https://doi.org/10.34074/rere.00502

Research Article

Strengthening Manufacturing Resilience: A Data-Driven Analysis of Key Supply Chain Enablers

Chunxue (Lynn) Ma, Jishuo (Jimmy) Sun, and Bing Dai

OTAGO POLYTECHNIC AUCKLAND INTERNATIONAL CAMPUS

ABSTRACT

Manufacturing supply chains face growing risks from events such as pandemics and climate-related disruptions, making supply chain resilience (SCR) increasingly essential for business continuity and competitiveness. This study adopts a quantitative research approach to examine the factors influencing SCR, drawing on a large dataset of manufacturing firms. Grounded in the dynamic capability view, the analysis focuses on key variables, such as supplier collaboration, lead time, transportation cost efficiency, supply chain complexity, and SCM practices. Using a combination of statistical techniques, including t-tests, ANOVA, correlation, and regression analysis, the study finds that stronger supplier collaboration and more efficient transportation significantly enhance resilience, while longer and more variable lead times reduce it. Notably, well-managed supply chain complexity also contributes positively to SCR. The findings advance theory by linking operational metrics to dynamic capabilities and offer practical guidance for improving resilience through logistics optimisation, collaboration, and data-driven planning. Overall, the research highlights SCR as a measurable and strategic capability essential for sustaining manufacturing performance in uncertain environments.

Keywords: Supply chain resilience, Manufacturing, Data analytics, Dynamic capabilities, Supplier collaboration

INTRODUCTION

Manufacturing is the backbone of the global economy, driving technological innovation, employment, and global trade. According to the United Nations Industrial Development Organisation (2024), manufacturing accounted for around 20% of the world's gross domestic product (GDP) in 2024. The key economic role of the sector was demonstrated by the industry's roughly 40% share of the GDP in China, which was much higher than the worldwide average (ChinaPower, 2023). However, several incidents, such as the COVID-19 pandemic and unprecedented climate-related disruptions, have shown how vulnerable the global industrial supply chain is (Khanzad & Gooyabadi, 2021; Um & Han, 2020). These disruptions promote the industrial demand for supply chain resilience (SDR). SCR has been scholarly defined as the ability to anticipate, absorb, and recover from disruptions while maintaining acceptable performance levels, and it has emerged as a critical performance metric (Loh & Tan, 2024). ElKhouly et al. (2020) suggested that strong SDR is essential for manufacturing companies that compete in turbulent markets to ensure production continuity, maintain competitiveness, and meet stakeholder expectations. The rise of Industry 4.0 technologies has greatly expanded the application opportunities of data analytics in the manufacturing industry (Saad et al., 2023). Manufacturers can systematically collect, integrate, and interpret vast amounts of data, effectively applying data analytics to maintain a competitive advantage (Pinochet et al., 2021). Decisions supported by data analytics are often timelier and more accurate, helping manufacturers optimise management decisions, enhance their ability to cope with uncertainty, and strengthen resilience (Kamble & Gunasekaran, 2020; Thirathon et al., 2022).

In the manufacturing sector, SCR is especially crucial since it helps manufacturers maintain operations and recover quickly from shocks (Ivanov & Dolgui, 2020). Particularly for the internationally interconnected manufacturers, SCR has transformed from a reactive measure to a strategic competence, guaranteeing long-term performance under uncertainty (Pettit et al., 2019; Tarigan et al., 2021). By employing a quantitative research approach, the objectives of this paper are to 1) identify the key factors that affect SCR and 2) put forward targeted recommendations to help manufacturers cope with challenges and support decision-making.

LITERATURE REVIEW

Supply Chain Resilience

SCR is widely considered a key capability for businesses to withstand and recover from interruptions while maintaining continuity. The common definition of SCR is the ability to anticipate, absorb, and recover from unfavorable events while maintaining acceptable performance levels (Loh & Tan, 2024; Wu et al., 2024). Zhou et al. (2024) categorise SCR into internal and external types, noting their differing emphases on threat mitigation. However, the scope and emphasis of SCR vary considerably across studies. For example, Um and Han (2021) conceptualise resilience as a dynamic capability that enables firms to reconfigure resources proactively, whereas Mwangola (2018) views resilience as a reactive capacity for recovery. This divergence reflects ongoing debates about whether resilience should be regarded primarily as an adaptive, proactive competence or as a set of reactive practices.

Many scholars have stressed the importance of effective supply chain management (SCM) for businesses in the manufacturing sector. Selepe and Makinde (2024) suggested that poor supply chain quality may cost manufacturing companies up to 55% of total product costs. SCR is a crucial criterion for assessing SCM as it improves the capacity to continue operating in the face of interruptions while advancing important SCM goals. SCR is an integrated capacity inside SCM that improves operational continuity, agility, and flexibility rather than existing as a stand-alone idea (Loh & Tan, 2024). SCM tactics, including supplier cooperation, internal integration, and visibility, are also now commonly acknowledged as key components of SCR (Asamoah et al., 2020; Zhou et al., 2024). Hussain et al. (2022) claim SCR promotes adaptability and proactive risk management in SCM. SCM activities, such as procurement, sourcing, logistics, and production, rely on a resilient infrastructure to mitigate risk and recover from disruptions (Tarigan et al., 2021; Wu et al., 2024). Businesses with strong SCM frameworks, supported by real-time data, a large supplier base, and backup plans, for example, were able to maintain service levels in the face of systemic shocks during the COVID-19 pandemic (Ivanov & Dolgui, 2020). Thus, developing SCR is essential for long-term competitiveness as well as reducing supply chain risks for manufacturers.

This study draws on the dynamic capabilities perspective, which explains how firms sustain competitiveness in turbulent environments through their capacity to a) sense opportunities and threats, b) seize them through timely resource commitments, and c) transform their structures and processes to remain aligned with changing conditions (Teece, 2007). Within this framework, SDR can be interpreted as an outcome of dynamic capabilities, as resilient firms continually sense potential disruptions, seize appropriate response options, and transform operational routines to maintain continuity. The concept of adaptive capacity captures the ability of organisations and supply chains to adjust, reorganise, and evolve when confronted with stress and uncertainty (Folke et al., 2010). Adaptive capacity represents the practical manifestation of dynamic capabilities by shaping how quickly and effectively firms adjust their operations. Accordingly, the factors examined in this study, such as supplier collaboration, digitalisation, internal integration, organisational culture, sustainability practices, and supply chain complexity, are viewed as enablers of adaptive capacity that reflect underlying dynamic capabilities driving resilience outcomes.

Key Enablers of SCR

Several enablers of SCR have been highlighted in prior studies. Supplier collaboration is one of the most frequently cited drivers of resilience, as close and transparent relationships with suppliers build trust, facilitate information sharing, and support joint problem-solving. These relational mechanisms enable firms to respond more quickly and effectively when facing disruptions, reducing recovery time and stabilising operations (Asamoah et al., 2020). Digitalisation and IT capabilities also represent a critical determinant of resilience. Emerging technologies, such as artificial intelligence, blockchain, and big data analytics, provide firms with advanced decision-making tools, predictive models, and real-time monitoring capabilities (Lin & Karia, 2024; Taha et al., 2025). This allows them to anticipate risks, detect early warning signals, and allocate resources more effectively during crises (Taha et al., 2025) . In addition, internal integration strengthens resilience by fostering coordination and information flow across functional departments. High levels of integration reduce silos, streamline processes, and enable more coherent decision-making, thereby enhancing the organisation's ability to adapt to changing circumstances (Tarigan et al., 2021).

