

DIGITAL SUPPLY CHAIN INTEGRATION: UNLEASHING THE POWER OF TECHNOLOGY TO ENHANCE SUPPLY CHAIN PERFORMANCE

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Abstract—The objective of the study is to develop a comprehensive scale and empirical validation of the model as an instrument for validity assessment of Digital Supply Chain Management (DSCM) dimensions by considering decision factors in determining supply performance. Based on the study of Indian production facilities, this paper studies five supply chain performance attributes: reliability and responsiveness for operational vs strategic perspectives; agility for flexible operations; cost as a management approach to identifying key processes potentially impacting costs at multiple levels within a system and assets utilisation for managing resources. The data were collected by a structured questionnaire from 152 employees to support the literature-based model investigating DSCM processes and their performance areas. The data was processed through Structural Equation Modeling (SEM) and Factor Analysis as an important implication for supply chain managers and researchers interested in optimising performance measures in the Indian manufacturing domain.

Keywords—SEM, CFA

I. INTRODUCTION

Supply Chain Management (SCM) involves comprehensive and systematic coordination of strategic planning, implementation, and supervision to ensure the efficient flow of goods from origin to destination. This requires seamless collaboration among multiple stakeholders, including vendors, entrepreneurs, distributors, merchants, and consumers, to guarantee the timely and cost-effective delivery of goods. The efficiency of SCM holds the utmost importance for businesses, as it enables process optimisation, cost reduction, heightened customer satisfaction, and a competitive edge in the constantly evolving global marketplace [1]. believe that “a supply chain consists of all parties involved, directly or indirectly, in fulfilling a customer request. Within each organisation, such as a manufacturer, the supply chain includes all functions in receiving and filling a customer request. These functions include, but are not limited to, new product development, marketing, operations, distribution, finance, and customer service” [2].

The Digital supply chain integrates digital technologies to boost visibility, efficiency, and collaboration from procurement to delivery. This optimisation aims to reduce costs, respond effectively to market demands, and foster stronger relationships with

partners & customers through data sharing and seamless communication. Additionally, digital supply chains enable flexible production, allowing quick adjustments to volumes, configurations, accurate demand forecasting and inventory management to optimise production schedules, minimising stockouts and enhancing overall sector performance [3].

This paper undertakes an empirical validation of the Digital Supply Chain through a two-fold approach. Firstly, the DSCM constructs are validated within the context of an Indian production unit. Secondly, the positive impact of the models on supply chain performance is tested. To accomplish our objectives, a conceptual model rooted in the existing literature and a survey were conducted among Indian production companies. Two fundamental research questions guide the research:

- RQ-1. How does the implementation of Digital Supply Chain Management (DSCM) processes impact the performance of the supply chain in Indian production facilities, considering performance indicators?
- RQ-2. What is the relationship between Digital Supply Chain Management (DSCM) processes, validated through a literature-based model, and supply chain performance by considering decision-making elements influencing the performance?

II. REVIEW OF LITERATURE

There is now a digital transformation (DT) taking place in the industrial supply chain as a result of the rising use of digital technology. By boosting its agility, DT ensures that the supply chain continues to function effectively regardless of whether the surrounding environment is calm or otherwise turbulent. There has been a growing amount of study conducted on the use of digital technologies and the ways in which these technologies influence supply chains. Despite this, there is not yet a complete theoretical framework that can incorporate all of the different applications, ramifications, and benefits that these technologies make available. It is our suggestion that data network technology (DT) might be used to improve supply chain performance by enhancing the capabilities of supply chain resilience (SCRes) and robustness (SCRob). This would help to reduce the gap that exists between supplies. This may be accomplished in a number of ways, one of which is by adapting the concept of the effect of the data network to the environment of the supply chain. We carried out a survey on a massive scale, gathered data from it, and then used a technique known as partial least squares

structural equation modeling (PLS-SEM) to analyze the findings in order to validate our hypothesis. The results provide evidence that DT has a positive influence on the efficiency of supply chain operations, and they also provide evidence that SCRob and SCRes play a mediating role in this relationship. Our objective is to provide a fresh theoretical perspective on the influence of supply chain data networks to the ongoing discussion on distributed ledger technology (DT) in the context of supply chains [4-5].

