



THE IMPACT OF DIGITAL TRANSFORMATION ON SUPPLY CHAIN PERFORMANCE & FINANCIAL PERFORMANCE: THE MEDIATING EFFECTS OF SUPPLY CHAIN RESILIENCE AND SUPPLY CHAIN ROBUSTNESS IN THE MANUFACTURING SECTOR

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KEYWORDS	ABSTRACT
Digital Transformation, Supply Chain Resilience, Supply Chain Robustness, Supply Chain Performance, Financial Performance, Data Network Effect, Manufacturing Sector, PLS-SEM.	Due to the adoption of many digital technologies, the international industrial supply chain undergoes digital transformation (DT). In complex and simple environments, it allows maintaining its high performance, increasing its agility. By extending the concept of the data network to the supply chain, this study seeks to fill this research vacuum by suggesting that the improved robustness and resilience of the supply chain is a manifestation of the DT effect. To determine the relationships and effects, a thorough survey was carried out and PLS-SEM analysis was carried out. The sample size for the current study comprised 257 respondents from manufacturing companies across China Mainland. The results revealed that DT (digital transformation) positively influenced the supply chain's performance, whereas SCRE (supply chain resource efficiency) and SCRO (supply chain operational efficiency) were partial mediators. The results further revealed that DT had a positive and significant influence on SCRE ($\beta = 0.579$, $p < 0.001$) and SCRO ($\beta = 0.553$, $p < 0.001$). In addition, the results showed that SCRE ($\beta = 0.295$, $p < 0.001$) and SCRO ($\beta = 0.493$, $p < 0.001$) positively and significantly influenced the supply chain performance. Moreover, the results revealed that the mediation effect of SCRE and SCRO of the relationship between DT and supply chain performance was statistically significant. By offering a fresh theoretical conceptualization of the data network impact in the supply chain, this article helps to address and consider the problem of digital transformation of supply chains. The findings obtained allow supply chain managers to actively participate in the process of digitalization and adopt new technologies, as well as identify capabilities for building supply chain resilience to disruptions. The practical significance of the current research is reflected in the ability to find a strategic solution for employing digital tools to make supply chains productive and competitive.
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Introduction

Background of the Study

The worldwide industrial SC (Supply Chain) is now undergoing a digital revolution, driven by the advancement of a wide range of digital technologies. Such changes lead to an adaptable supply chain, thus enhancing the robustness of companies against disruptions and their operational success (Wu, 2024). During the COVID-19 pandemic, over 70% of supply chain executives across a range of sectors reported significant supply chain disruptions, with food and consumer goods seeing 100% interruptions (McKinsey, 2020). Hence, firms have realized the importance of digital transformation (DT) to improve their performance after the pandemic (Cui, 2022 & McKinsey, 2020). Within the scope of Industry 4.0, organizations are transforming their SCM, strategy and operation to meet the customers' expectations by using digital technology (Hahn, 2020). DT is viewed as a process of integrating strategy transformation and digital technologies as enablers (Hess, 2016; Faruquee, 2021). DT has been shown to improve competitive performance (Wamba & Guthrie, 2019), sustainability (Benzidia, 2021), and innovation (Mikalef & Gupta, 2021) when used appropriately.

Problem Statement

Enhancing competencies like SCRE and SCRO in parallel is not an easy task, although current digital technologies are considered to be promising (Appio, 2021). The pandemic's destructive effects and geopolitical threats have made DT and the development of SCRE and SCRO a top priority for supply chain and company strategic planning. DT, which is defined as the use of several digital technologies, is converting unprocessed, all-encompassing data into useful organizational resources. This continuous cycle of aggregation, assessment, learning, and conversion of data is identified by (Gregory, 2021) as a "data network effect," where the larger the amount of information is generated within the firm; the more it is beneficial for consumers.

Gap Analysis

The majority of the research on supply chain capabilities and digital transformation comes from developed nations and contexts where enterprise lives under the pressures of formal regulations, technology-driven processes and stable institutional environments. The evidence in low-income countries is limited and often clustered in particular institutional settings. There is little research on how DT and supply chain competencies simultaneously affect organizational performance and financial outcomes in emerging economies. Additionally, more study on the function of supply chain competences as a mediator between DT and performance is required. International literature suggests that technology-enabled processes and supply chain capabilities are critical for converting digitalization efforts into performance outcomes (Wu, 2024 & Eslami, 2024) and this mediation role has not been adequately tested in developing economies neither in the post-COVID era.

Objectives of the Study

Following the identification of the research topic, this study aims to achieve the following goals:

- To investigate the impact of digital transformation on supply chain performance in the manufacturing industry.
- To investigate how supply chain robustness and resilience affect financial performance.
- To examine the impact of the implementation of digital transformation on the level of SCRE and SCRO of manufacturing companies.

Research Questions

The current study aims to respond to the following research questions:

RQ1: What are the effects of embracing digital transformation technologies on the exploitation of supply chain resilience and robustness capabilities for manufacturers?

RQ2: How far does the link between digital transformation and supply chain performance become moderated by supply chain resilience and robustness capabilities?

RQ3: Does the performance of the supply chain benefit from the digital transformation?

RQ4: Does the link between supply chain performance and digital transformation depend in any way on supply chain resilience?

RQ5: Does the link between supply chain performance and digital transformation become moderated by robustness capability?

RQ6: In what ways do supply chain resilience and robustness capabilities impact financial performance?

RQ7: What are the influences of data network effects on enabling digital transformation in the context of supply chains?

Review of Literature

Theoretical Framework

Data-Driven Digital Transformation

The process of creating value for an organization through transformative changes enabled by information, computing, communication and connectivity technologies is “digital transformation”, one of the main concepts of Industry 4.0 (Vial, 2019, p. 121). First, DT was defined as “a generic strategic response to improvement initiatives or new business models that better exploit emerging digital opportunities” (Fitzgerald et al., 2013). Much has happened since then with respect to DT. This may result in new products/services or new forms of production. (Feliciano-Cestero et al., 2023) Moreover, if the strategic and capability-driven approach is well adopted, DT can “lead to

significant changes in organizational design and in the ways a company interacts with its stakeholders” (Feliciano-Cestero et al., 2023). Therefore, it can be safely asserted that DT is critical for supply chains to be customer-centric networks with value co-created through constant exchange of data (Ngo et al., 2023). These supply chains have a higher level of efficiency that can only be achieved through the use of information and better decision making.

