Original Article
ISSN (Online): 2582-7472

ShodhKosh: Journal of Visual and Performing Arts
July-December 2025 6(2), 57–69

IMPACT OF INFORMATION TECHNOLOGY USAGE ON VISIBILITY RESILIENCE AND PERFORMANCE OF SUPPLY CHAIN MANAGEMENT: AN EMPIRICAL STUDY

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DOI
10.29121/shodhkosh.v6.i2.2025.6013

Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

ABSTRACT

Supply Chain Management (SCM) is broadly defined as the integrated coordination of activities involved in the procurement, transformation, and distribution of materials components, and finished goods from suppliers to end customer. As digital transformation reshapes global supply chains, the synergistic role of information technologies has garnered increasing scholarly attention.The current literature remains fragmented, especially in understanding how information technology usage jointly influence supply chain performance (SCP) through critical enablers particularly supply chain visibility (SCV) and supply chain resilience (SCR). This study addresses this gap by proposing and empirically testing a sequential mediation model in which SCV and SCR jointly mediate the relationship between information technology usage and SCP. Drawing upon the Resource-Based View, Dynamic Capabilities View, and Organizational Information Processing Theory, a conceptual framework is developed and validated using survey data from 600 supply chain professionals across key sectors in India. Partial Least Squares Structural Equation Modeling (PLS-SEM) reveals that information technology usage positively influence both SCV and SCR, further it reveled SCV significantly contributes to SCR and SCV and SCR sequentially mediate the relationship between IT usage and performance outcomes.The findings underscore the need for integrated digital strategies and enhanced visibility-resilience alignment, particularly in emerging economy contexts characterized by infrastructural and institutional volatility.The study contributes novel empirical evidence to the digital supply chain literature and offers actionable insights for practitioners navigating digital transformation in resource-constrained environments.

Keywords: Information Technology Usage; Supply Chain Visibility, Supply Chain Resilience, Supply Chain Performance, Resource-Based View (RBV), Dynamic Capabilities Theory, Technology Organization Environment (TOE) Framework, PLS-SEM, Sequential Mediation, Digital Transformation; Operations Management

1. INTRODUCTION

Supply Chain Management (SCM) focuses on aligning procurement, production, and distribution processes across the supply network to improve overall efficiency (Panigrahi et al., 2025; Anwar et al., 2025). It involves key functions like demand forecasting, inventory management, logistics, and customer satisfaction (Panigrahi et al., 2025).SCM has shifted from a cost-focused model to a flexible, technology-driven function that emphasizes agility, responsiveness, and collaboration (Zaman et al., 2025; Mubarik et al., 2025). It combines inter and intra organizational processes and coordinates operations among suppliers, manufacturers, and customers (Lilja, 2025; Akushie & Yornu, 2025).The digital transformation of SCM, powered by innovations like IoT, AI, and cloud computing, is crucial for improving real-time insights, flexibility, and strategic alignment (Drake & Sherwin, 2025; Shoukat, 2024). The COVID-19 pandemic emphasized the need for resilience and pushed companies toward localized, flexible, and technology-supported frameworks (Kashem et al., 2024; Handfield et al., 2020). As a result, concepts like Supply Chain Visibility (SCV), Supply Chain Resilience (SCR), and Supply Chain Performance (SCP) have become essential capabilities (Ivanov & Dolgui, 2020;

Dubey et al., 2021).SCV is ability of company to access and share real-time data throughout the supply network, enabling quick responses (Barratt & Oke, 2007; Wang et al., 2020). SCR refers to the ability to anticipate, absorb, and recover from disruptions (Pettit et al., 2013; Ponomarov & Holcomb, 2009). In recent years the digitalisation of supply chains has emerged as an area of intense attention for companies in search of survival possibilities through an uncertain market scenario, operational halts, and increasing customer expectations. Technologies with focus on Enterprise Resource Planning (ERP), Internet of Things (IoT), Radio Frequency Identification (RFID) and Cloud Computing are increasingly being used to enhance responsiveness, automate procedures, and enhance decision-making (Gunasekaran et al., 2017; Dubey et al., 2021)