A plethora of technologies are the driving force behind the advancements in supply chain management and digital breakthroughs. These include, but are not limited to, technologies such as artificial intelligence and robotics, blockchain technology, cloud computing, augmented reality, radio frequency identification, the internet of things, 3D printing, and advanced analytics. In the last section of the study, the researchers address how the rising digitization of the sector may be used to the applications of 5G technology [6].

III. ADVANCEMENT OF THE INDIAN PRODUCTION DEVELOPMENT SECTOR PERSPECTIVE

The recent advancements in the Indian production sector have marked substantial growth, significantly contributing to the nation's economic progress. This sector has played a pivotal role in job creation, fostering innovation, and propelling the nation forward. According to official data, India's industrial production experienced a remarkable 5.7 per cent growth in July, reaching a five-month high. This upturn is attributed to the commendable performance of the manufacturing, logistics, mining, and energy sectors. The Index of Industrial Production (IIP) indicated a growth of 2.2 per cent in July 2022, reflecting the sector's positive momentum. Notably, the manufacturing sector exhibited a robust growth of 4.6 per cent in July 2023 compared to 3.1 per cent in the previous year. However, there was a decline of 2.7 per cent in consumer durables output, contrasting with a 2.3 per cent growth in the corresponding period last year. Infrastructure and construction goods experienced a notable growth of 11.4 per cent, surpassing the 4.8 per cent expansion recorded in the same period a year ago. These statistics underscore the potential for improvement in production units, prompting further exploration in this direction. They collectively highlight the dynamic evolution of the Indian production development sector, showcasing a promising trajectory of technological prowess, significant economic contributions, and a steadfast commitment to sustainable practices in the current era[7-10].

IV. MODEL DEVELOPMENT

A literature review analysis was conducted, considering 459 research papers from different sources by referring to Emerald Insight, Wiley Publications, Scopus, and UGC Care. The tabulated analysis of construct extraction and support from various authors are presented below.

TABLE 1: CONSTRUCTS EXTRACTION WITH AUTHORS REFERENCES

S. No.	Constructs	Reference
1	Predictive Analytics	[5], [6], [7]
2	Warehouse Automation	
3	Smart Logistics-4.0	
4	Real-Time Planning	
5	Supply Chain Cloud	

V. CONSTRUCT EXPLANATION

Predictive Analytics: Utilizes algorithms and real-time data structures to forecast future demand, enabling businesses to make proactive decisions and optimise inventory levels. **Warehouse Automation:** Implements robotics and automated systems to enhance efficiency and speed in warehouse operations, reducing labour costs and improving overall supply chain performance. **Smart Logistics 4.0:** Integrates IoT, and data analytics to create an intelligent and interconnected ecosystem, enhancing visibility, and responsiveness throughout the SC's. **Real-Time Planning:** Enables instantaneous adjustments to supply chain processes based on live data, fostering agility and allowing businesses to adapt quickly to changes in demand, disruptions. **Supply Chain Cloud:** Utilizes cloud-based platforms to centralise and share supply chain data, promoting collaboration, scalability, and accessibility while enhancing overall transparency and responsiveness in the SC network. In the DSC, decision-making elements are critical factors that shape the overall performance of the SCM. A well-crafted digital strategy enhances visibility, responsiveness, and agility, contributing to a high-performing supply chain. Digital supply chain integration with the decision-making element of a Supply chain is as follows:

TABLE 2: PREDICTIVE ANALYTICS

S. No.	DSCM-Dimensions	Predictive Analytics - Decision-Making Elements of Supply Chains	Reference
1	Demand Forecasting	Using historical data and algorithms to predict future demand aids in better planning and inventory management.	[5], [8], [6], [9]
2	Capacity Planning	Predictive models to forecast production and resource allocation, for improving operational efficiency.	
3	Supplier Performance	Analyzing supplier data to anticipate potential disruptions, ensuring reliable sourcing, and mitigating supply chain risks.	
4	Supplier Demand	Predicting supplier order patterns to optimise inventory.	
5	Predictive Maintenance	Sensor data and machine learning to predict equipment failures, reduce downtime, and improve production schedules.	
6	Quality Control	Predictive models to identify defects early, preventing production delays and minimising product recalls.	
7	Transportation	Predicting shipping requirements and potential delays, optimising	

		routes, and reducing transportation costs.	
8	Last Mile Delivery	Data can be used to enhance delivery scheduling and tracking for improved customer service and satisfaction.	