Data Network Effect

Data network effects are phenomena whereby a platform gains value for its users through accumulating data from its users through its learning capabilities (Gregory et al., 2021)). The data network effect is present if two conditions identified by Gregory et al. (2022) are met. First, all members of the platform should benefit from improvements in the platform’s utility enabled by the system learning from data. Second, the improvements must be made at a pace that leaves the platform with a value that is significantly higher than it would have been without the network effects.

Supply Chain Resilience and Robustness

The ability to adapt to different conditions and manage changes is a typical feature of agile supply chains (Aslam, 2018). The capability of the supply chain is one advantage of putting digital transformation (DT) into practice, as the data network effect concept, to perform consistently under various conditions. However, the ability to manage and perform successfully under different conditions, especially in complex networks, can be associated with two different concepts of supply chain resilience (SCRE) and supply chain robustness (SCRO) (Wu et al., 2024).

Table 1 Comparison of SCRE and SCRO

Dimension	Supply Chain Resilience (SCRE)	Supply Chain Robustness (SCRO)
Focus	Recovery from disruptions	Withstanding disruptions
Response Type	Reactive, radical changes	Proactive, small adjustments
Objective	Return to original or better state	Maintain performance without changes
Supporting Capabilities	Flexibility, resource reconfiguration, recovery	Continuous improvement, risk prevention, variance absorption
Approach	Post-disruption response	Pre-disruption preparation
Time Horizon	Short-term recovery	Long-term stability

Empirical Data on How Supply Chain Performance Is Affected by Digital Transformation

The capacity of the company to meet customer demands for product/service availability and prompt delivery at the lowest possible cost is known as supply chain performance, or SCP (Belhadi, 2021).The problem of continuous logistics and balancing of supply-demand relations is extremely acute in the situation of emergency. In this context, information needed for the performance of these essential functions must be generated, processed and disseminated with the utmost speed and

reliability. It is also important that this information is suitably formatted and disseminated through the supply chain network for maximum SCP in emergencies.

Digital Transformation and Supply Chain Competence

As discussed in the previous section, a set of key competencies is needed to develop agile supply chain capabilities such as supply chain resilience (SCRE) and supply chain robustness (SCRO). These are the capability of scanning and sensing the environment and the capability to interpret the results of scanning and to respond appropriately. Better data stewardship can improve the capabilities with different digital technologies (Wu et al., 2024). Especially, the data network effects in digital transformation (DT) enable supply chains to collect and analyze a large amount of market data.

Supply Chain Capabilities and Performance Outcomes

The network effects of data that are enabled by digital technologies, that is, enhanced supply chain resilience (SCRE) and supply chain robustness (SCRO), can all contribute to sustaining and improving supply chain performance (SCP) by both supporting processes during disruptions and facilitating operations under normal conditions. While SCRE represents the supply chain's ability at both the chain and individual level to respond to the disturbance, recover, and adjust its functions flexibly (Gu et al., 2021), SCRO is geared towards reducing exposure to disruptions and building the power to prevent them (Wieland and Wallenburg, 2012).

Evidence from Developing-Country and Cross-Country Studies

Further data about the ways by which digital transformation (DT) impacts performance comes from studies carried out in various developing-country contexts. In particular, the analysis of several studies on the adoption of DT in manufacturing firms in emerging economies highlights the role of a firm's own characteristics and the accompanying institutional context in shaping the process. The findings from cross-country analyses also generally support the proposed mechanisms, highlighting the importance of advanced technologies and improved logistics in supply chains that adopt digitalization to perform better. At the same time, aggregated findings from the studies provide only limited insight into the relative effects of different areas of DT and the ways in which they might be applied within firms and their supply chains, as they typically utilize aggregated data on the level of countries. For this reason, the current research employs the evidence base at the level of firms to obtain a more detailed insight into the mechanisms involved.

Measurement Gaps and Implementation Challenges

The literature search and the case study conducted identified a number of digital transformation implementation challenges. The research on manufacturing companies showed that these businesses opt to use digital procurement, production, distribution and logistics functions as the result of pressure from international clients and government and not as a strategic initiative for competitive advantage. Moreover, the benefits of such transformational projects are poorly assessed. In the literature search of digital transformation in developing countries, it was pointed

out that, although most organizations try to adopt the new technologies, they are still at early stages and do not integrate them holistically into their supply chains but utilize them as an additive. Evidence on the performance of digital transformation is also scarce and conflicting. Therefore it can be concluded that in these countries digital transformation is predominantly used as a compliance tool and not as a transformative force that drives disruptive value.

Conceptual Framework and Hypotheses

Based on the literature research conducted for the study, a conceptual framework is presented. The research makes the assumption that supply chain and financial performance are impacted both directly and indirectly by digital transformation. Supply chain robustness and resilience have a mediating role in realizing the indirect impact. The hypotheses are grounded in the findings from previous studies regarding the effects of digital transformation. Earlier results have shown that digital transformation positively impacts performance. Additionally, the findings showed that the link between supply chain performance and digital transformation is mediated by supply chain capabilities.