The current literature points out three main weaknesses.First, several studies measure digital technologies individually that are concentrating exclusively on isolated tools like ERP (Sharma et al., 2021), IoT (Wang et al., 2020), or RFID (Hofmann et al., 2019).This fragmented approach hampers our comprehension of how various technologies interact throughout the supply chain to generate systemic value. Second, while concepts like SCV and SCR are often acknowledged as essential facilitators of performance, their roles as mediators are still under-explored and inadequately validated (Wieland & Wallenburg, 2022). There are few studies that theorize and empirically test the sequential process by which digital technologies reinforce SCV, which in turn enhances SCR, thereby contributing to better performance (Pettit et al., 2019; Yu et al., 2023).Third, most empirical studies focus on industrialized nations, whereas emerging economies such as India are often neglected in spite of remarkable levels of digital growth under initiatives like Digital India and Smart Logistics (Kamble et al., 2020; Gupta et al., 2020). Given these significant gaps, this study seeks to contribute to current knowledge .

Through the design and empirically testing of a sequential mediation model, this research makes three important contributions. Firstly, it offers a holistic understanding of the impact of multiple IT tools, transcending the reductionism of single-technology models. Secondly, it conceptualizes and empirically analyzes the sequential mediating roles played by SCV and SCR and thus contributes further to our understanding of how IT use is associated with SCP. Third, by focusing on India, the research supplies vital empirical data from an influential rising economy and facilitates contextualization of digital supply chain theory.

2. LITERATURE REVIEW

The integration of Information Technology (IT) into supply chain management (SCM) has fundamentally transformed the operational and strategic dimensions of modern supply chains. It enables firms to enhance agility, visibility and coordination across various functions and entities (Reaidy et al., 2024; Zhao et al., 2023). IT supports efficient communication, real-time data sharing and collaborative decision-making across geographically dispersed supply chain partners (Dubey et al., 2019). Enterprise Resource Planning (ERP), Blockchain, Artificial Intelligence (AI), Internet of Things (IoT) and Cloud Computing are widely deployed to streamline supply chain in business environments and have become indispensable for achieving supply chain resilient activities and improve integration (Ivanov & Dolgui, 2019).

2.1. THE IT USAGE AND SUPPLY CHAIN PERFORMANCE

Supply Chain Performance (SCP) refers to the capacity of supply chain to meet customer requirements effectively while optimizing resources, minimizing costs, and supporting strategic objectives (Beamon, 1999; Gunasekaran & Kobu, 2007). SCP is inherently multidimensional, encompassing operational efficiency, responsiveness, flexibility, reliability, and innovation (Neely et al., 2005; Chopra & Meindl, 2016).IT technologies have been found to enhance operational efficiency, flexibility, and responsiveness in different studies, to supplement each other to improve supply chain performance (SCP) (Zhang et al., 2016; Sharma et al., 2021).The Internet of Things (IoT) enhances SCP by facilitating real-time visibility, smart tracking and predictive analytics, enabling firms to anticipate disruptions and respond proactively (Ben-Daya et al., 2019).Technologies such as IoT, RFID, Cloud Computing and ERP foster transparency, predictive decision-making and cross-functional integration, thereby improving SCP through increased speed, accuracy and resilience (Gonzalez et al., 2021; Patel et al., 2023).Thus, in line with extant literature and theory, this study proposes:

H1: Information technology usage has a positive influence on supply chain performance

2.2. IT USAGE AND SUPPLY CHAIN VISIBILITY

SCV is the ability of monitoring inventory, orders, and information across the supply chain in real-time (Barratt & Oke, 2007).SCV has become critical for improving agility, responsiveness and proactive risk management (Brandon-Jones et al., 2014; Yu et al., 2021; Dubey et al., 2020). Information Technology (IT) enables SCV by supporting the real-time flow of data, enhancing collaboration and integrating supply chain operations (Fosso Wamba et al., 2020; Gunasekaran et al., 2017; Queiroz et al., 2022)..Although prior studies establish the technical contributions of IT tools to SCV, there is a lack of holistic models capturing the integrated influence of these technologies across sectors.This study aims to bridge these gaps by examining the direct relationship between IT usage and SCV in a unified empirical framework.Thus, in line with extant literature and theory, this study proposes:

H2: Information technology usage contribute positively to supply chain visibility.

