ISSN: 3049-7159

Review Article

Journal of Business and Econometrics Studies

Optimising Supply Chain Resilience and Efficiency Using Artificial Intelligence in Response to Disruptions

Michael Kwakye Agyapong

Tiffin University, USA

Corresponding author

Michael Kwakye Agyapong, Tiffin University, USA.

Received: May 07, 2026; **Accepted:** May 13, 2026; **Published:** May 19, 2026

ABSTRACT

This study investigates the role of Artificial Intelligence (AI) in enhancing supply chain resilience and efficiency during disruptions. Drawing on the Dynamic Capabilities Theory, it evaluates how AI-driven demand forecasting, predictive analytics, and optimization algorithms support supply chain adaptability, continuity, and performance in the face of crises such as pandemics and geopolitical instabilities. Using a quantitative research design, data were collected from 228 firms in Pittsburgh, Pennsylvania, all of which have adopted AI in their operations. The findings reveal that AI-driven demand forecasting ($\beta = 0.771$), AIpowered predictive analytics ($\beta = 0.091$), and AI-based optimization algorithms ($\beta = 0.083$) significantly and positively influence supply chain efficiency during disruptions. Factor analysis confirmed the strong construct validity of the model, while regression analysis demonstrated a high explanatory power ($R^2 = 0.878$). This research contributes a novel, holistic framework that integrates technological, organizational, and human factors, offering actionable insights for businesses aiming to build resilient and agile supply chains. It further recommends adopting advanced AI tools, fostering cross-functional collaboration, and implementing continuous monitoring to sustain long-term supply chain performance.

Introduction

Disruptions to commercial supply chains can have significant economic impacts. Managing risk and vulnerability associated with supply chains has therefore assumed some urgency. Resilience is the capacity of a system to adapt to change and deal with surprises while retaining the system's basic function and structure which has emerged as an important tool for managing supply chain risk and vulnerability maintain that the supply chain is resilient to promptly respond to operational disruptions through agile contingency planning and forecasting, right from material sourcing to logistics and finally to the delivery of the products and services [1-4].

Kaul and Khurana suggest that supply chain resiliency can be achieved through the use of Artificial intelligence (AI) in shipping and delivery optimization, managing warehouse capacity, tracking inventory, demand forecasting of specific parts and components, improving worker safety, and ensuring transaction records are valid across global supply chains [5]. CortesKatsaliaki et al. denote that supply chain resilience refers to the potential of the supply chain to predict, adapt, and respond to any disruption, while sustaining operational continuity and competitiveness [6]. Resistance and recovery are the two major facets of this process. Murcia et al. argue that AI presents a game-changing opportunity to improve supply chain resilience. Rane, Choudhary, and Rane argue that AI technologies, including machine learning, predictive analytics, and the Internet of Things (IoT), enable risk prediction, operational optimization, and accelerated recovery from disruptions [7].

In the modern world and its globally integrated economy, supply chain resilience is going to be a key factor for firms to remain open and competitive given several disruptions. The increasing trend of catastrophes-peril events, such as pandemics, natural calamities, and geopolitical conflicts, brings to the fore those important vulnerabilities in traditional supply chain models [8]. Therefore, there is a greater demand for creating resilient, flexible, and more intelligent supply chain systems capable of sustaining shocks and rapidly recovering. Supply chain resilience involves the potential of a supply chain to be able to anticipate, prepare for, respond to, and recover from sudden disruption. Resilience provides for continuity in supply chains and ensures that a business can sustain and adapt to shocks. Sawik argues that recent events, such as the COVID-19 pandemic, have placed in sharp focus the need for resilient supply chains [9].

Citation: Michael Kwakye Agyapong. Optimising Supply Chain Resilience and Efficiency Using Artificial Intelligence in Response to Disruptions. J Bus Econo Stud. 2026. 3(3): 1-9. DOI: doi.org/10.61440/JBES.2026.v3.133.

According to Eyo-Udo by utilizing AI, businesses can enhance their decision-making procedures, obtain a better understanding of their supply chain operations, and preserve their competitive advantage in the face of uncertainty [10]. The integration of AI technologies with organizational change management processes is a significant gap in the literature on supply chain resilience and AI use. While supply chain resilience can be improved using AI technologies, the management of the organizational changes necessary for an effective AI adoption is not well covered by existing frameworks.

The motivation for this research stems from a critical gap in the current literature on the integration of AI technologies in supply chain resilience. While extensive research has explored the individual applications of AI, there has been limited investigation into how these technologies can be holistically integrated to enhance overall supply chain resilience. This gap is significant because, in practice, supply chains face complex and multifaceted challenges that require a coordinated approach to AI adoption. Furthermore, the current literature often overlooks the organizational and human factors that affect the successful implementation of AI, such as change management, customization, and real-time adaptability.

The study is to achieve three objectives which include: analyzing the impact of AI-driven demand forecasting on supply chain efficiency during disruptions; examining the relationship between AI-powered predictive analytics and supply chain resilience during supply chain disruptions and Evaluating the role of AI-based optimization algorithms in improving supply chain flexibility during disruptions.