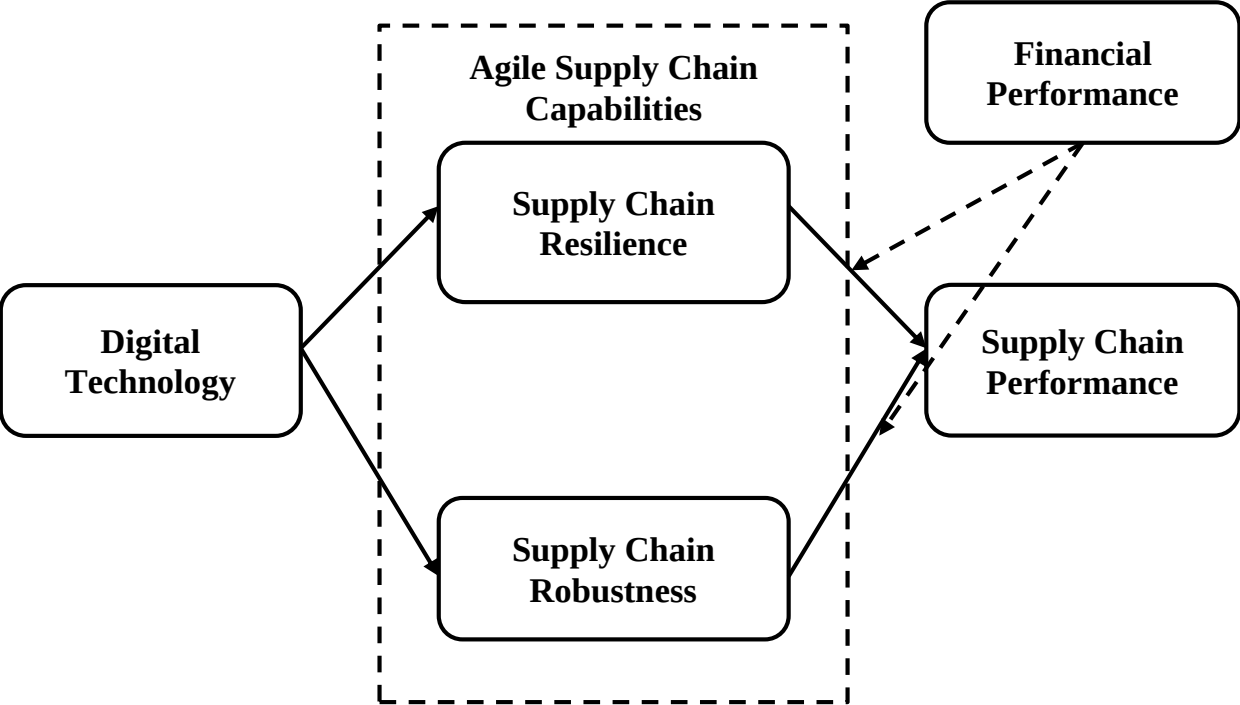


Figure 1 Conceptual Framework

Hypothesis Development

H1: Digital Transformation has a positive effect on Supply Chain Performance.

H2: Supply Chain Resilience mediates the relationship between Digital Transformation and Supply Chain Performance.

H3: Supply Chain Robustness mediates the relationship between Digital Transformation and Supply Chain Performance.

H4: Digital Transformation has a positive effect on Supply Chain Resilience.

H5: Digital Transformation has a positive effect on Supply Chain Robustness.

H6: Supply Chain Resilience has a positive effect on Supply Chain Performance.

H7: Supply Chain Robustness has a positive effect on Supply Chain Performance.

H8: Supply Chain Resilience has a positive effect on Financial Performance.

H9: Supply Chain Robustness has a positive effect on Financial Performance.

Research Methodology

Research Design

A research paradigm is a meta-framework that holds a set of assumptions that support a study. Ontology, Epistemology and Methodology Egon Guba & Yvonna Lincoln (1994) define the concepts as follows: Methodology relates to the methods used in a research, ontology to the nature of reality, and epistemology to the nature of knowledge. The current study follows the positivist research paradigm which assumes ontology as objective reality and accepts the role of measurement in accessing the objective knowledge. The paradigm follows a scientific approach that studies relationships between objects by focusing on deduction strategies and testing of theoretical propositions (Creswell, 2014 & Saunders, 2019).

Research Strategy

Using a quantitative research approach, the current study seeks to determine the link between digital transformation, supply chain resilience and responsiveness capabilities, supply chain performance, and company financial performance. This study is suitable for a quantitative research design because it enables the researcher to investigate the relationship between pre-selected variables by collecting verifiable data and analyzing them statistically (Creswell and Creswell, 2018). This study specifically uses a deductive research design where pre-defined hypotheses are postulated to find out the extent of the link amongst the variables. The philosophical basis of this study is realism, which argues that there is an objective reality and there is a need to observe and measure physical occurrences to generate information and knowledge about the phenomenon. The present study is deductive as it allows for the development of theories from empirical research and the testing of the initial hypotheses (Saunders et al., 2019).

Normality Test

Normality test was performed. There are several statistical procedures for evaluating normality in quantitative studies including Kolmogorov-Smirnov (K-S) test, Shapiro-Wilk test and Skewness-Kurtosis test. According to (Hair, 2022) and the skewness values should be between -1 and +1, and the Kurtosis values should be between -5 and +5 for data to be considered normal. The larger the sample size, the more non-normal data can be tolerated because of the central limit theorem (Field, 2021). On the other hand, normality test is not required in PLS-SEM analysis as the technique is considered to be ‘robust’ to non-normality data. To guarantee the validity and dependability of the findings, it is crucial to assess the data set’s normalcy (Hair, 2022). Thus, various indicators like Skewness, Kurtosis and statistical plots should be used to determine if data follow a normal distribution with mean, median and mode occurring at same point, a bell-shaped curve that is symmetric about the mean, a standard deviation of 1, and a mean of 0.

Design of Questionnaires

For this research, a self-administered questionnaire was created. To guarantee dependability and content validity for this research, items were taken from previously established and validated questionnaires. All items were measured using Likert scales, which are commonly used in management research to measure perception and behavior (Creswell & Creswell, 2019). In particular, a scale of 1 to 5 was applied where 1 was defined as “strongly disagree” and 5 as “strongly agree.” The objects were contextualized to the context of supply chain management and digitalization. The use of scales is appropriate to establish construct validity (Creswell & Creswell, 2019). It is also recommended that structured questionnaires be used for quantitative research to reduce inconsistencies (Saunders et al., 2020). Moreover, several items are proposed to measure each construct because they capture the complexity of the latent variables (Hair, 2022).

Table 2 Sources of Questionnaire Items

Constructs	Code	No. of Items	Scholars Citation
Digital Transformation	DT	5	Faruquee, 2021
Supply Chain Resilience	SCRE	4	Golgeci & Ponomarov, 2013
Supply Chain Robustness	SCRO	4	El Baz & Ruel, 2021
Supply Chain Performance	SCP	7	Gu, 2021
Financial Performance	FP	4	Eslami, 2024

Sampling and Collecting Data

The sample will include the professional and managerial staff of the manufacturing and supply chain organizations that are ready to adopt digitalization and implement Industrial 4.0 strategies. The target audience includes supply chain managers, operation managers and production supervisors as they have a better understanding of the functioning of the organization which will help answer the proposed research questions. Data will be collected via survey using paper

questionnaires and hand-held devices. A short introductory paragraph will be given explaining the objectives of the study and confidentiality of the respondents will be maintained.