2.3. USE OF IT AND SUPPLY CHAIN RESILIENCE

SCR refers to a supply chain's capacity to foresee, absorb, and recover from disruptions (Pettit et al., 2013; Chowdhury et al., 2019). It is enhanced by IT through the supply of data-driven risk management, decentralized planning, and response in real-time.IoT provides early warning, while ERP and Cloud platforms provide scenario planning and rapid reconfiguration (Dubey et al., 2020; Rajesh, 2020).The literature consistently acknowledges that Information Technology (IT) forms the cornerstone of modern resilience strategies by enhancing sensing, response and recovery capabilities (Ivanov & Dolgui, 2020; Dubey et al., 2020).Despite substantial evidence confirming the role of IT in building resilience, prior literature often treats SCR as an operational consequence rather than a distinct, measurable construct within IT-enabled supply chains. There is also a lack of sector-diverse longitudinal studies in emerging markets, particularly in volatile post-pandemic contexts. This study addresses these gaps by evaluating the direct impact of IT on SCR using an integrated empirical framework.

H3: The use of information technology have a positive effect on supply chain resilience.

2.4. ROLE OF SUPPLY CHAIN VISIBILITY AND SUPPLY CHAIN RESILIENCE

SCV provides the information basis that allows firms to detect anomalies, predict disruptions, and initiate contingency plans (Brandon-Jones et al., 2014; Dubey et al., 2019). Visibility facilitates rapid response, which forms the essence of building resilience. Visibility is thus not an outcome but an antecedent to resilience. Yu et al. (2018) reported that visibility significantly enhances key performance metrics such as order fulfillment, inventory turnover and service level. Moreover, visibility contributes to improved coordination and trust among supply chain partners, facilitating collaborative planning and execution (Srinivasan & Swink, 2018).Thus, in line with extant literature and theory, this study proposes:

H4: Supply Chain Visibility (SCV) has a direct impact on Supply Chain Performance (SCP).

According to Pettit et al. (2013), resilient supply chains are more adaptable and responsive, leading to better customer satisfaction, reduced operational inefficiencies and greater financial stability. Similarly, Scholten and Schilder (2015) showed that resilience capabilities such as flexibility, redundancy and agility lead to better performance, especially under stress conditions.The Dynamic Capabilities Theory provides a theoretical foundation for this relationship. It posits that firms with superior dynamic capabilities, such as resilience, can better sense and respond to environmental changes, thereby achieving superior performance (Teece, 2007).Therefore, building on both empirical evidence and theoretical grounding, the study hypothesizes:

H5: Supply Chain Resilience (SCR) has a direct impact on Supply Chain Performance (SCP).

2.5. MEDIATING ROLES OF SUPPLY CHAIN VISIBILITY AND SUPPLY CHAIN RESILIENCE

SCV and SCR are both possible mediators of the IT–SCP relationship. SCV allows proactive decision-making and coordination, whereas SCR provides continuity in the event of disruptions. Prior research has established these capabilities as separate mediators, but the literature is limited regarding sequential mediation, where visibility generates resilience, and which leads to performance (Tukamuhabwa et al., 2015; Wieland & Wallenburg, 2022).Supply Chain

Resilience (SCR) has increasingly emerged as a critical construct in understanding how Information Technology usage (ITU) contributes to superior Supply Chain Performance (SCP). Grounded in the Dynamic Capabilities Theory (DCT) and the Resource-Based View (RBV), this relationship posits that IT adoption alone does not automatically yield performance improvements. Rather, its value materializes when IT enables dynamic capabilities orsuch as resilience orthat allow firms to respond to, absorb and recover from disruptions effectively (Dubey et al., 2021; Gu et al., 2021). These perspectives argue that IT by itself does not generate competitive advantage unless it is integrated into capabilities such as Supply Chain Visibility (SCV) and Supply Chain Resilience (SCR) (Teece, 2007; Barney, 1991).Therefore, building on both empirical evidence and theoretical grounding, the study hypothesizes:

H6: Supply chain visibility acts as a mediator between IT usage and supply chain performance.

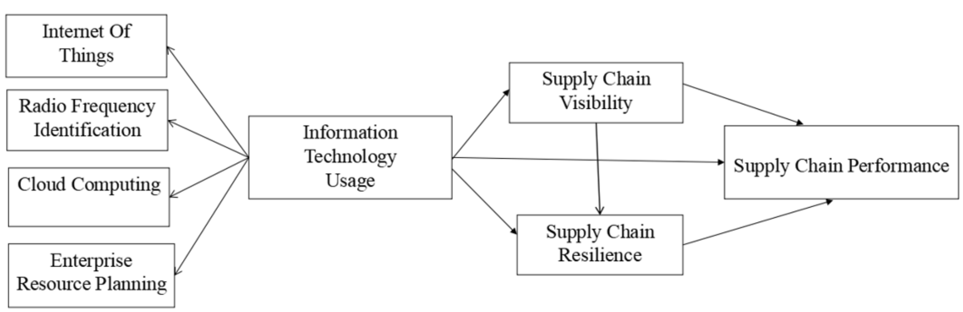
H7: Supply chain resilience acts as a mediator between IT usage and supply chain performance.