TABLE 3: WAREHOUSE AUTOMATION SCALE ITEMS

S.No.	DSCM-Dimensions	Warehouse Automation - Decision-Making Elements of Supply Chains	Reference
1	Demand Forecasting	Automation tools analyze historical data and real-time inputs to predict demand, optimising inventory planning accurately.	[5], [8], [6], [9]
2	Resource Planning	Automation systems allocate resources efficiently based on demand forecasts and workload analysis.	
3	Order Processing	Automated order fulfilment systems process and prioritise incoming orders, reducing lead times errors.	
4	Inventory Management	Automation helps monitor inventory levels and implement just-in-time inventory strategies.	
5	Material Handling	Automated conveyors, robotics, and AGVs (Automated Guided Vehicles) move materials and components in production.	
6	Production Scheduling	Self-driven real-time adjustments to production schedules, optimising manufacturing lead times.	
7	Order Picking	Automated order picking through robotics and pick-to-light systems, increasing accuracy and speed.	
8	Shipping and Tracking	Automation aids in label printing, parcel sorting, and shipment tracking, ensuring timely and error-free deliveries.	

TABLE 4: SMART LOGISTICS-4.0 SCALE ITEMS

S.No.	DSCM-Dimensions	Smart Logistics Incorporating - Decision-Making Elements of Supply Chains	Reference
1	Demand Sensing	Advanced data analytics and IoT sensors leading to accurate demand forecasting and adaptive planning.	[5], [8], [6], [9]
2	Network Optimization	Intelligent logistics systems optimise supply chain networks using AI algorithms, considering multiple variables for efficient planning.	
3	Supplier Collaboration	Real-time data sharing and blockchain technology enhance supplier transparency and collaboration, improving sourcing efficiency.	
4	Supplier Risk Management	Innovative logistics tools monitor supplier data and external factors, mitigating risks and ensuring continuity in the supply chain.	

5	Smart Manufacturing	IoT-enabled devices and data analytics optimise production processes & manufacturing operations.	
6	Quality Assurance	Intelligent sensors and AI inspect products in real time, minimising delays during the manufacturing process.	
7	Real-Time Tracking	IoT sensors and GPS tracking enable end-to-end visibility of shipments, facilitating efficient last-mile delivery and customer notifications.	
8	Autonomous Delivery	Smart logistics integrate autonomous vehicles and drones for quick and cost-effective deliveries, enhancing delivery speed and accuracy.	

TABLE 4: REAL-TIME PLANNING SCALE ITEMS

S.No.	DSCM-Dimensions	Real-Time - Decision-Making Elements of Supply Chains	Reference
1	Dynamic Demand Forecasting	Real-time data algorithms update demand forecasts, continuously enabling more accurate planning.	[5], [8], [6], [9]
2	Adaptive Inventory Management	Real-time planning adjusts inventory levels based on demand fluctuations and supply chain disruptions, optimising stock levels.	
3	Real-time Supplier Collaboration	Immediate data sharing and communication with suppliers for agile sourcing decisions, ensuring a resilient supply chain.	
4	Instant Supplier Performance Monitoring	Real-time tracking of supplier metrics to identify and address potential issues, maintaining high-quality sourcing.	
5	Agile production Scheduling	Real-time planning allows rapid adjustments to production schedules, accommodating changing priorities and reducing lead times.	
6	Shop Floor Visibility	Real-time monitoring of production processes and equipment enhances efficiency, identifies bottlenecks, and optimises manufacturing.	
7	Dynamic Route Optimization	Utilising real-time traffic and delivery data to optimise delivery routes, reducing transportation costs and delivery time frames.	
8	Real-Time Shipment Tracking	Providing customers with live tracking updates for their orders, improving transparency and customer satisfaction.	