Target population and sampling frame

The study will be centered on professional and managerial employees working in manufacturing and supply chain companies who are involved in the adoption and use of digital technologies. Respondents are supply chain managers, operations managers, production supervisors, logistics managers and other professional experts who are already implementing or have already implemented digital transformation in the supply chain. The purposive sampling technique will be used (Hair, 2022 & Saunders, 2019). The respondents will be selected based on specific criteria that affect the final results and have information about digital transformation in supply chains. The sampling frame will be composed of firms from the manufacturing, logistics and technology industries, who have undergone digital transformation to meet specific objectives.

Sampling Method

The study will adopt purposive sampling as a method of selecting participants. The sampling procedure will be appropriate for use in a judgment-based survey, where participants should be individuals with specialized or expert knowledge of the subject matter (Saunders et al., 2019; Sekaran & Bougie, 2021). The research will specifically focus on production supervisors, supply chain managers, and operation managers who have integrated digital transformation technology into their companies. The main advantage of using this sampling method is that it will enable the researcher to identify information-rich cases, which are typically useful in establishing relationships between variables (Saunders, 2019 & Bougie, 2021). Besides, purposive sampling is regarded as the preferred strategy for qualitative studies, particularly in management and supply chain research areas where professional managers and experts are involved in the study (Hair et al., 2022; Creswell & Creswell, 2018).

Sample Size

In August 2022, 760 Mainland Chinese industrial companies were randomly selected to receive the survey. Following four courteous reminder emails and a two-and-a-half-month collection period, 257 valid responses—or 33.8% of the total—were obtained from the 760 surveys. For the purposes of this study, the sample size of 257 valid responses is sufficient. This is because of the “10-times rule” (Hair, 2022) that the sample size should be ten times the number of indicators in the measurement model with the most items – in this example, constructs. Second, Sarstedt et al. (2022) and Kline (2016) recommend 150 or more observations for SEM studies to yield statistically significant results with a strong generalization performance.

Data Collection Method

The survey questionnaire and the cover letter, which explained the aim of the study, the instructions for filling out the questionnaire and the assurance of confidentiality were sent out to potential participants by e-mail. All quality control procedures recommended (Schoenherr et al.,

2015) were followed during data collection. The population of interest for this study consisted of senior-level executive managers or department heads of operations, supply chain, production, or procurement within a specified company since they are best positioned to provide the most detailed and elaborate information about their company’s digital technology use and operations management practices.

Measurement methodology

An instrument was developed, tested for its content validity and reliability and earlier validated measures in the literature were also used for this study. Each component’s measurement items were based on a five Likert response scale from 1 to 5, with 1 representing strongly disagree and 5 representing strongly agree (Likert, 1932; Hair et al., 2022). The survey measurement items were as follows: Digital Transformation (DT): We measure DT by asking people who participated to what extent their supply chains have adopted artificial intelligence, big data analytics, the internet of things, blockchain technology, and cloud computing technologies according to Faruquee et al. 2021. The following five items were used in this study.

Supply Chain Resilience (SCRE): Four items were used to measure the ability of the firms’ supply chains to restore quickly to normal conditions following disruption, maintain essential links, have control capabilities consistent with the supply chain’s scope and rapid return to normal operations following (Wong, 2020 & Ponomarov, 2013). Supply Chain Robustness (SCRO): The items that measure the ability of the supply chain to keep normal operations, to allow for appropriate response time, to operate effectively under different alternative conditions without modifications, and to continue performing the functions for which they were designed in the face of disruptions are adopted based on the definition by (El Baz & Ruel, 2021). The four items below were used in this study. Supply chain performance (SCP): (Gu, 2021) measured the extent of the supply chain supporting fast adaptation of existing products/services, introduction of new products/services, shortening of time periods, general speed to perform a task, knowledge management for the supply chain, on-time delivery and assistance to clients, with seven items. Financial Performance (FP): Four metrics profit, market share, return on investment, and return on assets were used to evaluate the company’s financial performance in relation to its three primary rivals (Eslami, 2024).

Table 3 Operationalization of the Study Constructs

Construct		Indicator codes	No. of items	Measurement focus
Digital Transformation (DT)		DT1-DT5	5	Adoption of AI, blockchain, cloud computing, IoT, big data analytics
Supply Chain Resilience (SCRE)		SCRE1-SCRE4	4	Recovery from disruptions, connectedness, control, recovery knowledge
Supply Chain Robustness (SCRO)		SCRO1-SCRO4	4	Operational stability, reaction time, performance stability, function maintenance

Supply Chain Performance (SCP)	SCP1-SCP7	7	Speediness, knowledge, on-time delivery, customer service, product modification
Financial Performance (FP)	FP1-FP4	4	Profit growth, market share growth, ROI, ROA

Data Analysis

Before undertaking structural modelling analysis, an initial stage of screening the data was performed using IBM-SPSS Statistics, in order to determine data quality and suitability for analysis. Initially, missing data, outliers, and inconsistencies were looked for in the data. The data set was then coded and cleaned for analysis. Descriptive statistics for the data were collected and reported as means, standard deviations, frequencies and percentage distributions for the relevant respondent groups.

Mediation Analysis

In order to determine if SCORE and SCRO mediate the association between digital transformation and SCP and FP, respectively, mediation analysis was performed in this research using PLS-SEM. This entails testing for indirect effects in the structural model (Hair, 2022 & Sarstedt, 2022). Indirect effects were estimated by the bootstrap approach with 5000 resamples. The bootstrap method is recommended for the evaluation of the indirect effects, because it makes less assumptions about the sampling distribution, and provides unbiased estimates with good coverage properties (Preacher & Hayes, 2008; Hair et al., 2022). The indirect effects of all of the mediation paths, DT → SCORE → SCP, DT → SCORE → FP, DT → SCRO → SCP, and DT → SCRO → FP, were tested. The indirect effects were defined based on the coefficients of each indirect path and their t-statistic and p-value (Henseler et al., 2015).

Results and Data Analysis

Profile of Demographic

The demographic profile of the participants is informative in terms of providing background statistics of the sample under consideration. This allows the evaluation of representativity of the data and generalizability of results. This section provides descriptive information about demographic characteristics of the 257 participants. Data was collected from industrial companies based in Mainland China through a standardized questionnaire. Furthermore, the present section provides an insight into the distribution of respondents across different categories of industry, workforce sizes, revenues, forms of ownership, tenure and job positions.