H8: Supply chain visibility and supply chain resilience sequentially mediate between IT capabilities and supply chain performance.

2.6. THEORETICAL UNDERPINNING

This study uses three interlinked theory schools of thought, namely the Resource-Based View (RBV), the Dynamic Capabilities View (DCV), and the Organizational Information Processing Theory (OIPT). These theories collectively provide a compelling explanation for the manner in which digital technologies, when properly implemented, can transform supply chains through higher levels of visibility, greater resilience, and improved performance.The RBV takes its foundation on the argument that firms gain enduring competitive advantage by acquiring and deploying valuable, rare, inimitable, and non-substitutable strategic resources (Barney, 1991).For supply chains, new digital technologies such as ERP, IoT, RFID, and Cloud Computing are being increasingly considered strategic IT capabilities through which firms are able to process information, automate coordination, and improve responsiveness (Gunasekaran et al., 2017; Wamba et al., 2017).However, the presence of resources does not necessarily mean improved performance. The DCV identifies organizational routines enabling firms to reconfigure and transform resources to dynamic contexts (Teece, 2007). Supply Chain Visibility (SCV) and Supply Chain Resilience (SCR) are considered dynamic capabilities, with the capacity of companies to sense, react, and bounce back from disruptions (Wieland & Wallenburg, 2022; Dubey et al., 2021).When viewed from an OIPT angle, companies must align information-processing abilities with environmental uncertainty to be potent (Galbraith, 1973). Digital technologies enable information flow and processing, and when coupled with SCV and SCR, enable better decision-making in the face of volatility (Flynn et al., 2020; Bag et al., 2021).

The above discussion and hypothesis leads to the formation of theoretical framework as shown in figure-1.



3. RESEARCH DESIGN

A cautious approach was followed in designing the survey instruments for collecting data for the study. The first step in preparing the survey instrument involved identifying the key constructs and variables relevant to the research objectives. This was achieved through an extensive review of existing literature, theoretical frameworks and expert consultations. The identified constructs and variables formed the foundation for developing the survey questionnaire. Once the constructs and variables were determined, a comprehensive item pool of 60 items was generated. This involved compiling a list of potential items that captured the different dimensions of each construct. The items were drafted based on established measurement scales from previous studies, existing validated questionnaires and expert knowledge. The five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree) was chosen for respondents to express their opinions. Five-point Likert scales are also in line with most research in the management of initiating the questionnaire survey began with meticulously formulating a detailed questionnaire.

3.1. DATA COLLECTION

This section presents the demographic profile of the respondents who participated in the empirical survey. A total of 600 valid responses were collected from professionals working across various sectors of the supply chain in India. The respondents were selected using a stratified random sampling technique to ensure broad representation from manufacturing, FMCG, retail, logistics and pharmaceutical industries.The demographic variables considered include gender, age, education level, work experience and organizational sector. The data were analyzed using SPSS version 26 to generate frequency distributions and percentage

Table 1

Demographic profile

Source(s): Author

Category	Sub-category	Frequency	Percentage
Gender	Male	420	70.0%
	Female	180	30.0%
Age Group	20–29 years	180	30.0%
	30–39 years	240	40.0%
	40–49 years	120	20.0%
	50 and above	60	10.0%
Education Level	Bachelor's Degree	240	40.0%
	Master's Degree	300	50.0%
	Professional Diploma/Certification	60	10.0%
Work Experience	Less than 5 years	180	30.0%
	5–10 years	240	40.0%
	More than 10 years	180	30.0%
Sector of Employment	Manufacturing	150	25.0%
	FMCG	120	20.0%
	Retail & E-commerce	90	15.0%
	Logistics & Distribution	120	20.0%
	Pharmaceuticals	120	20.0%