TABLE 6: SUPPLY CHAIN CLOUD SCALE ITEMS

S.No.	DSCM-Dimensions	Supply Chain Cloud - Decision-Making Elements of Supply Chains	Reference
1	Cloud-based Demand Planning	Utilizing cloud platforms for collaborative demand forecasting, facilitating data sharing and consensus-driven planning.	

2	Integrated Sales and Operations Planning	Cloud-based tools allow real-time alignment of sales and operations teams, ensuring efficient planning cycles.	[5], [8], [6], [9]
3	Cloud-Based Collaboration	Enabling seamless information exchange and document sharing with suppliers, improving procurement efficiency.	
4	Supplier Performance Analytics	Cloud-based analytics provide insights into supplier performance, helping identify top-performing sourcing partners.	
5	Cloud-Based Manufacturing Execution System	Leveraging cloud technology for real-time monitoring of production processes and optimising shop floor operations.	
6	Collaborative Product Development	Cloud platforms foster cross-functional collaboration, expediting new product introductions and reducing time-to-market.	
7	Cloud-Based Warehouse Management	Managing real-time inventory and fulfilment processes, enhancing order delivery accuracy and speed.	
8	Last Mile Delivery Optimization	Cloud-powered route planning and real-time tracking improve last-mile delivery efficiency and customer experience.	

VI. PERFORMANCE ATTRIBUTES

Reliability: measures the consistency and predictability of supply chain processes, ensuring timely and accurate product or service delivery. A reliable supply chain, therefore, is believed to minimise lead times and variability, both crucial elements for 'time-sensitive' industries. **Responsiveness:** focuses on the supply chain's agility in adapting to changes in customer demand or market conditions, dynamic markets and gaining a competitive advantage[10]. **Agility** examines a SC's ability to quickly reconfigure processes to handle unexpected changes while ensuring effective disruption management and seizing opportunities. **Costs** are a vital performance attribute involving optimising SC's expenses through process enhancements, lean practices, and supplier collaboration, crucial for competitiveness and profitability[10]. **Asset Management Efficiency:** assesses how effectively a SC manages assets like inventory, equipment, and facilities, aims to reduced holding costs and improved operational efficiency[11].

VII. HYPOTHESES DEVELOPMENT

The hypothesis relating to Digital Supply Chains and Supply Chain performance suggests that incorporating advanced digital technologies and data-driven processes in supply chain operations can optimise the performance of supply chains. By utilising technologies like Predictive Analytics, Warehouse Automation, Smart Logistics-4.0, Real-Time Planning, and Supply Chain Cloud, digital supply chains are expected to improve efficiency, visibility, agility, and collaboration throughout the entire supply chain network. As a result, this should lead to

reduced lead times, minimised costs, optimised inventory management, and ultimately heightened customer satisfaction. [5].

- Predictive Analytics → H1-Predictive Analytics significantly impact performance.
- Warehouse Automation → H2-Warehouse-Automation significantly impacts performance.
- Smart Logistics-4.0 → H3-Smart Logistics significantly impacts performance.
- Real-Time Planning → H4-Real-time Planning significantly impacts performance.
- Supply Chain Cloud → H5-Supply Chain Cloud significantly impacts performance.

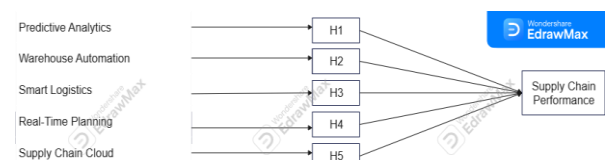


FIGURE 1 - HYPOTHESIS DEVELOPMENT

VIII. RESEARCH METHODOLOGY

❖ Questionnaire design/research instrument

The research tool employed in this investigation was devised after thoroughly examining pertinent literature, as outlined in Table 2-4. We incorporated various methodologies, encompassing an analysis of numerous iterations of the Supply Chain process.