Beyond these operational enablers, organisational and strategic orientations also shape resilience. Organisational culture has been identified as a determinant of SCR, since the effectiveness of technology adoption depends on cultural values that encourage openness, adaptability, and learning. Without complementary organisational and cultural changes, new technologies may fail to translate into greater resilience (Gani et al., 2022; Shah et al., 2023). Similarly, sustainability-oriented management practices, including those aligned with environmental, social, and governance (ESG) principles, enhance resilience by reinforcing stakeholder trust, building social capital, and promoting long-term cohesion across supply chain partners (Wu et al., 2024). Another determinant is supply chain complexity (SCC), defined as the degree to which supply chains are composed of numerous and diverse elements that interact in unpredictable ways (Akin, 2022; Bode & Wagner, 2015; Bozarth et al., 2009). Complexity can manifest in large and diverse supplier bases, heterogeneous internal processes, or varied customer requirements, each of which increases uncertainty and coordination challenges. However, SCC can also enhance resilience by providing redundancy, access to diverse knowledge resources, and greater adaptive capacity (Akin, 2022).

Digital Technologies for Data Analytics in SCR

The application of technology for data analytics in SCR research has expanded in recent years, with various methods employed to investigate resilience drivers and outcomes. In the past decade, digitalisation has consistently emerged as a key development trend for industrial SCM (Liu & Chiu, 2021). Supply Chain 4.0 can be seen as the application of the Industry 4.0 concept, providing the foundation and data support for the digital SCM (Lin & Karia, 2024; Liu & Chiu, 2021). Emerging digital technologies, including AI, big data, blockchain, and digital twins, have also been integrated into SCR research, supporting quick decision-making (Shah et al., 2023; Taha et al., 2025). Big data analytics is a collection of data, analytical tools, computer algorithms, and techniques to derive meaningful insights and patterns from large industrial datasets (Kamble & Gunasekaran, 2020). Some scholars have even defined supply chain digitalisation as technology that integrates all supply chain functions of manufacturing to improve decision-making and management levels (Lin & Karia, 2024). Companies that are unprepared to capture these digital and technological advancements are likely to be left behind (Bai et al., 2020). In summary, digital technologies help industrial enterprises capture large amounts of real data in the supply chain, providing a solid foundation and foundation for data-driven resilience strategies.

Recent studies have applied a variety of data analytics methods to investigate SCR. Descriptive and diagnostic approaches have been used to summarise resilience characteristics and explore correlations between variables (Mahira, Santosa, et al., 2023), while regression analysis has examined the effects of factors such as integration, collaboration, and risk exposure (Huang et al., 2023; Hussain et al., 2022). Prescriptive methods have also been employed to classify firms into different resilience profiles (Um & Han, 2020; Wu et al., 2024). While these approaches provide useful insights, most remain focused on single aspects of resilience or rely on limited case-based evidence. What is still lacking is large-scale empirical research that systematically evaluates multiple operational determinants of resilience in an integrated framework. This study addresses that gap by applying various statistical techniques to a large-scale dataset of manufacturing firms, in order to offer systematic and generalisable evidence on the drivers of supply chain resilience.

METHODOLOGY

To examine factors influencing SCR, this study conducted various quantitative analyses on a real-world supply chain dataset from 999 leading manufacturing companies (Kaggle, 2024). SCR is a key factor influencing SCM and has a significant impact on operational performance for companies (Alkhatib & Momani, 2023; Budwal, 2022). In the manufacturing industry, companies are increasingly relying on intelligent systems and digital tools to improve the SCR (Rizki et al., 2022). Using authentic industry data enables the study of SCR in a realistic context, as recommended by (Um & Han, 2020). The dataset categorises companies based on implemented SCM strategies such as Just-In-Time, Cross-Docking. The dataset is also structured with both categorical and numerical variables, which enables comprehensive use of descriptive, diagnostic and predictive analytics to capture essential indicators relevant to SCR, including supplier lead time variability, collaboration levels, and transportation cost efficiency. The key variables of this dataset analysed were summarised in Table 1.

These approaches align with recent methodological recommendations to be based on real-world industry data analytics rather than hypothetical or simulated scenarios (Condon et al., 2023; Mahira, Santosa, et al., 2023). The dataset reflects consolidated records from actual firms and provides a credible foundation for analysing resilience in the manufacturing sector.

The Preparation for Data Analytics

To ensure data quality and consistency, data preparation is necessary for data analytics. The data cleaning process is the first step of the overall analytical approach of this report. Data cleaning is a critical stage in the data analytics process, as poor-quality data can lead to misleading results, unreliable patterns, and biased conclusions, including a) handling missing values, b) detecting and addressing outliers, and c) standardising data formats (Rahm, Do, et al., 2000). Research has shown that following established cleaning procedures ensures that downstream analyses are based on consistent and reliable inputs (Elmobark, 2024). These cleaning steps can improve the reliability and validity of subsequent statistical procedures (Mahira, Santosa, et al., 2023).

Justification of Relevant Variables for SCR

Variables related to SCR were carefully selected following initial data preparation and informed by theoretical support. Drawing on the dynamic capability view and incorporating relevant literature (e.g., Teece, 2007; Zhou et al., 2024), this study identified supplier collaboration, SCM practices, lead time, transportation, and supply chain complexity

Table 1: Key Variables of the Dataset

NO.	*Variable*	*Description*	*Datatype*
1	SCM Practices	Supply Chain Management strategy adopted	Categorical
2	Supplier Count	Number of suppliers used	Numerical
3	Lead Time (days)	Average time taken to receive supplies	Numerical
4	Customer Satisfaction (%)	Customer satisfaction rating	Numerical
5	Supplier Lead Time Variability (days	Variability in lead time across suppliers	Numerical
6	Transportation Cost Efficiency (%)	Efficiency in transportation costs	Numerical
7	Supply Chain Complexity Index	Complexity level of the supply chain	Categorical
8	Supplier Collaboration Level	Level of collaboration with suppliers	Categorical
9	Supply Chain Resilience Score	Score indicating the resilience of the supply chain	Numerical

as core factors of SCR. For example, supplier relationships reflect the dynamic capabilities of the external supply chain, while transportation efficiency influences the responsiveness of the entire supply chain and is also the most susceptible to disruptions. Lead time factors reflect the timeliness of the supply chain. Therefore, this selection of variables reflects both operational realities and the theoretical conception of SCR as a dynamic strategic capability.