3.2. NON-RESPONSE BIAS

Non-response bias poses a significant threat to the generalizability and validity of survey-based research findings, particularly when exploring complex interrelationships such as those between IT usage and supply chain dynamics (Chen & Paulraj, 2004). To ensure the robustness of the present study and to affirm that the sample adequately represents the broader target population, rigorous diagnostic procedures were employed. In line with the procedural recommendations of Armstrong and Overton (1977), responses were chronologically divided into early and late respondent groups, with the assumption that late respondents are more likely to resemble non-respondents.Independent sample t-tests were subsequently conducted across all primary constructs ERP, IoT, RFID, Cloud Computing, Supply Chain Visibility, Resilience, and Performance. The results indicated no statistically significant differences ($p > 0.05$) at the 95% confidence interval between early and late respondents across these constructs. This statistical parity confirms that non-response bias does not pose a significant threat to the integrity of the dataset, thereby enhancing the credibility and reliability of the empirical results derived from the survey

3.3. COMMON METHOD BIAS (CMB)

Given the reliance on self-reported data collected through a structured questionnaire, addressing the risk of Common Method Bias (CMB) was essential to ensure the integrity of the results. Following the recommendations by

Podsakoff et al. (2003), two key procedural and statistical remedies were adopted.First, procedural safeguards were employed during the survey administration, most notably by ensuring respondent anonymity and clearly communicating that there were no right or wrong answers. This strategy was intended to minimize social desirability bias and encourage candid responses.Second, statistical techniques were used to detect any underlying CMB. Harman's single-factor test was conducted using unrotated exploratory factor analysis. The analysis revealed that the first factor accounted for less than 50% of the total variance, indicating that no single latent factor dominated the data structure.The combination of these procedural and statistical controls affirms that the findings of this study are free from significant common method variance, thereby strengthening the credibility and internal validity of the empirical insights derived from the analysis

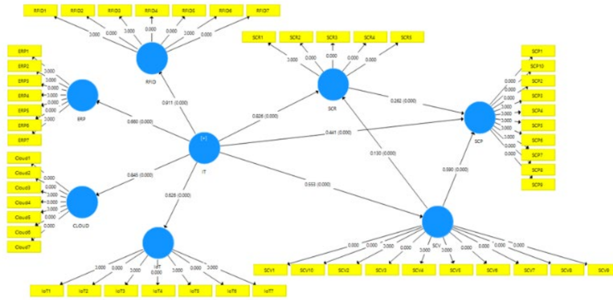
4. QUANTITATIVE STUDY: DATA ANALYSIS

A survey-based research design was employed to assess the proposed theoretical framework empirically.A structured, survey-based research design was employed to empirically validate the proposed theoretical framework examining the influence of Information Technology usage on supply chain visibility, resilience, and performance. The research instrument was meticulously developed based on established constructs and validated scales, drawing from extant literature across supply chain management, information systems, and organizational capabilities. The questionnaire was tailored to capture perceptions of key technological dimensions (ERP, IoT, RFID, Cloud Computing) and their impact on strategic supply chain outcomes.The data collection was conducted between March and April 2023, targeting mid- to senior-level supply chain professionals across manufacturing, automotive, and retail sectors in India. To ensure broad industrial representation and regional diversity, purposive sampling was implemented across six industrial zones. The final sample was drawn from professionals with demonstrable experience in technology-enabled supply chain operations. All collected responses were cleaned and coded, followed by statistical analysis using SPSS Version 26 for preliminary diagnostics and SmartPLS 4 for structural equation modeling.This research design facilitated robust empirical assessment of both direct and mediating effects within the proposed model, offering contextually rich and statistically sound insights into the digital transformation of supply chains in the Indian context .

To ensure the robustness and statistical integrity of the dataset, a comprehensive psychometric evaluation was conducted prior to structural modeling. In line with the multivariate diagnostic approaches suggested by Dubey et al. (2015) and Cohen et al. (2003), Mahalanobis distance was computed to detect potential multivariate outliers across predicted constructs. Observations exceeding the critical chi-square value were examined and subsequently excluded to maintain data normality and homogeneity.Descriptive statistics were also examined to assess the underlying distributional properties of the observed data. As emphasized by DeCarlo (1997), skewness and kurtosis offer critical insights into the shape and symmetry of the data distribution. In the present study, the mean values for the constructs ranged from 2.94 to 3.82, with an average standard deviation of 0.65, indicating moderate dispersion around the central tendency.The skewness value for the aggregated dataset was observed at 1.534, and the kurtosis was measured at 3.411. Both indices fall well within the recommended thresholdsskewness < 2 and kurtosis < 7 as outlined by Curran et al. (1996), thereby affirming the approximate normality of the data required for PLS-SEM analysis. These results validate the appropriateness of the dataset for further exploratory and confirmatory statistical procedures, ensuring unbiased estimation and enhancing the reliability of the analytical outcomes.