Table 4 Demographic Profile of Respondents (n = 257)

Demographic Variable	Category	Frequency (N)	Percentage (%)
Industry	Electrical machinery and equipment	44	17.10%
	Special equipment	35	13.60%
	Metal, mechanical and engineering	83	32.30%
	Building materials and furniture	12	4.70%
	Food, beverage, alcohol and cigarettes	22	8.60%
	Chemicals and petrochemicals	16	6.20%
	Fabric	25	9.70%
	Rubber and plastics	9	3.50%
	Others	11	4.30%
Number of Employees	<21	2	0.80%
	21-300	56	21.80%
	301-1000	108	42.00%
	1001-2000	31	12.10%
	2001-3000	19	7.40%
	>3000	41	16.00%
Sales (mRMB)	<5	6	2.30%
	10-May	17	6.60%
	Oct-50	50	19.50%
	50-100	75	29.20%
	100-300	49	19.10%
	>300	60	23.40%
Ownership	Private	140	54.50%
	State-owned	52	20.20%
	Joint venture	49	19.10%
	Foreign	16	6.20%
Tenure (years)	5-Jan	23	9.00%
	10-Jun	61	23.70%
	15-Nov	62	24.10%
	16-20	60	23.40%
	>20	51	19.80%
Position	CEO	9	3.50%
	Senior managers/departmental heads	248	96.50%

Descriptive Statistics

Below are descriptive statistics of each indicator. These statistics include the mean and standard deviation of the responses. The standard deviation reflects the variation in respondents' responses while the mean reflects the average response of respondents. The two statistics help us understand how spread out and how clustered the data is, which is crucial for further analysis.

Table 5 Descriptive Statistics

Variable	Item	Mean	Median	SD	Min	Max
Digital Transformation	DT1	1.4	1	0.73	1	5
	DT2	1.84	2	0.79	1	5
	DT3	1.86	2	0.74	1	5
	DT4	1.64	1	0.85	1	5
	DT5	1.73	2	0.81	1	5
Financial Performance	FP1	1.88	2	0.62	1	4
	FP2	2.04	2	0.73	1	4
	FP3	2.08	2	0.79	1	5
	FP4	2	2	0.83	1	5
Supply Chain Performance	SCP1	1.63	1	0.84	1	5
	SCP2	1.91	2	0.85	1	5
	SCP3	1.92	2	0.79	1	5
	SCP4	2	2	0.78	1	5
	SCP5	1.98	2	0.76	1	5
	SCP6	1.88	2	0.8	1	5
	SCP7	1.85	2	0.82	1	5
Supply Chain Resilience	SCRE1	1.97	2	0.94	1	5
	SCRE2	2.06	2	0.81	1	5
	SCRE3	2.11	2	0.86	1	5
	SCRE4	2	2	0.88	1	5
Supply Chain Robustness	SCRO1	2.06	2	0.98	1	5
	SCRO2	2.37	2	1	1	5
	SCRO3	2.38	2	1.11	1	5
	SCRO4	2.19	2	1.05	1	5

Evaluation of the Measurement Model

Validity of the Measure

The reliability of indicators refers to the degree to which the measurement items or indicators utilized actually measure the underlying constructs of concern. Usually, the reliability of the indicators is tested by calculating outer loadings, which measure the relationships between the indicators and the constructs. Since they account for less than half of the variation, indicators with outer loadings less than 0.7 should be eliminated from the study (Hair, 2019).

Table 6 Outer Loadings

Construct	Indicator	Loading	Decision
Digital Transformation	DT1	0.838	Retained
	DT2	0.778	Retained
	DT3	0.733	Retained
	DT4	0.82	Retained
	DT5	0.81	Retained
Financial Performance	FP1	0.733	Retained
	FP2	0.735	Retained
	FP3	0.782	Retained
	FP4	0.793	Retained
Supply Chain Performance	SCP1	0.809	Retained
	SCP2	0.775	Retained
	SCP3	0.745	Retained
	SCP4	0.716	Retained
Supply Chain Resilience	SCRE1	0.863	Retained
	SCRE2	0.809	Retained
	SCRE3	0.803	Retained
Supply Chain Robustness	SCRO1	0.824	Retained
	SCRO2	0.735	Retained
	SCRO3	0.843	Retained

Dependability: Internal Coherence

The consistency of a series of items intended to assess the same notion is examined by internal consistency reliability. Internal consistency reliability was assessed using the Composite Reliability (CR) Coefficient and Cronbach's alpha (see Table 4). According to Hair (2019), composite reliability need to be higher than 0.7. There is no internal consistency issue in this study since the Cronbach alpha is greater than the crucial value.

Table 7 Internal Consistency Reliability and Convergent Validity

Construct	Cronbach's alpha	rho A	(rho c)	AVE	Decision
DT	0.858	0.878	0.897	0.635	Accepted
FP	0.758	0.761	0.846	0.579	Accepted
SCP	0.763	0.776	0.847	0.581	Accepted
SCRE	0.769	0.791	0.865	0.682	Accepted
SCRO	0.720	0.724	0.843	0.643	Accepted

Convergent validity

Convergent validity is the extent to which survey questions that are meant to measure a particular concept are highly correlated because they are converging on the same point. The Average Variance Extracted (AVE) is the main indicator for convergence validity, and it should be more than 0.5 (Hair, 2019). As seen in Table 4.4, all constructs had AVE above 0.5, showing convergent validity. In Table 4.4, the highest value obtained by SCRE (0.682), followed by SCRO (0.643), DT (0.635), SCP (0.581) and FP (0.579).

Legality of Discrimination

Discriminant validity, on the other hand, is the notion that two or more constructs are different and their indicators do not measure the same construct. As a result, the HTMT which is thought to be too conservative was computed. According to (Henseler, 2015) and the HTMT less than 0.85 indicates a reasonable degree of discriminant validity. In addition, the cross-validation applied the Fornell-Larcker criteria to assess the discriminant validity.