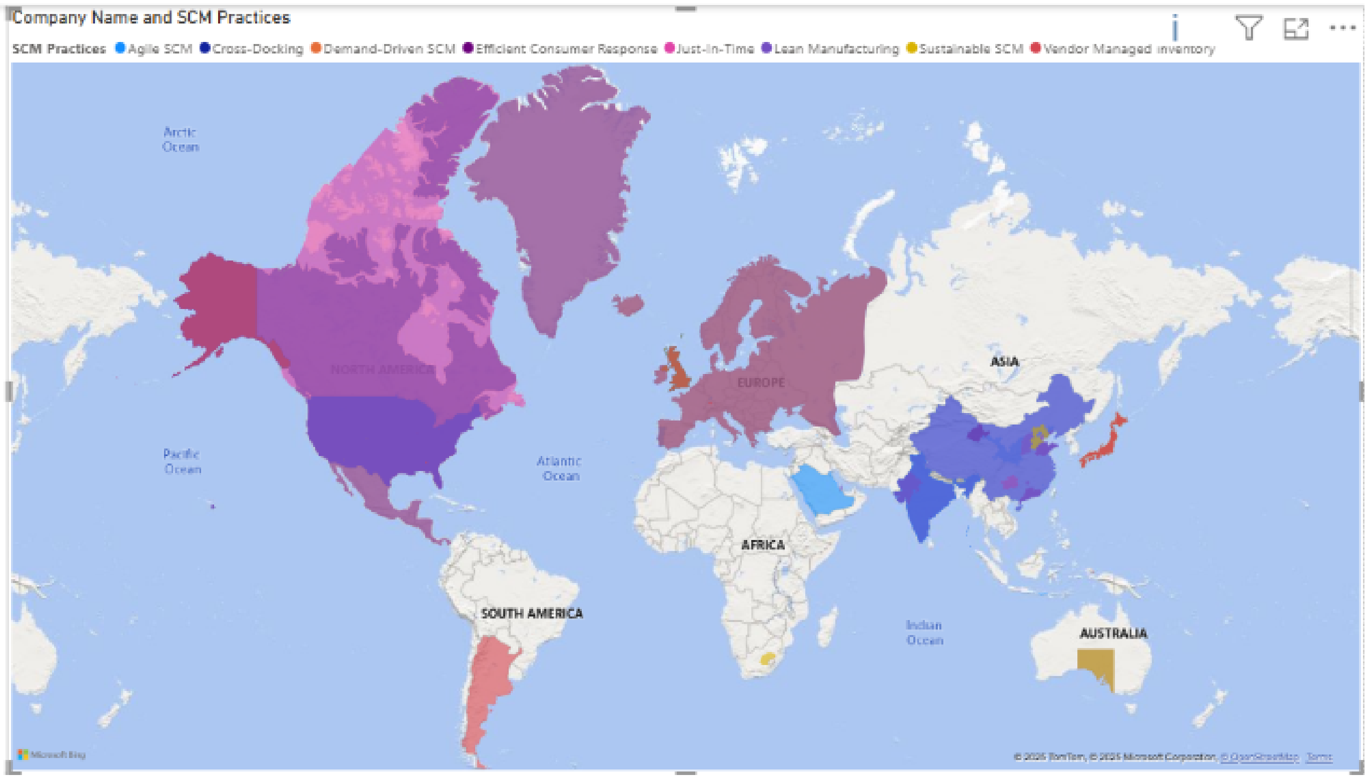
Variable selection is also based on literary support. Supplier collaboration enhances information exchange and adaptive capacity (Issah et al., 2024) Key components of SCR are flexibility and recovery capabilities, enhanced by the application of SCM (Loh & Tan, 2024). The overall SCR can be negatively impacted by longer supplier lead times, which can make it more difficult to absorb and bounce back from disruptions (Chang & Lin, 2019). Transportation can significantly enhance a supply chain's ability to quickly respond to disruptions and recover effectively (Ambra et al., 2024). The complexity of supply chains significantly affects SCR and can be regulated through big data analytics capabilities and organisational adaptability (Iftikhar et al., 2023). According to Gani et al. (2022), these factors are consistent with current empirical research that links to improved resilience performance in industrial environments. A strong analytical basis for evaluating SCR is provided by these factors taken together, which capture the firm's capacity to perceive, adjust, and react to disturbances (Asamoah et al., 2020; Zhou et al., 2024).

After identifying relevant variables, appropriate data analytics methods were defined. This structured approach ensured the validity of the analysis and provided reliable insights and actionable recommendations for manufacturing companies. The full data preparation, selection workflow and the data analytics process are summarised in Figure 1. This visual representation provides a clear outline and framework for the report.

The Visualisation for the Dataset

The manufacturing companies in this dataset use different SCM strategies. Figure 1 illustrates the widespread adoption of diverse SCM practices, particularly in developed countries, highlighting a clear global trend toward supply chain digitalisation. China stands out for its diversified implementation of multiple practices.

Figure 1: World map of manufacturers practising SCM



Data Analytical Techniques

The data analytics focused on exploring the determinants of SCR in the industrial sector, applying a variety of analytical methods to enhance the depth and comprehensiveness of the findings. When dealing with critical business data, the proper analytical methods are crucial to conclusions and results (Condon et al., 2023). ANOVA and linear regression are used for this data problem to examine the relationships between SCR and its potential drivers. Descriptive analytics provide an overview of the data distribution and initial patterns, can visualise relevant data and express differences more intuitively and establish a strong foundation for deeper analysis (Gunasekaran et al., 2017), while diagnostic testing highlights performance gaps that firms must address (Condon et al., 2023). Each method was selected for its specific strengths. However, the reliance on secondary data constrained the customisation of variables and may have introduced measurement bias. Combining the different methods for analysis builds a comprehensive and reliable evaluation framework.

Figure 2: Procedures

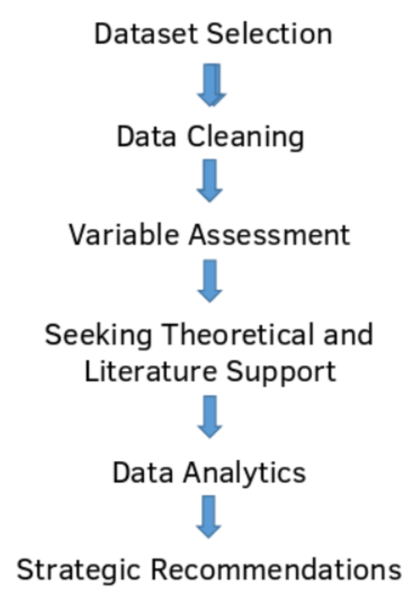
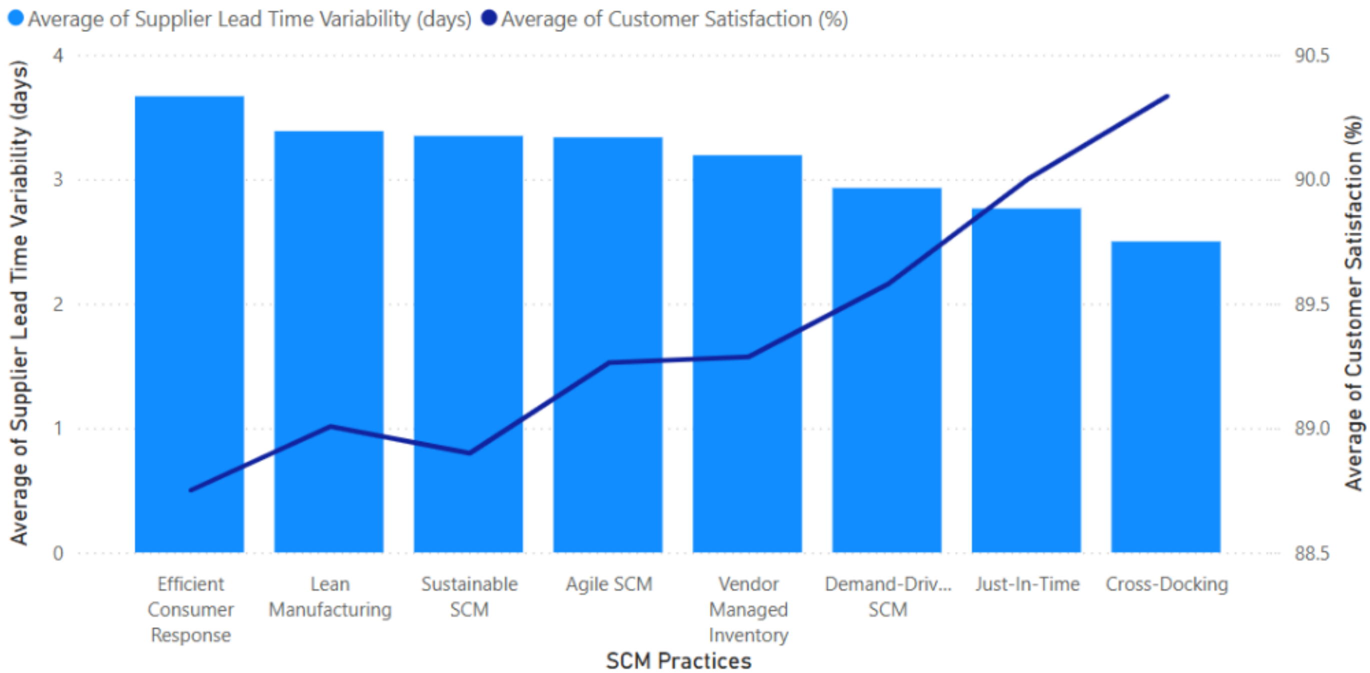