4.1. MEASUREMENT VALIDATION

To determine the sample's adequacy for factor analysis, an initial evaluation was performed using the Kaiser-Meyer-Olkin (KMO) test for sampling appropriateness. The resulting KMO statistic was 0.758, indicating the sample was apt for factor analysis. Subsequently, wecarried out an exploratory factor analysis, which grouped the variables into seven distinct factors, each with an Eigenvalue above 1. Combined, these factors represented 69.46% of the overall variance. A subsequent validity check was performed. Using the benchmarks set by Fornell and Larcker (1981), both convergent and discriminant validities were ascertained. Detailed results, including normalized factor loadings, Average Variance Extracted (AVE), can be found in Table 1.The derived values from Table 2 for standardized factor loading, AVE, and SCR comfortably exceed the prescribed thresholds. Ideally, factor loadings should surpass 0.7, albeit values above 0.5 remain acceptable. Our analysis indicates factor loadings ranging from 0.657 to 0.958. Similarly, benchmark values for SCR and AVE are >0.7 and > 0.5, respectively. Figure 2 illustrates the structural model that was tested during this stage of analysis.



Given these metrics, it is evident that the constructs within our theoretical model possess robust convergent validity.For the establishment of discriminant validity, it is imperative to accurately evaluate and distinguish between the specified variables or constructs. To assess the inter-factor correlations, a correlation matrix was formulated. This matrix was subsequently refined in alignment with the procedures recommended by Fornell and Larcker (1981). As depicted in Table 3, the diagonal values representing the square root of the Average Variance Extracted (AVE) consistently exceed their respective off-diagonal values, which denote the correlation coefficients. Given these observations, the study confirms the discriminant validity of the constructs. The study also evaluated discriminant validity employing the heterotrait– monotrait (HTMT) ratio of correlations method, in line with the suggestions of Henseler et al. (2015). As articulated in Table 3, all recorded ratios fell under the 0.9 threshold, thus substantiating the discriminant validity of the model in question.The process of hypothesis testing is carried out through regression analysis. The outcomes of this hypothesis testing are showcased in Table 4. Examining regression analysis outcomes shows that all the relationships established by the theoretical framework exhibit notable statistical significance at a significance level of $p < 0.05$.

Table 2

Convergent validity Source(s): Author

Items	Loading	AVE	Items	Loading	AVE
ERP1	0.835		SCV1	0.712	
ERP2	0.790		SCV2	0.849	
ERP3	0.807		SCV3	0.848	
ERP4	0.814		SCV4	0.847	0.605
ERP5	0.807	0.736	SCV5	0.834	
ERP6	0.804		SCV6	0.863	
ERP7	0.829		SCV7	0.865	
CC1	0.855	0.714	SCV8	0.840	
CC2	0.867		SCV9	0.840	
CC3	0.869		SCV10	0.838	
CC4	0.866		SCR1	0.907	
CC5	0.863		SCR2	0.908	
CC6	0.851		SCR3	0.895	0.580
CC7	0.865		SCR4	0.910	
IOT1	0.809	0.592	SCR5	0.902	
IOT2	0.835		SCP1	0.885	
IOT3	0.805		SCP2	0.861	

IOT4	0.785		SCP3	0.871	0.623
IOT5	0.806		SCP4	0.885	
IOT6	0.804		SCP5	0.880	
IOT7	0.795		SCP6	0.875	
RFID1	0.881	0.501	SCP7	0.892	
RFID2	0.883		SCP8	0.890	
RFID3	0.868		SCP9	0.882	
RFID4	0.896		SCP10	0.867	
RFID5	0.881				
RFID6	0.880				
RFID7	0.873				

Table 3 Discriminant validity
Source(s): Author

Fornell and Larker criterion								
	Cloud	ERP	IoT	RFID	SCP	SCR	SCV	IT USAGE
Cloud	0.862							
ERP	0.312	0.813						
IoT	0.558	0.121	0.806					
RFID	0.677	0.595	0.415	0.880				
SCP	0.278	0.671	0.232	0.563	0.879			
SCR	0.700	0.370	0.487	0.711	0.263	0.904		
SCV	0.333	0.642	0.236	0.493	0.748	0.326	0.834	
ITUSAGE	0.833	0.683	0.607	0.917	0.653	0.653	0.653	0.653