❖ Sample size and data collection

Of the respondents from production units and establishments in India, 252 were approached to build a representative sample; however, only 152 responded, focusing on domains like business supply chain management, production, and delivery. A selection process identified respondents from SCM areas. The data collection process utilised nominal and interval scales for the selected groups. We captured the respondents' demographic profiles using a nominal scale, while item measurement employed the interval scale. The response rate was 60.31 per cent, reflecting the respondents' breakdown by company size.

❖ Data analysis

11.3.1 Sample Characteristics. Based on data, 48.7% of respondents were employed in private limited companies, while 39.5% were employed in public sector companies and 9.9% in government-owned PSU corporations in India. The establishment years of companies varied from approximately 16.8% to 0.1%; establishment years less than 5 is 16.8%, 05-10 is 41.1%, 11-20 is 34.5%, and 21-30 years is 1.0%.

❖ Test of reliability

We assessed the reliability of the survey instrument for the DSCM framework using Cronbach's alpha[11]. The framework includes Predictive Analytics, Warehouse Automation, Smart Logistics-4.0, Real-Time Planning, and

Supply Chain Cloud. Cronbach's alpha generally determines the internal consistency of construct items, ensuring they effectively measure a single construct. In terms of its scores, [12] proposed reliability to be categorised as unacceptable if $\alpha < 0.70$, fair if $0.70 \leq \alpha < 0.80$, good if $0.80 \leq \alpha < 0.90$, and finally, excellent if $\alpha \geq 0.90$. As regards our findings, the average values, standard deviations, and Cronbach's α coefficients for DSCM modules within the Indian production sector do indicate a satisfactory level of reliability ($\alpha = 0.94$) for the 40 proposed DSCM constructs with loadings above or equal to 0.50.

❖ Test of Validity

Based on [13] and [14], we used three critical parameters to assess discriminant validity. They include factor correlations, maximum shared variance (MSV), average shared variance (ASE), and the square root of AVE compared to inter-construct correlation values below 0.80, as suggested by [15]. Our results reveal that MSV values are consistently lower than the mean shared variance of the factors. The statistical analysis in Table 7 demonstrates that the square root of AVE surpasses inter-construct correlations, establishing discriminant validity for all latent constructs [6].

TABLE 7: CONVERGENT-DISCRIMINANT VALIDITY INDEX

Constructs-DSCM	C-R	AVE	MSV	MaxR-(H)	Warehouse Automation	Predictive Analytics	Smart Logistics	Real-Time Planning	Supply Chain Cloud
Warehouse Automation	0.913	0.549	0.272	0.928	0.741				
Predictive Analytics	0.884	0.508	0.091	0.919	0.302	0.713			
Smart Logistics	0.895	0.5	0.272	0.919	0.522	0.286	0.707		
Real-Time Planning	0.89	0.601	0.193	0.946	0.439	0.215	0.283	0.775	
Supply-Chain Cloud	0.874	0.537	0.169	0.914	0.411	0.29	0.24	0.269	0.733

The content and construct validity of the DSCM process were assessed by confirmatory factor analysis (CFA) loadings. Content validity measures how well the survey items measure against intended constructs. To evaluate the 't' test, a Confirmatory Factor Analysis (CFA) for model fit construct validity and Structural Equation Modeling for marginal analysis and variability of different samples. In this study, the goodness-of-fit indexes that we used were a χ^2 statistics to degree of freedom ratio ($\chi^2/\text{d.f.}$) $< 2-1$ and Comparative Fit Index (CFI) must be at least 0.90 as well as a Root Mean Square Error of Approximation value no more significant than 0.08 concerning Table 8, confirms that all five constructs achieved an adequate level of goodness-of-fit results. Initially, data were subjected to factor analysis using SPSS software, employing principal

component analysis as the extraction method and varimax with Kaiser Normalization rotation as the rotation method, which converged after 19 iterations. Six items were eliminated during this process, thereby meeting the criteria of eigenvalues exceeding 1 while demonstrating an acceptable level of total variance explained among the 34 items. Then, we conducted CFA with structural equation modelling (SEM) using AMOS 24.0 to establish the scale's validity. Following recommendation, the items with factor loadings below 0.50 were eliminated, reducing the initial 40 items to a final set of 34 items. We achieved one of our primary research objectives by identifying 34 items and categorising them into five constructs relevant to the core processes of demand and supply chain management (DSCM).