Figure 3 shows that different SCM practices have different delivery variability times, among which cross-docking has the lowest average variability and the highest customer satisfaction. This shows that the smaller the variation in the lead cycle, the higher the customer satisfaction.

Figure 3: Impact of SCM Practices on Supplier Lead Time Variability and Customer Satisfaction



RESULTS

Descriptive and Diagnostic Analytics

The *t*-test is one of the commonly used analytical techniques in diagnostic analytics (Condon et al., 2023). The result of the t-test of supplier collaboration level and SCR is seen in Table 2 and Figure 4. The mean is a key number in descriptive analytics (Condon et al., 2023). Firms with high supplier collaboration reported a significantly higher resilience score (M = 89.5) compared to medium collaboration (M = 84.92). The t-test confirms a significant difference between them ($p < 0.01$). This indicates that supplier partnerships substantially enhance SCR.

The ANOVA test is also one of the commonly used analytical techniques in diagnostic analytics (Condon et al., 2023). The result of the ANOVA test between supply chain complexity and SCR is shown in Table 3. Firms with high complexity showed the highest average resilience score (M = 91.38), followed by low (M = 88.44) and medium complexity groups (M = 86.66). ANOVA results confirm a significant difference among the groups, suggesting that increased complexity, when properly managed, can enhance resilience capabilities ($F = 428.56$, $p < 0.01$).

The result of the ANOVA test of SCM practice on SCR is shown in Table 4 and Figure 5. Results reveal significant differences in resilience scores across various SCM practices ($p < 0.05$). While the overall means are relatively close, practices like Just-In-Time (M = 89.26) and Cross-Docking (M = 88.94) show slightly higher resilience compared to others. The findings suggest that SCM choices can influence SCR.

The result of the correlation test between various variables and SCR is shown in Table 5. The result reveals that lead time ($r = -0.72$) and supplier lead time variability ($r = -0.76$) have fairly strong negative influences on resilience scores. Additionally, Transportation Cost Efficiency (r = 0.81) shows a very strong positive relationship with resilience.

Table 2: SCR by Supplier Collaboration Levels: t-Test: Two-Sample Assuming Equal Variances

	High	*Medium*
Mean	89.545322	84.9238095
Variance	4.5996999	1.29353958
Observations	684	315
Pooled Variance	3.5584418	
Hypothesised Mean Difference	0	
df	997	
t Stat	35.979469	
P(T<=t) one-tail	1.13E-182	
t Critical one-tail	1.6463834	
P(T<=t) two-tail	2.26E-182	
t Critical two-tail	1.9623462	

Figure 4: Average SCR by Supplier Collaboration Levels

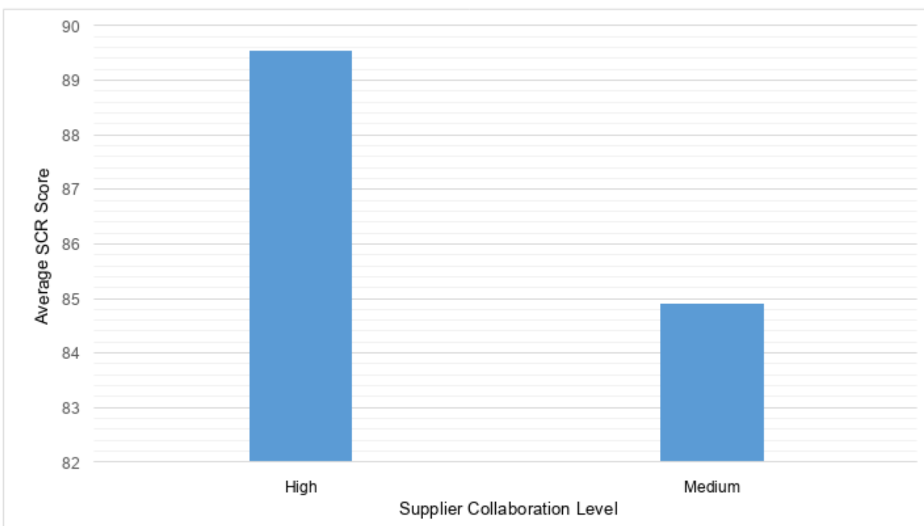


Table 3: ANOVA Test between Supply Chain Complexity and SCR: Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
High	236	21565	91.37712	4.2444104
Medium	586	50782	86.6587	4.9226335
Low	177	15653	88.43503	2.8721751

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	3771.568	2	1885.784	428.55994	5.2E-135	3.004761
Within Groups	4382.68	996	4.400281			
Total	8154.248	998				

Table 4: The ANOVA test of SCM Practice on SCR: Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Agile SCM	312	27572	88.37179	9.192514
Cross-Docking	18	1601	88.94444	2.879085
Demand-Driven SCM	57	5036	88.35088	6.053258
Efficient Consumer Response	12	1056	88	3.636364
Just-In-Time	34	3035	89.26471	9.230838
Lean Manufacturing	326	28586	87.68712	7.895649
Sustainable SCM	69	6065	87.89855	9.563086
Vendor Managed Inventory	171	15049	88.00585	7.064671

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	145.462	7	20.78029	2.571334	0.01251	2.018803
Within Groups	8008.786	991	8.08152			
Total	8154.248	998				