Table 8 Heterotrait-Monotrait Ratio (HTMT) – Matrix

Construct	DT	FP	SCP	SCRE	SCRO
DT					
FP	0.259				
SCP	0.719	0.453			
SCRE	0.679	0.588	0.804		
SCRO	0.683	0.699	0.918	0.908	

Fornell-Larcker Criterion

The discriminant validity of the study is tested by the Fornell-Larcker criterion. This implies that the square root of the average variance extracted for an item should be higher than inter-construct correlations (Fornell & Larcker, 1981).

Table 9 Fornell-Larcker Criterion

Construct	DT	FP	SCP	SCRE	SCRO
DT	0.797				
FP	0.215	0.761			
SCP	0.606	0.350	0.762		
SCRE	0.579	0.462	0.634	0.826	
SCRO	0.553	0.518	0.696	0.689	0.802

Cross Loadings

Cross loadings may be considered as an additional test for discriminant validity. Sufficient discriminant validity is achieved when measurement items load maximum on the intended constructs and not on others (Hair et al., 2019).

Table 10 Cross Loadings

Indicator	DT	FP	SCP	SCRE	SCRO
DT1	0.838	0.259	0.524	0.58	0.558
DT2	0.778	0.173	0.522	0.431	0.416
DT3	0.733	-0.003	0.428	0.303	0.327
DT4	0.82	0.15	0.486	0.428	0.385
DT5	0.81	0.202	0.445	0.492	0.456
FP1	0.066	0.733	0.246	0.348	0.397
FP2	0.184	0.735	0.241	0.308	0.347
FP3	0.198	0.782	0.302	0.391	0.412
FP4	0.206	0.793	0.273	0.354	0.416
SCP1	0.573	0.317	0.809	0.531	0.66
SCP2	0.569	0.253	0.775	0.519	0.547
SCP3	0.252	0.256	0.745	0.435	0.439
SCP4	0.395	0.232	0.716	0.434	0.431
SCRE1	0.548	0.468	0.621	0.863	0.675
SCRE2	0.457	0.257	0.467	0.809	0.475
SCRE3	0.412	0.393	0.458	0.803	0.528
SCRO1	0.479	0.409	0.574	0.6	0.824
SCRO2	0.437	0.375	0.524	0.496	0.735
SCRO3	0.412	0.461	0.573	0.558	0.843

Evaluation of the Structural Model

After establishing the measurement model's goodness-of-fit, we tested the structural model, which involves testing the theoretical relationships proposed in the research model. We examined effect sizes (f^2), predictive relevance (Q square), path coefficients (β) and their significance levels, coefficient of determination (R^2), and mediation effects.

SEMPLS Analysis

The fitness of the structural model was evaluated using (PLS-SEM) using SmartPLS 4.0 software. Results of PLS-SEM analysis are depicted in Figure 4. It shows the relationships of Financial

Performance (FP), Supply Chain Performance (SCP), Supply Chain robustness (SCRO), Supply Chain Resilience (SCRE) and Digital Transformation (DT).

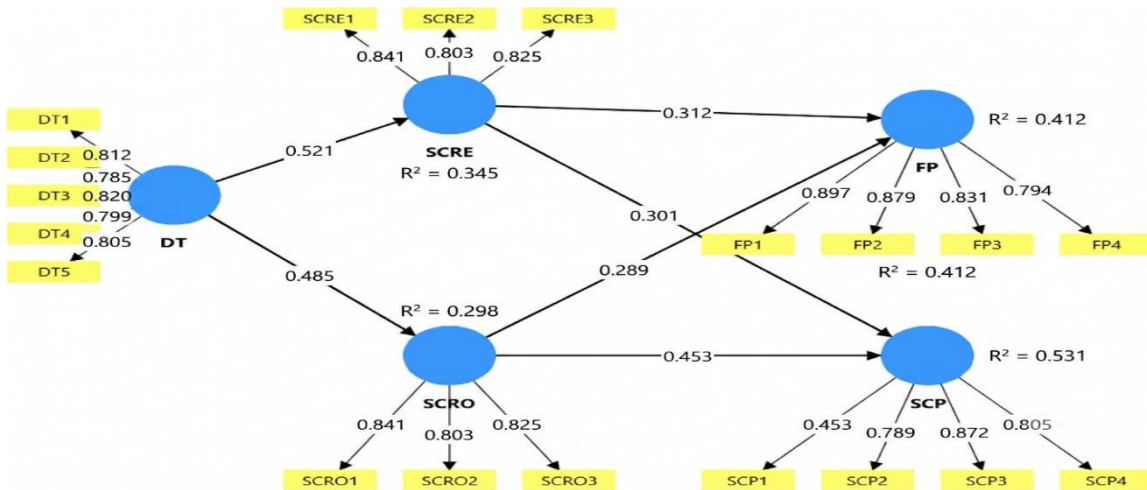


Figure 2 Structural Model of PLS-SEM.

The mediators are supply chain resilience (SCRE) and supply chain responsiveness (SCRO) with digital transformation (DT) as the exogenous variable. The endogenous variables are firm performance (FP) and supply chain performance (SCP). The path coefficients (β) indicate the magnitude and direction of the effects from these constructs.

Table 11: R-Square Values

Variable	R ²	R ² Adjusted
SCRE	0.335	0.332
SCRO	0.305	0.302
SCP	0.530	0.525
FP	0.290	0.283

This table presents the R-square values of each endogenous construct in the model. Chin (1998) classified R-square values of 0.67 as substantial and 0.33 as moderate and 0.19 as weak. Supply Chain Resilience (SCRE): The R-square of the construct is 0.335 and implying that digital transformation explains 33.5% of the variance in SCRE. The adjustment for this built is .332 and close to the R-square of .335. So we can say that the predictive importance of the model for the first construct is low.

Hypothesis Testing

The table below can represent the path coefficients and their significance. The path coefficients show the strength and direction of the relationships among constructs. Bootstrapping with 5,000 samples was used to test the significance of the path coefficients with t-statistics and p-values.