Table 4 HTMT criterion for discriminant validity
Source(s): Author

Heterotrait-Monotrait Ratio (HTMT)							
	Cloud	**ERP**	**IoT**	**RFID**	**SCP**	**SCR**	**SCV**
Cloud							
ERP	0.334						
IoT	0.587	0.119					
RFID	0.715	0.636	0.427				
SCP	0.290	0.712	0.236	0.586			
SCR	0.742	0.397	0.505	0.750	0.274		
SCV	0.351	0.688	0.242	0.518	0.779	0.344	

Table 5 Results of hypothesis testing

Source(s): Author's findings

Path	β	σ	T-Statistic	P-Value	Support
IT → SCP	0.441	0.073	6.041	0.000	Supported
IT → SCR	0.826	0.036	22.940	0.000	Supported
IT → SCV	0.553	0.041	13.480	0.000	Supported
SCR → SCP	0.262	0.033	7.930	0.000	Supported
SCV → SCP	0.590	0.053	11.132	0.000	Supported
SCV → SCR	0.130	0.031	4.190	0.000	Supported

4.2. DISCUSSION ON RESULTS OBTAINED

The Structural Equation Modeling (SEM) technique was employed to evaluate the proposed hypotheses by analyzing the standardized path coefficients (β), standard errors (σ), t-statistics, and p-values. Consistent with the guidelines of Hair et al. (2017), the model confirms statistical significance where t-values exceed 1.96 and p-values are below 0.05.

All hypothesized direct and indirect relationships in the theoretical framework are supported and statistically significant, highlighting the robustness and validity of the structural model.

The beta coefficient for the path from IT usage to Supply Chain Performance (IT → SCP) is 0.441 ($t = 6.041$, $p < 0.001$), confirming a direct and positive effect of information technology on overall performance outcomes.This finding is also consistent with Gunasekaran et al. (2017) and Rajesh & Ravi (2015), who demonstrated that IT integration enhances forecasting accuracy and operational efficiency.

The path coefficient from IT to Supply Chain Visibility (IT → SCV) is 0.553 ($t = 13.480$, $p < 0.001$), suggesting a strong and positive relationship.This observation aligns with the findings of Helo and Hao (2016), Francisco and Swanson (2018), and Srinivasan and Swink (2018), who emphasize the visibility-enhancing role of digital platforms in reducing latency and enabling faster decision-making.

The impact of IT on Supply Chain Resilience (IT → SCR) is both significant and profound, with a beta value of 0.826 ($t = 22.940$, $p < 0.001$). This is supported by the Dynamic Capabilities Theory, which asserts that firms must reconfigure resources to respond to environmental changes (Teece et al., 1997; Dubey et al., 2020). The result corroborates Pettit et al. (2010) and Brandon-Jones et al. (2014), who affirm that IT usage significantly contributes to agility, redundancy, and recovery planning.

The relationship between SCV and SCP (SCV → SCP) is statistically significant ($\beta = 0.590$, $t = 11.132$, $p < 0.001$). Enhanced visibility allows firms to synchronize supply and demand, reduce the bullwhip effect, and improve delivery accuracy. This supports the arguments of Caridi et al. (2010) and Koçoğlu et al. (2011), who highlight that visibility reduces uncertainty and promotes efficient resource allocation, thereby driving performance excellence.

Similarly, the path from Supply Chain Resilience to Supply Chain Performance (SCR → SCP) yields a positive and significant coefficient of 0.262 ($t = 7.930$, $p < 0.001$). This finding reiterates that resilience—marked by preparedness, adaptability, and swift recovery—enables firms to maintain service levels despite external shocks. The result aligns with Ponomarov and Holcomb (2009), Mandal (2017), and Scholten and Schilder (2015), who affirm that resilient supply chains outperform less prepared counterparts in turbulent environments.

The model also supports several mediating and sequential effects:

SCV mediates the IT–SCP relationship (Indirect Effect = 0.326, $p < 0.001$): This suggests that IT influences SCP not only directly but also by enhancing visibility, which in turn improves performance. This aligns with Fayezi et al. (2017) and Zhong et al. (2016), who established the indirect pathway through which IT capabilities translate into performance gains via visibility.

SCR mediates the IT–SCP relationship (Indirect Effect = 0.216, $p < 0.001$):This effect further validates the resilience-building capacity of IT systems.he findings echo those of Chowdhury and Quaddus (2017) and Dubey et al. (2019), who confirmed resilience as a critical mediator in performance frameworks.