Figure 5: Average SCR by SCM Practice Types

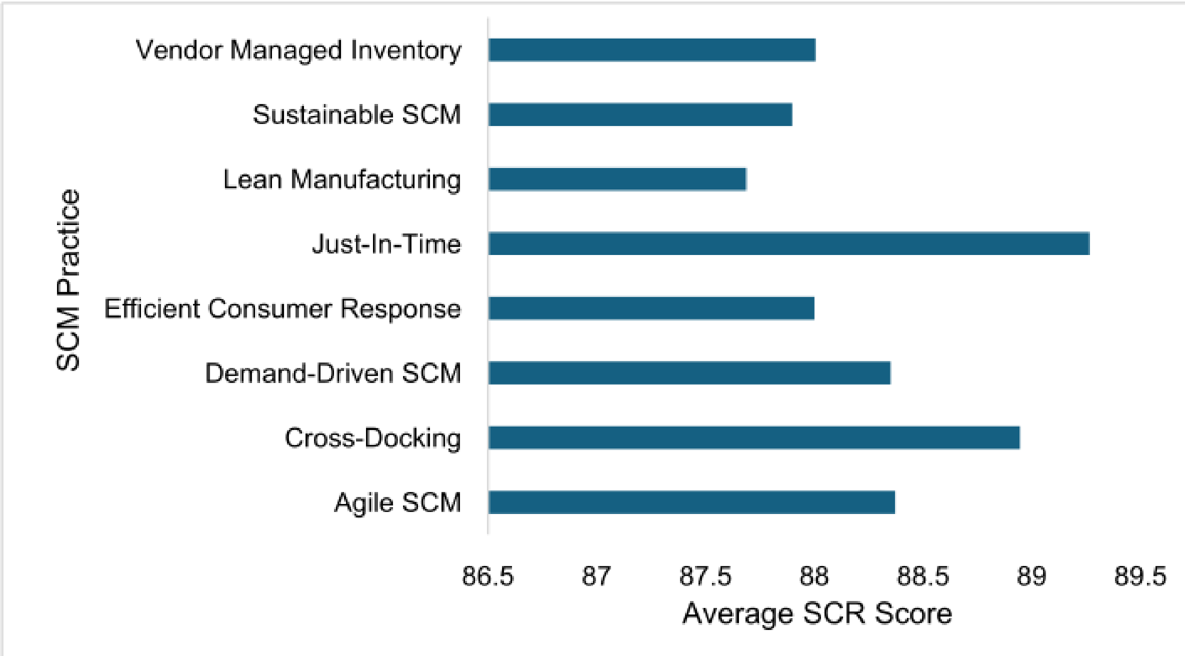


Table 5: Correlation Test between Different Variables and SCR

	Lead Time (days)	*Supplier Lead Time Variability (days)*	*Transportation Cost Efficiency (%)*	*Supply Chain Resilience Score*
Lead Time (days)	1			
Supplier Lead Time Variability (days)	0.804311956	1		
Transportation Cost Efficiency (%)	-0.647150697	-0.788143055	1	
Supply Chain Resilience Score	-0.721586796	-0.755917006	0.809356194	1

Predictive Analytics

Correlation test reveals associations, which cannot lead to causal inferences (Gershman & Ullman, 2023). Therefore, regression analysis provides a more reliable approach to uncover potential causal structures (Chang & Lin, 2019; Li et al., 2023) found through multi-level simulation that extending the delivery time will reduce the recovery speed and crisis response capabilities. Budwal (2022) emphasised that SCR can not only reduce risk exposure but also improve customer satisfaction. Therefore, using resilience as a dependent variable and lead factors as independent variables for regression analysis can help companies fully understand the adaptability and recovery potential in complex supply chain networks. The result of linear regression analysis is shown in Tables 6 - 7 and Figures 6 - 7.

Table 6: Linear Regression for Lead Time and SCR

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.721586796
R Square	0.520687503
Adjusted R Square	0.520206749
Standard Error	1.979947895
Observations	999

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	4245.815163	4245.815	1083.063	2.149E-161
Residual	997	3908.433085	3.920194		
Total	998	8154.248248			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	93.70504534	0.181809426	515.4026	0
Lead Time (days)	-0.490587541	0.014906982	-32.9099	2.1E-161

	Lower 95%	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	93.3482723	94.06181838	93.3482723	94.0618184
Lead Time (days)	-0.519840201	-0.46133488	-0.5198402	-0.4613349

Table 7: Linear Regression for Supplier Lead Time Variability and SCR

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.755917006
R Square	0.57141052
Adjusted R Square	0.570980641
Standard Error	1.872255601
Observations	999

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	4659.423234	4659.423	1329.235	1.2485E-185
Residual	997	3494.825014	3.505341		
Total	998	8154.248248			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	92.5370374	0.135644677	682.2018	0
Supplier Lead Time Variability (days)	-1.358343633	0.037257071	-36.4587	1.2E-185

	Lower 95%	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	92.27085558	92.803219	92.27085558	92.8032192
Supplier Lead Time Variability (days)	-1.43145491	-1.285232	-1.43145491	-1.2852324

Linear regression results indicate that both Lead time and Supplier lead time variability have significant negative impacts on SCR. The models yield high explanatory power, with R^2 values of 0.52 and 0.57, meaning over half of the variance in resilience scores is explained by these variables. The F-statistics ($F = 1083.06$; $F = 1329.24$, $p < 0.01$) confirm that the models are significant overall. Specifically, each day of added lead time reduced resilience by 0.49 points ($\beta = -0.491$), and variability had an even stronger effect ($\beta = -1.36$). These correlation tests and linear regression results show that both lead time and supplier lead time variability have similar effects on SCR in the one dataset, indicating that it is not surprising that lead time factors are a key determinant of SCR and demonstrating the reliability of the dataset.

The scatter plots illustrate a clear negative linear relationship between lead factors and SCR. These visuals reinforce regression results, highlighting that delivery consistency (low variability) has an even stronger impact on resilience than speed alone. Predictive analytics enables robust causal inference and future-oriented decision-making (Li et al., 2023) that overcomes the ambiguity of correlational insights (Gershman & Ullman, 2023).

A separate linear regression analysis was conducted for transportation cost efficiency. The result is shown in Table

8 and Figure 8. The result showed that transportation cost has a strong positive impact on SCR ($p < 0.01$). The blue diamonds in the line fit plot represent the actual observed values, while the orange squares indicate the predicted values from the regression model. The close alignment between the actual and predicted points suggests a strong linear relationship, confirming the high R^2 value (0.655) from the regression output. As transportation cost efficiency increases, SCR also rises, supporting the regression findings.