TABLE 8: CONSTRUCT VALIDITY TEST OF VARIOUS SCALES

Scale	No. of parameters	Standardise Regression Weight	Goodness of Fit Indices				
			CFI	NFI	GFI	AGFI	CMIN/DF
Predictive Analytics	7	.551-.831	0.951	0.841	0.856	0.78	1.364
Warehouse Automation	8	.592-.784					
Smart Logistics-4.0	8	.642-.720					
Real-Time Planning	5	.765-.793					
Supply Chain Cloud	6	.719-.830					

Authors argued that determining an acceptable model fit, as indicated by various indices, depends on factors like sample sizes, data type, and acceptable score ranges. However, proposed that utilising the (CFI) Comparative Fit Index and (RMSEA) Root Mean Square Error of Approximation in single-instance analyses is more

favourable for substantiating the considered SEM framework. We documented most of the goodness of fit measures from the model fit summary obtained using AMOS 24.0, as shown in Table 8.

IX. RESULT AND DISCUSSION

The results indicate that digital supply chain integration, powered by advanced technologies such as AI, IoT, and blockchain, significantly enhances supply chain performance. Companies that have adopted digital solutions report improved visibility, faster decision-making, and reduced operational costs. The integration of real-time data analytics and automation has led to more efficient inventory management, streamlined logistics, and better demand forecasting. The discussion highlights that

while digital transformation offers substantial benefits, challenges like cybersecurity risks, data privacy concerns, and the high costs of implementation need to be addressed. Overall, the findings suggest that digital integration is key to creating agile, efficient, and resilient supply chains capable of adapting to dynamic market conditions. Based on the structural equation modelling (SEM) analysis, all path coefficients show statistical significance at 0.05, with t-values exceeding 2.0, indicating their robustness. Consequently, all hypotheses are accepted, except for the Supply Chain Cloud.

TABLE 9 - DSCM RESULTS SHOWING IMPACT ON SUPPLY CHAIN PERFORMANCE

DSCM Impact on Performance	Path Coefficient	S.E.	t-value	P	Status
Predictive Analytics → Performance	0.21	0.063	3.351	***	H1-Accepted
Warehouse Automation → Performance	0.332	0.063	5.254	***	H2-Accepted
Smart-Logistics-4.0 → Performance	0.304	0.069	4.386	***	H3-Accepted
Real-Time Planning → Performance	0.184	0.054	3.383	***	H4-Accepted
Supply-Chain Cloud → Performance	-0.007	0.059	-0.124	0.902	H5-Rejected

Comparable research methodologies and statistical techniques, such as Confirmatory Factor Analysis (CFA), SEM, and multiple regression, have been utilised by various studies [19]. Predictive analytics, warehouse automation, intelligent logistics, and real-time planning processes positively affect supply chain performance. The digitalisation of supply chains helps streamline it while optimising inventory management, reducing lead times, improving demand forecasting accuracy, coordination & communication among stakeholders, and reducing delays. These results of our study concur with studies by [5] and [20], while empirically proving that DSCM significantly impacts SCM performance and increases the scope of automation and intelligent monitoring capabilities that lead to reduced errors, thereby minimising operational costs and benefitting from enhanced transparency and efficient DSCM.

X. CONCLUSIONS

The research analysed the relationship among DSCM attributes by emphasising the SCs within Indian production facilities. Our findings underscore the importance of DSCM in optimising the management of the entire supply chain to empirically evaluate the DSCM model within the context of the production sector in India. The results do have far-reaching ramifications for professionals working in the domain of SCM that aligns with the principles of digital supply chain governance. As proposed, the conceptual frameworks of DSCM and performance metrics of the Indian production industry tend to exhibit significant interconnections with various facets of logistics industry,

handling distribution, exchange of information, supplier relationships, inventory control, and purchasing business operations.

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