, M.L.; funding acquisition, M.L., N.Z., M.Z.H., M.Z.M.S. and X.C. All authors have read and agreed to the published version of the manuscript.

Funding

This work received no external funding.

Institutional Review Board Statement

Not applicable. This study was based entirely on secondary, anonymized, firm-level data made publicly available by the World Bank Enterprise Surveys program, and did not involve any new interaction with human participants or animals.

Informed Consent Statement

Not applicable. The World Bank Enterprise Surveys obtained informed consent from participating firms during the original data collection, and the present study analyzed only de-identified aggregate records.

Data Availability Statement

The firm-level data that support the findings of this study are openly available from the World Bank Enterprise Surveys at https://www.enterprisesurveys.org. Processed datasets and SmartPLS model files are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

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