Figure 6: Scatter Plot of Lead Time

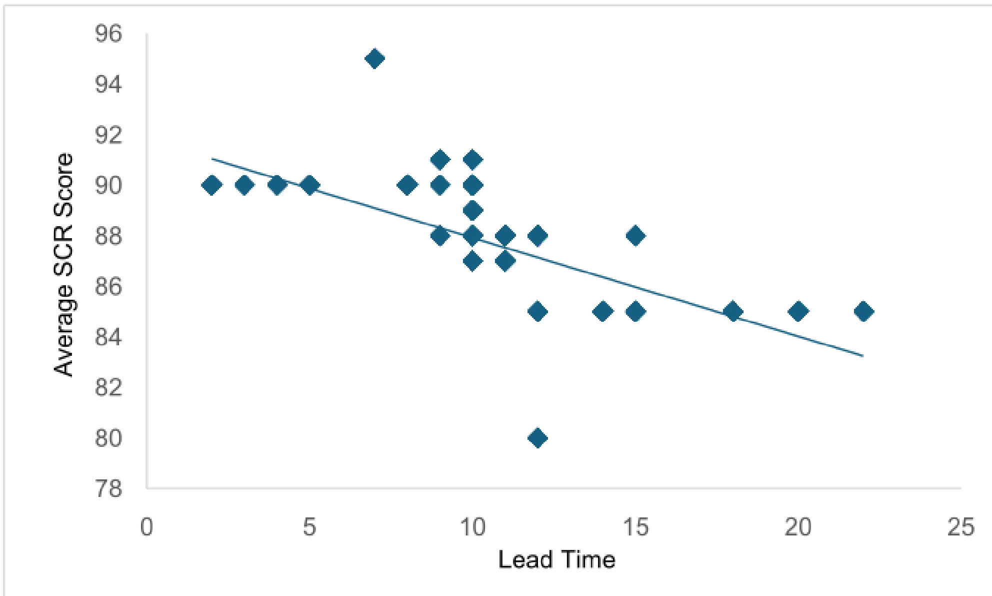


Figure 7: Scatter Plot of Supplier Lead Time Variability

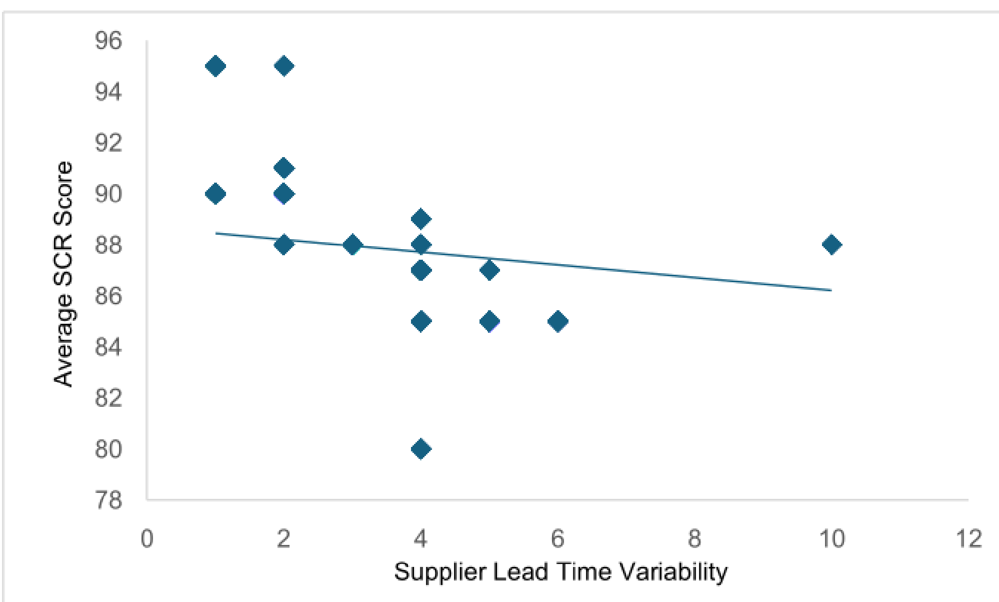


Table 8: Linear Regression Analysis Between Transportation Cost Efficiency and SCR

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.80935619
R Square	0.65505745
Adjusted R Square	0.65471147
Standard Error	1.67964604
Observations	999

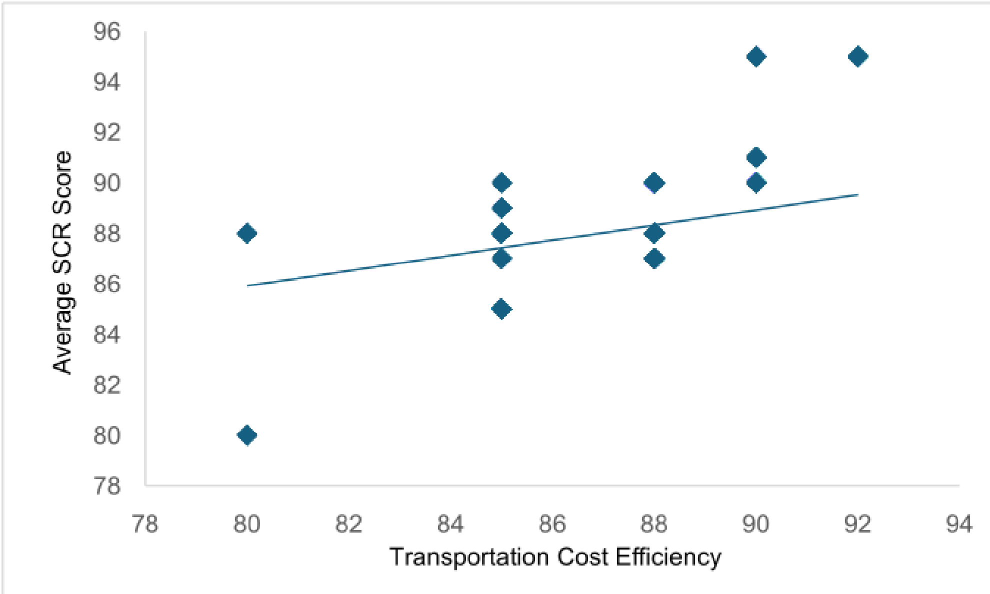
ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	5341.50105	5341.50105	1893.336	1.15E-232
Residual	997	2812.74719	2.82121083		
Total	998	8154.24825			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	3.33594871	1.94849081	1.71206797	0.087195
Transportation Cost Efficiency (%)	0.97247298	0.02234929	43.5124852	1.2E-232

	Lower 95%	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-0.4876649	7.159562	-0.4876649	7.1595623
Transportation Cost Efficiency (%)	0.92861594	1.01633	0.928615939	1.01633

Figure 8: Scatter Plot of Transport Cost Efficiency



DISCUSSION

This study identifies several findings and statistically significant factors that influence SCR in the industrial sector. Through descriptive and diagnostic analytics, supplier collaboration was found to have a strong positive association with resilience scores, while longer lead time and greater lead time variability were consistently linked to lower SCR. These associations were supported by predictive analytics, which showed that resilience declined measurably with each additional day of lead time. In particular, demand unpredictability and variability in supply deliveries were shown to have especially detrimental impacts, as they amplify the bullwhip effect and disrupt production schedules. On the other hand, supplier cooperation and transportation cost efficiency demonstrated a strong positive correlation with SCR, suggesting that logistics optimisation tools such as AI-based routing, real-time tracking with IoT sensors, and predictive inventory systems are essential to resilience building. This also reinforces the dynamic capability view, which holds that inter-organisational partnerships and advanced digitisation strengthen a firm's capacity to sense disruptions, reallocate resources, and maintain continuity in turbulent environments (Zhou et al., 2024).

While supply chain complexity has traditionally been viewed as a risk factor, recent studies suggest that well-managed complexity can also enhance resilience by increasing flexibility and resource redundancy, particularly in high-performing firms (Iftikhar et al., 2023). The findings here are consistent with prior work showing that unmanaged complexity impairs adaptive capacity by reducing visibility and coordination (Tarigan et al., 2021). At the same time, complexity can strengthen adaptive capacity when supported by mechanisms such as supplier diversification, flexible production systems, and digital platforms that integrate real-time data across tiers. These results also confirm that different SCM practices, including collaboration, integration, and sustainability initiatives, contribute jointly to SCR rather than in isolation. The findings validate the importance of these key enablers and emphasise that resilience emerges from the interaction of multiple factors, such as collaboration, logistics efficiency, digitalisation, and complexity management, rather than from any single determinant. Future research should therefore examine additional factors not captured by this dataset, such as organisational culture, regulatory frameworks, and industry-specific policies, which are likely to further shape how firms build and sustain resilience.

This study also provides implications for firms in the manufacturing industry from two specific aspects. From a practical perspective, the findings offer several recommendations for industrial firms seeking to strengthen their supply chain resilience. Firms should prioritise efforts to reduce lead time variability through improved demand forecasting, supplier performance monitoring, and process standardisation. At the same time, investing in supplier collaboration by fostering transparency, joint problem-solving, and information sharing can enhance responsiveness and flexibility during disruptions. High levels of collaboration are not only associated with greater resilience but also support long-term risk mitigation (Gershman & Ullman, 2023; Issah et al., 2024). In addition, improving transportation cost efficiency plays a vital role in supply chain resilience. Companies should adopt logistics optimisation tools and route planning algorithms to manage costs while maintaining service levels. Managers are also encouraged to adopt data analytics as an ongoing tool for resilience assessment and decision-making rather than a one-off exercise. Future research should build on these insights by applying longitudinal designs and mixed methods approaches to capture the dynamic evolution of resilience and to test interventions aimed at improving supply chain performance in uncertain environments for manufacturing companies.