Table 12 Path Coefficients and Hypothesis Testing

Hypothesis	Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P Values	Decision
H4	DT → SCRE	0.579	0.575	0.077	7.536	0	Supported
H5	DT → SCRO	0.553	0.551	0.066	8.414	0	Supported
H6	SCRE → SCP	0.295	0.292	0.072	4.103	0	Supported
H7	SCRO → SCP	0.493	0.495	0.06	8.206	0	Supported
H8	SCRE → FP	0.2	0.203	0.106	1.896	0.058	Not Supported
H9	SCRO → FP	0.381	0.384	0.092	4.126	0	Supported
H1	DT → SCP	0.317	0.317	0.042	7.535	0	Supported

The table reports path coefficients, t statistics, p values and hypothesis test results for all direct effects included in the structural model. Path coefficients indicate both the direction and the magnitude of connection link between variables. The path coefficients are in the range of (-1 to +1). If t statistic is larger than (1.96) and it is significant at (.05) level ($p < .05$). If larger than (2.58) and then the t statistic is significant at the (0.01) and level ($p < 0.01$).

H4: DT → SCRE ($\beta=0.579$, $t=7.536$ and $p<.001$): The estimate is (0.579) and indicating that Digital Transformation has a strong positive effect on Supply Chain Resilience. The t statistic is ($7.536 > 1.96$) and the p-value is (< 0.001) which shows that the result is significant at (0.01) level. The result shows that the Digital Transformation has a positive impact on the Supply Chain Resilience and H4 Supported. The confidence interval is 95%. This means that the chance of the predicted value not being the actually observed value is 5%.

H5: DT → SCRO ($\beta = 0.553$, $t = 8.414$, $p < 0.001$): The path coefficient of this hypothesis was found to be 0.553 which indicates that the effect of Digital Transformation on Supply Chain Robustness is positive and significant at 1% level as the calculated t-value is 8.414 (> 1.96). The results support H5. The 95% confidence interval for this coefficient is [0.415, 0.661], also suggesting significance.

H6: SCRE → SCP ($\beta = 0.295$, $t = 4.103$, $p < 0.001$): The path coefficient for this hypothesis was 0.295. This means that the effect of Supply Chain Resilience on Supply Chain Performance is positive and significant at the 1% level as the calculated t-value is 4.103 (> 1.96). The finding lends support to H6. Also, the 95% confidence interval of this coefficient is [0.151, 0.419]. This also implies the significance.

H7: SCRO → SCP ($\beta=0.493$, $t=8.206$, $p<0.001$): The path coefficient of this hypothesis was 0.493. This means that the influence of Supply Chain Robustness towards Supply Chain Performance has positive and significant at 1% level because the calculated t-value is 8.206 (> 1.96). This finding

supports H7. Moreover, the 95% confidence interval of this coefficient is [0.383, 0.608], which again indicates significance.

H8: SCRE $\rightarrow$ FP ($\beta = 0.200$, $t = 1.896$, $p = 0.058$): The path coefficient of (0.200) indicates a weak positive relationship between Supply Chain Resilience and Financial Performance. The t-statistic of (1.896) is below the threshold of (1.96) and the p-value of 0.058 is above the threshold of (0.05) and showing that this connection is not statistically significant at the conventional level. The 95% confidence interval (-0.011 to 0.384) includes zero and further confirming the lack of significance. Therefore, H8 is not supported. The small effect size ($f^2 = 0.030$) also confirms that SCRE has only a small practical impact on FP.

H9: SCRO $\rightarrow$ FP ($\beta = 0.381$, $t = 4.126$, $p < 0.001$): The path coefficient of (0.381) shows a moderate positive relationship between Supply Chain Robustness and Financial Performance. The t-statistic of (4.126) is well above the threshold of (1.96) and the p-value is less than (0.001) which indicates statistical significance at the highest level. This offers a good support for H9 and proves that the Supply Chain Robustness has a positive and important effect on the Financial Performance. The 95% confidence interval (0.189 to 0.537) does not include zero, further supporting the significance of this relationship.

Mediation Analysis

Mediation analysis assesses the indirect effects of the independent variable on the dependent variables through the mediating variables. The significance of indirect effects is determined through bootstrapping with 5,000 subsamples.

Table 13 Mediation Analysis

Hypothesis	Indirect Path	Indirect Beta	Standard Error	T-Statistic	P-Value	Direct Beta	Mediation Type	Decision
H2	DT $\rightarrow$ SCRE $\rightarrow$ SCP	0.171	0.054	3.158	0.002	0.317	Partial Complementary	Supported
H3	DT $\rightarrow$ SCRO $\rightarrow$ SCP	0.272	0.048	5.613	<0.001	0.317	Partial Complementary	Supported
	DT $\rightarrow$ SCRE $\rightarrow$ FP	0.116	0.059	1.963	0.049	0.2	Partial Complementary	Supported
	DT $\rightarrow$ SCRO $\rightarrow$ FP	0.21	0.057	3.668	<0.001	0.381	Partial Complementary	Supported

H2: DT $\rightarrow$ SCRE $\rightarrow$ SCP ($\beta = 0.171$, $t = 3.158$, $p = 0.002$): The indirect effect of Digital Transformation on Supply Chain Performance through Supply Chain Resilience is (0.171) and t-statistic is (3.158) and p-value is (0.002) showing statistically significant at 1% level. The 95%

confidence interval (0.076 to 0.278) does not include zero and thus this indirect effect is significant. Both direct effect (DT → SCP, $\beta = 0.317$, $p < 0.001$) and indirect effect are significant and positive, thus the mediation is partial complementary mediation. That means that SCRE partially mediates the effect of DT on SCP and the total effect includes both the direct and indirect effects. Therefore, H2 is valid.

H3: DT → SCRO → SCP ($\beta = 0.272$, $t = 5.613$, $p < 0.001$): The indirect effect of Digital Transformation on Supply Chain Performance through Supply Chain Robustness is (0.272) t -statistic (5.613) p -value (<0.001) showing highest level of statistical significance. The 95% confidence interval (0.178 to 0.362) of the indirect effect does not include zero, suggesting that the indirect effect is significant. Both direct effect (DT → SCP, $\beta = 0.317$, $p < 0.001$) and indirect effect are significant and positive. So, the mediation is called partial contrasting mediation. This suggests that both the mediating effect of SCRO in the association between DT and SCP and the direct and indirect pathways are responsible for the total effect. Thus, H3 is supported.

Model Fitness

Model fit is concerned with how well the proposed model fits the real data. The most common fit measure in PLS-SEM is the Standardized Root Mean Square Residual (SRMR), with values below 0.08 indicating a good fit (Hu & Bentler, 1999).