A sequential mediation through SCV and SCR (IT → SCV → SCR → SCP) is also statistically supported (Indirect Effect = 0.020, $p < 0.001$), though the effect size is relatively modest. The result confirms that visibility enhances resilience, which in turn drives performance. This layered relationship confirms the cascading influence of digital capability development, as earlier noted by Christopher and Peck (2004) and Kamalahmadi and Parast (2016).

In conclusion, all hypothesized paths are statistically supported, reinforcing the theoretical premise that Information Technology serves as a strategic enabler of both visibility and resilience, which in turn enhance supply chain performance. These insights offer robust empirical support for the strategic integration of IT in supply chain management frameworks, particularly within the evolving digital landscape of emerging economies

5. DISCUSSION, IMPLICATIONS, AND CONTRIBUTIONS

The findings validate that IT use greatly increases SCP ($\beta = 0.441$, $p < 0.001$), as evidenced by previous studies that associated digital technologies with operational agility, efficiency, and responsiveness (Gunasekaran et al., 2017; Dubey et al., 2021). IT has positive impacts on both SCV ($\beta = 0.603$) and SCR ($\beta = 0.568$), reflecting the value proposition of real-time information, traceability, and risk management abilities.Interestingly, both SCV and SCR act as important mediators between IT and SCP, supporting that the returns to technology investments come mainly through capability development. Further, the research establishes a sequential effect of mediation—IT → SCV → SCR → SCP—emphasizing that visibility is a crucial facilitator of resilience, driving performance in turn. This nested mechanism is a key theoretical contribution because existing research has tended to view SCV and SCR separately from each other instead of as dynamic capabilities that are interconnected.

5.1. IMPLICATIONS

Managerially, the results imply that strategic IT alignment with supply chain objectives is crucial. Companies ought not to implement technologies in separation but concentrate on integrated systems (e.g., ERP, IoT, RFID, Cloud) that facilitate cross-functional coordination. Training and change management investments are also imperative to maximize IT use. In addition, SCV's sequential role to SCR implies that managers must focus on visibility efforts prior to building resilience because the latter is a prerequisite for adaptive actions.

Policymakers can facilitate digital transformation through enabling infrastructure development, encouraging public–private partnerships, and encouraging technology uptake particularly among SMEs. This also contributes to enhanced digital supply chains, which aligns with the overarching sustainability objectives of SDG 9 (Industry, Innovation and Infrastructure).

5.2. THEORETICAL CONTRIBUTIONS

This research offers theory contributions in three ways. Firstly, it expands the RBV and DCT conceptualizations by empirically confirming SCV and SCR as mediating mechanisms that operationalize IT capabilities. Secondly, it proposes a new sequential mediation model a shift from conventional single-mediator models that sheds light on the layered construct of capability development within digital supply chains. Third, by referencing OIPT, the research underscores the significance of information-rich environments in realizing supply chain responsiveness and adaptability. Last, the integrated framework incorporates components from the Knowledge-Based View, proposing that SCV boosts knowledge flows that, in return, facilitate resilience.

5.3. PRACTICAL CONTRIBUTIONS

The study provides pragmatic recommendations for practitioners. It legitimizes IT investments by providing clear evidence of their material impacts on visibility, resilience, and performance. Supply chain executives can leverage these results in guiding digital transformation initiatives, improving supplier alignment, and mitigating risk. Technology suppliers can also benefit from the findings in the context of aligning solutions to customer performance metrics.

Policymakers can take note of digital literacy initiatives, infrastructure expansion, and regulatory environments enabling IT interoperability among supply chains.

6. CONCLUSION AND FUTURE RESEARCH

In spite of its contribution, the research is not without limitations. Cross-sectional design limits causal inference and fails to reflect temporal dynamics. The responses were self-reported, which could bring biases. Further, IT was analyzed as a composite construct; subsequent research could break down the effects of discrete technologies . The research primarily conducted for FMCG and manufacturing industries in India can also restrict generalizability.

Future studies might bridge these gaps by using longitudinal designs, making cross-country or sectoral comparisons, and investigating moderating factors like culture and leadership. Multi-level models that capture data across various organizational levels would yield deeper insights. Adding environmental and social measures may also enhance the understanding of IT's value to sustainable supply chain systems.

CONFLICT OF INTERESTS

None.

ACKNOWLEDGMENTS

None.

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