From a management perspective, this study suggests that enhancing SCR requires an integrated approach. As multiple studies have demonstrated, SCM is increasingly digitalised, and managers should prioritise investments in emerging technologies (e.g., AI and blockchain technology) and equipment to stay current. Beyond stabilising lead time processes and reducing delivery variability, firms should invest in supplier development programmes, implement real-time monitoring systems, and standardise inbound logistics to mitigate upstream uncertainties (Ambra et al., 2024; Chang & Lin, 2019). Supplier collaboration should move beyond contractual coordination to joint risk assessment, shared contingency planning, and digital information sharing (Issah et al., 2024). Transportation cost efficiency, strongly associated with SCR, can be improved through AI-based route optimisation and predictive maintenance tools (Li et al., 2023). Managers must also recognise that resilience is shaped by complex interactions across technological, structural, and relational domains. Hence, resilience initiatives should align with organisational culture, ESG goals, and regulatory expectations (Wu et al., 2024). Instead of viewing SCR as a single performance metric, industrial firms should treat it as a strategic capability requiring long-term investment and cross-functional integration. Future policies must embed resilience into both operations and strategic planning frameworks.

CONCLUSION

Using a real-world dataset of manufacturing companies, this study applied descriptive, diagnostic, and predictive analytics to investigate the factors that influence SCR in the industrial sector. The findings indicate that lead time and its unpredictability have a detrimental impact on resilience, but supplier cooperation and the economy of transportation are powerful facilitators. These results support earlier literature claims about how inter-organisational collaborations and operational stability contribute to resilience (Tarigan et al., 2021; Zhou et al., 2024). These results are conceptually based on the dynamic capability view, which defines resilience as a firm's ability to recognise risks, grasp opportunities, and reallocate resources in reaction to disturbance (Teece, 2007), supporting operational insights. The study contributes to SCR research by demonstrating how measurable supply chain practices map onto these dynamic capabilities, providing both theoretical and practical value. From a management perspective, the findings offer clear strategies for improving resilience through supplier engagement, logistics optimisation, and real-time monitoring. Nevertheless, the modest explanatory power of regression models suggests that other factors, such as digital maturity or regulatory conditions, may also play important roles. Future research should adopt longitudinal and multi-level approaches to capture the evolving and context-specific nature of SCR and better understand how different capability configurations shape resilience across industrial environments.

This study also has several limitations. First, the use of cross-sectional data restricts our understanding of how SCR capabilities evolve over time, particularly under conditions of frequent or prolonged disruptions. Second, the analysis did not examine the potential interaction effects among determinants or the moderating influence of contextual variables such as organisational culture or ESG governance, both of which may play important roles in fostering resilience (Wu et al., 2024). Third, we did not test the combined effects of these determinants on SCR using multiple regression or other advanced analytical methods (e.g., structural equation modeling and hierarchical regression), which could provide deeper insights into their joint influence. In addition, the absence of contextual segmentation across industries or regulatory regimes constrains the explanatory depth of the dataset. Despite these limitations, the application of data analysis techniques has produced valuable findings consistent with the dynamic capability view (Teece, 2007). To advance this line of research, future studies should employ longitudinal and multi-level designs to capture the dynamic development of resilience, while also adopting prescriptive analytics to generate insights tailored to different types of enterprises.

REFERENCES

Akin, M. (2022). Order from chaos: a meta-analysis of supply chain complexity and firm performance. *Journal of Supply Chain Management*, *58*(1), 3–30. https://doi.org/10.1111/jscm.12264

Alkhatib, S. F., & Momani, R. A. (2023). Supply Chain Resilience and Operational Performance: The Role of Digital Technologies in Jordanian Manufacturing Firms. *Administrative Sciences*, *13*(2). https://doi.org/10.3390/admsci13020040

Ambra, A., Luca, V., Giona, C., Giacomo, V., & Frank, S. (2024). Adapting to disruptions: Managing supply chain resilience through product rerouting. *Science Advances*, *10*(3), eadj1194. https://doi.org/10.1126/sciadv.adj1194

Asamoah, D., Agyei-Owusu, B., & Ashun, E. (2020). Social network relationship, supply chain resilience and customer-oriented performance of small and medium enterprises in a developing economy. *Benchmarking: An International Journal*, *27*(5), 1793–1813. https://doi.org/10.1108/BIJ-08-2019-0374

Bai, C., Dallasega, P., Orzes, G., & Sarkis, J. (2020). Industry 4.0 technologies assessment: A sustainability perspective. *International Journal of Production Economics*, *229*, 107776. https://doi.org/10.1016/j.ijpe.2020.107776

Bode, C., & Wagner, S. M. (2015). Structural drivers of upstream supply chain complexity and the frequency of supply chain disruptions. *Journal of Operations Management*, *36*(1), 215–228. https://doi.org/10.1016/j.jom.2014.12.004

Bozarth, C. C., Warsing, D. P., Flynn, B. B., & Flynn, E. J. (2009). The impact of supply chain complexity on manufacturing plant performance. *Journal of Operations Management*, *27*(1), 78–93. https://doi.org/10.1016/j.jom.2008.07.003

Budwal, P. (2022). *Supply chain resilience and customer satisfaction: A thematic analysis* (tech. rep.). Pennsylvania State University. https://doi.org/0.13140/RG.2.2.33147.80163

Chang, W.-S., & Lin, Y.-T. (2019). The effect of lead-time on supply chain resilience performance. *Asia Pacific Management Review*, *24*(4), 298–309. https://doi.org/10.1016/j.apmrv.2018.10.004

ChinaPower. (2023). Unpacking China's GDP China Power. https://chinapower.csis.org/tracker/china-gdp/

Condon, D., Drougas, A., & Abrokwah, M. (2023). The Mean May Not Mean What You Think It Means: The Use and Misuse of Measures of Central Tendency. *Journal of Applied Business and Economics*, *25*(4). https://doi.org/10.33423/jabe.v25i4.6341

ElKhouly, S. E., Ali, H. F., & Yehia, E. A. (2020). The impact of enterprise resource planning (ERP) system on supply chain performance: Case study on Ezz Steel Group. *Competition Forum*, *18(1/2)*, 131–147.