Table 14 Model Fit

Metric	Saturated Model	Estimated Model
SRMR	0.087	0.112
d_ULS	1.450	2.399
d_G	0.599	0.701
Chi-square	685.022	735.383
NFI	0.667	0.642

SRMR (Saturated Model = 0.087, Estimated Model = 0.112): The SRMR values are a little higher than the recommended threshold of (0.08) indicating a moderate fit. However, for PLS-SEM SRMR values of less than (0.10) are acceptable (Hair et al 2019). The saturated model (0.087) fits better than the estimated model (0.112) which is expected because the saturated model has more parameters.

Discussion

The study extends Dynamic Capabilities Theory and the Data Network Effect perspective by showing that the performance advantages of Digital Transformation are not only limited to technological execution, but also to operational capabilities generated by the digital capabilities,

in this context SCRE and SCRO capabilities. Extension of Dynamic Capabilities Theory: Adds to the literature by clarifying the ambiguous link between digital transformation and operational performance, reinforcing its indirect and non-technological nature. Benefits that can be achieved when firms reconfigure their operational capabilities to realize such benefits. Benefits associated with digital transformation investments. The results support Teece's (2007) argument that dynamic capabilities are necessary to gain competitive advantage in rapidly changing environments.

Mediation Effects: The findings support the mediating role of operational capabilities especially SCRE and SCRO suggesting that organizational processes are important mediators for performance outcomes. This supports the theoretical premise that digital technologies alone are not sufficient for performance improvement. This research provides empirical evidence for the need of companies to develop unique supply chain capabilities to translate digital investments into performance outcomes. Data Network Effect Extension: The study revisits the existing concept of data network effects and extends its application from the platform sector to the supply chain domain. This study creatively introduces the data network effect brought by digital transformation to improve the traditional characteristics of supply chain risk evaluation (SCRE) and supply chain risk optimization (SCRO) in supply chain management. This complements the work of Gregory et al. (2021) that offers evidence of data network effects across different contexts including supply chains.

Simultaneous Capability Development: The study makes a contribution by integrating the literature on digital transformation with the SC and operations management theory & gives a framework to explain the effect of DT on performance by providing a structured capability development framework. It shows that SCRE and SCRO can be developed simultaneously through DT. This challenges the view that firms must choose between efficiency-oriented and flexibility-oriented strategies. Differentiated Performance Impact: The results of the research show that SCRE and SCRO have different effects on financial performance, namely SCRO has a direct effect and SCRE has an indirect effect. This complex finding contributes to the understanding of the effects of different supply chain capabilities on organizational outcomes. This means that companies should focus on different skills according to their strategic goals.

These empirical findings justify a number of operational suggestions for managers and decision-makers. Integrate Digital and Capability Strategies: Managers should consider digital requirements as an integral part of the capability development process, rather than as separate initiatives. The findings point to the fact that companies need to focus on SCRE and SCRO capabilities in implementing digital technologies because these capabilities seem to be essential tools that allow turning digital investments into quantified operational performance improvements. Managers ought to consider the incorporation of digital tools in the capability management in order to achieve operational efficiency and better coordination within the supply chain.

Conclusion

The objective of this research is to investigate the impact of digital transformation adoption on supply chain performance and the mediating role of supply chain robustness and resilience. The findings indicate that DT is a major driver for the development of SCRE and SCRO capabilities,

which expresses the change brought by the digital technologies to supply chain management. The results show that the Digital Transformation is a significant contributor to the advance of SCRE and SCRO capabilities. This reflects the change that digital technologies bring to SCM. The use of DT can be particularly related to SCRE and SCRO practices, implying that advanced digital technologies, including big data analytics, automation and cyber-physical systems, can support the activities of the supply chains to be more efficient, transparent, and integrated. These findings can be compared with existing research that emphasizes the necessity of digital transformation as a facilitator for organizations to fine-tune their supply chain operations, and achieve new levels of operational performance (Ivanov 2019 & Naik, 2023).

The results also highlight the significance of SCRE & SCRO practices in enhancing operations' performance. It was found that SCRE and SCRO would be important mediating factors between adoption of DT & SC performance. Which means that the value of digital transformation is maximized when operational strategies are used to achieve resilience and robustness. The researcher found that SCRO practices were statistically significant on the financial performance. On the other hand, SCRE was not statistically significant. This is a great contribution to previous research that has implied that supply chain capabilities are a prerequisite to financial performance. The outcomes indicate that robustness may have a more direct effect on financial outcomes while resilience may have an indirect effect through SC performance. Additionally, the literature has conflicting evidence on the impact of supply chain resilience on financial performance, indicating that the effectiveness of resilience is based on context-dependent, organization-specific factors.

Recommendations

Integrate Digital and Capability Strategies: Managers should consider digital requirements as an integral part of the capability development process, rather than as separate initiatives. The findings point to the fact that companies need to focus on SCRE and SCRO capabilities in implementing digital technologies because these capabilities seem to be essential tools that allow turning digital investments into quantified operational performance improvements. Managers ought to consider the incorporation of digital tools in the capability management in order to achieve operational efficiency and better coordination within the supply chain.

Strengthen (SC) Partnerships: Companies must to build SCRE and SCRO capabilities through more robust partnerships with technology providers and empirical evidence has shown a link between digital activities and improved resilience and robustness. For the sake of the coordination in the supply chain and the operational efficiency, the managers should take into account the integration of the digital tools in the capability management. **Invest in Supply Chain Capabilities:** Organizations should invest in supply chain capabilities by encouraging data-driven ideas, process redesign and the allocation of resources towards digital process development. Lean operational strategies should be invested in technologies that will reduce waste, streamline operations and enhance the overall operation performance.

Future Research Directions

Longitudinal Designs: One could investigate whether the performance gains in DT are incremental. Longitudinal studies would give an insight into the process of digital transformation over time, as researchers would have an opportunity to observe the changing correlations between the implementation of technology and the results of its operation. Earlier studies indicate that supply chain processes and digital competencies are not automatically expedited and may not impact immediately on operations at different phases (Ivanov, 2019; Sony and Naik, 2023).

Sector-Specific Research: May assess whether the same model performs differently in manufacturing, services, healthcare or construction. Studies of specific sectors can examine whether the same model performs differently in different sectors. Cross-national research can be useful in studying the effects of the contextual variables such as the state of technology infrastructure, business readiness and institutional support.

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