Elmobark, N. (2024). A comprehensive framework for modern data cleaning: Integrating statistical and machine learning approaches with performance analysis. *Upubscience*, *1*, 20–28. https://doi.org/10.61784/adsj3003

Gani, M. O., Yoshi, T., & Rahman, M. S. (2022). Optimizing firm's supply chain resilience in data-driven business environment. *Journal of Global Operations and Strategic Sourcing*, *16*(2), 258–281. https://doi.org/10.1108/JGOSS-02-2022-0013

Gershman, S. J., & Ullman, T. D. (2023). Causal implicatures from correlational statements. *PloS One*, *18*(5), 1–8. https://doi.org/10.1371/journal.pone.0286067

Gunasekaran, A., Subramanian, N., & Papadopoulos, T. (2017). Information technology for competitive advantage within logistics and supply chains: A review. *Transportation Research Part E: Logistics and Transportation Review*, *99*, 14–33. https://doi.org/10.1016/j.tre.2016.12.008

Huang, Y.-F., Phan, V.-D.-V., & Do, M.-H. (2023). The impacts of supply chain capabilities, visibility, resilience on supply chain performance and firm performance. *Administrative Sciences*, *13*(10), 225. https://doi.org/10.3390/admsci13100225

Hussain, G., Nazir, M. S., Rashid, M. A., & Sattar, M. A. (2022). From supply chain resilience to supply chain disruption orientation: the moderating role of supply chain complexity. *Journal of Enterprise Information Management*, *36*(1), 70–90. https://doi.org/10.1108/JEIM-12-2020-0558

Iftikhar, A., Purvis, L., Giannoccaro, I., & Wang, Y. (2023). The impact of supply chain complexities on supply chain resilience: the mediating effect of big data analytics. *Production Planning & Control*, *34*(16), 1562–1582. https://doi.org/10.1080/09537287.2022.2032450

Issah, O., Aidoo-Acquah, K., & Eric, D. B. (2024). The influence of supplier relationship management on supply performance: the moderating effect of employee commitment. *African Journal of Procurement, Logistics & Supply Chain Management*, 7(8), 55–71. https://doi.org/10.4314/ajplscm.v7i8.4

Ivanov, D., & Dolgui, A. (2020). Viability of intertwined supply networks: extending the supply chain resilience angles towards survivability. A position paper motivated by COVID-19 outbreak. *International Journal of Production Research*, *58*(10), 2904–2915. https://doi.org/10.1080/00207543.2020.1750727

Kaggle. (2024). Supply Chain Management Data Set. %7Bhttps://www.kaggle.com/datasets/lastman0800/supply-chain-management/data%7D

Kamble, S. S., & Gunasekaran, A. (2020). Big data-driven supply chain performance measurement system: a review and framework for implementation. *International Journal of Production Research*, *58*(1), 65–86. https://doi.org/10.1080/00207543.2019.1630770

Khanzad, G., & Gooyabadi, A. (2021). Development of Strategic Resilience Framework for Small Businesses Post-COVID-19. *Businesses*, *1*(3), 127–141. https://doi.org/10.3390/businesses1030010

Li, Y., Yoshida, K., Kaufman, J. S., & Mathur, M. B. (2023). A brief primer on conducting regression-based causal mediation analysis. *Psychological Trauma: Theory, Research, Practice, and Policy*, *15*(6), 930. https://doi.org/10.1037/tra0001421

Lin, S., & Karia, N. (2024). Impact of digitalization on supply chain performance in the manufacturing industry: A literature review. *Global Business & Management Research*, *16*.

Liu, K. P., & Chiu, W. (2021). Supply Chain 4.0: the impact of supply chain digitalization and integration on firm performance. *Asian Journal of Business Ethics*, *10*(2), 371–389. https://doi.org/10.1007/s13520-021-00137-8

Loh, K. B., & Tan, C. L. (2024). Enhancing Supply Chain Resilience through Supply Chain Integration, Learning, Agility, and Digital Transformation. *Global Business and Management Research*, *16*(3), 118–144.

Mahira, M., Santosa, W., et al. (2023). The Effect Of Supply Chain Risk on Resilience: Mediation Role of Supply Chain Integration. *Journal of International Trade, Logistics and Law*, *9*(2), 111–120.

Mwangola, W. (2018). Conceptualizing Supply Chain Resilience: An Alternative Dynamic Capabilities Perspective. *American Journal of Management*, *18*(4). https://doi.org/10.33423/ajm.v18i4.186

Pettit, T. J., Croxton, K. L., & Fiksel, J. (2019). The Evolution of Resilience in Supply Chain Management: A Retrospective on Ensuring Supply Chain Resilience. *Journal of Business Logistics*, *40*(1), 56–65. https://doi.org/10.1111/jbl.12202

Pinochet, C., Luis, H., Amorim, G. d. C., Belli, L. J., Durval, d. S., & Cesar, A. d. (2021). Consequential factors of Big Data's Analytics Capability: how firms use data in the competitive scenario. *Journal of Enterprise Information Management*, *34*(5), 1406–1428. https://doi.org/10.1108/JEIM-11-2020-0445

Rahm, E., Do, H. H., et al. (2000). Data cleaning: Problems and current approaches. *IEEE Data Eng. Bull.*, *23*(4), 3–13.

Rizki, A. F., Murwaningsari, E., & Sudibyo, Y. A. (2022). Does green supply chain management improve sustainable performance? *International Journal of Energy Economics and Policy*, *12*(6), 323–331. https://doi.org/0.32479/ijeep.13648

Saad, S., Bahadori, R., Bhovar, C., & Zhang, H. (2023). Industry 4.0 and Lean Manufacturing – a systematic review of the state-of-the-art literature and key recommendations for future research. *International Journal of Lean Six Sigma*, *15*(5), 997–1024. https://doi.org/10.1108/IJLSS-02-2022-0021

Selepe, R., & Makinde, O. (2024). Analysis of factors and solutions to poor supply chain quality in a manufacturing organisation. *Journal of Transport and Supply Chain Management*, *18*(0), 9. https://doi.org/10.4102/jtscm.v18i0.989

Shah, J., Sharma, M., & Joshi, S. (2023). Digital Supply Chain Management: A Comprehensive Review Using Cluster Analysis, with Future Directions and Open Challenges. *International Journal of Supply and Operations Management*, *10*(3), 337–364. https://doi.org/10.22034/ijsom.2023.109914.2739

Taha, A., Khawaja, S., Qureshi, F., & Wahsheh, F. R. (2025). Employing artificial intelligence to improve the supply chain's resilience and performance: Moderating the impact of supply chain dynamics. *Problems and Perspectives in Management*, *23*(1), 741. https://doi.org/10.21511/ppm.23(1).2025.55

Tarigan, Z. J. H., Siagian, H., & Jie, F. (2021). Impact of internal integration, supply chain partnership, supply chain agility, and supply chain resilience on sustainable advantage. *Sustainability*, *13*(10). https://doi.org/10.3390/su13105460

Teece, D. J. (2007). Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, *28*(13), 1319–1350. https://doi.org/10.1002/smj.640

Thirathon, U., Wieder, B., & Ossimitz, M.-L. (2022). Determinants of analytics-based managerial decisionmaking. *International Journal of Information Systems and Project Management*, *6*(1), 27–40. https://doi.org/10.12821/ijispm060102

Um, J., & Han, N. (2020). Understanding the relationships between global supply chain risk and supply chain resilience: the role of mitigating strategies. *Supply Chain Management: An International Journal*, *26*(2), 240–255. https://doi.org/10.1108/SCM-06-2020-0248

Wu, C.-H., Zhou, Y., Zhang, N., Wang, Y., Zhang, X., & Zhang, D. (2024). The Impact of Supply Chain ESG Management on Supply Chain Resilience With Emerging IT Technologies: Based on Supply Chain Network Capabilities. *Journal of Organizational and End User Computing (JOEUC)*, *36*(1), 1–31. https://doi.org/10.4018/JOEUC.356497

Zhou, J., Hu, L., Yu, Y., Zhang, J. Z., & Zheng, L. J. (2024). Impacts of IT capability and supply chain collaboration on supply chain resilience: empirical evidence from China in COVID-19 pandemic. *Journal of Enterprise Information Management*, *37*(2), 777–803. https://doi.org/10.1108/JEIM-03-2022-0091