The novelty of this research lies in its comprehensive approach, combining the technological, organizational, and human factors into a single framework to provide actionable insights for enhancing supply chain resilience. Addressing this gap is crucial because it offers a holistic view of how AI can be effectively leveraged to improve supply chain resilience in a real-world context. By integrating diverse AI technologies and addressing the accompanying organizational challenges, this research provides a more practical and applicable solution for businesses looking to enhance their resilience against disruptions. The framework's ability to adapt to various industries and operational scales adds value, making it relevant to various supply chain contexts.

Theoretical and Hypothesis Development

Dynamic Capabilities Theory

One relevant theory applicable to optimizing supply chain resilience and efficiency using AI in response to disruptions is the "Dynamic Capabilities Theory" by Teece [11]. It has been theorized that firms should develop and reconfigure their resources and capabilities in response to altered environments if they want to retain their competitive advantage. When applied to supply chain management, it emphasizes the need for organizations to have the capability to sense, seize, and reconfigure resources-technology, processes, and people to adapt to disruptions.

Dynamic capability theory by Teece suggests that firms have to continuously adapt their resources to remain competitive in changing environments [11]. In supply chain management, AI supports these capabilities in sensing disruptions, seizing opportunities, and reconfiguring operations in real-time. Rane et al. assert that AI detects potential risks early by analyzing data from various sources like weather reports and IoT sensors that enable proactive measures to mitigate disruption impacts [12]. For example, predictive analytics can estimate transportation delays so that companies can adjust routes or schedules before there is an issue.

Shobhana asserts that AI-powered tools come up with alternative actions to keep the business running, such as sourcing from different suppliers or changing the production schedules, following the identification of any disruption [13]. For example, AI will consider various shipment routes and suggest the best concerning cost and risk. Additionally, AI helps the company in the dynamic reconfiguration of its supply chain operations due to changes. For example, if one of the key suppliers is showing delays, AI can recommend alternatives or adjust inventory levels to reduce risk and sustain efficiency. Rane et al. maintained that Machine learning models can further fine-tune demand forecasting and adjust production schedules dynamically according to the latest data [12].

With AI techniques like predictive analytics, optimization algorithms, NLP, machine learning, and RPA, companies can act with enhanced sensing, analyzing, and responding effectively to any form of disruption; they can automate routine tasks and make better decisions. Finally, AI allows firms to dynamically adjust their supply chains promptly for enhanced resilience and efficiency, thereby creating a competitive edge in the turbulent global marketplace.

AI-Driven Demand Forecasting and Supply Chain Efficiency During Disruptions

Muthukalyani indicates that AI-driven demand forecasting is a method that uses artificial intelligence (AI) and machine learning to predict future demand for products or services [14]. It is more accurate than traditional methods because it can process large amounts of data, identify complex patterns, and adapt to changes in market conditions. Shobhana indicates that this method is more accurate than traditional methods that rely on historical sales data and simple statistical models [15].

Verma's (2024) paper and the research by Kumari et al. (2024) present Artificial Intelligence as a game-changing force in supply chain management. In the study specifically, AI applications in demand forecasting, real-time inventory management, and dynamic optimization have been discussed. It highlights how AI-driven solutions, such as machine learning and digital twins, have brought about remarkable improvements in logistics costs, inventory levels, and service delivery. The paper emphasizes that AI implementations are strategically relevant to the business objectives to deal effectively with supply chain complexities. The paper uses case studies to show how AI enhances decision-making, transparency, and resilience across industries. On the other hand, Kumari et al. (2024) give more of a broad overview of the impact of AI on discussing more varied applications in supply chain management. These include demand forecasting, inventory optimization, supply chain planning, predictive maintenance, route optimization, supplier relationship management, warehouse automation, and blockchain integration. The paper illustrates how AI enables companies to optimize their inventories, reduce downtime, enhance the efficiency of transportation, and improve supplier relationships. It also shows the role of AI in the automation of warehouse processes and ensuring greater transparency and security by means of blockchain integration. The study, in general, points out how AI-driven solutions ensure efficiency, visibility, and competitiveness in an increasingly dynamic market.

Both studies provide valuable insights for an empirical review of AI in supply chains, showing how AI applications can enhance operational efficiency, reduce costs, enhance decisionmaking, and drive greater resilience and competitiveness in supply chains across industries. Therefore the study hypothesis that:
H1: *ai-driven demand forecasting has a positive and significant influence on supply chain efficiency during disruptions*

AI-powered predictive analytics and Supply Chain Efficiency During Disruptions
Predictive analytics in supply chain management streamlines supply chain operations and provides several advantages (Ghodake et al., 2024). By providing the correct product at the right time, organisations increase customer happiness, improve decision-making, lower expenses related to stockouts or overstock, and gain better visibility. Businesses may improve the sustainability and environmental impact of supply chains by utilising AI's predictive analytics. According to Kumari et al. (2024), manufacturers may minimise product waste in the marketplace, optimise truckloads, and forecast the most effective transport routes by utilising AI and machine learning algorithms.

Nimmagadda's study, in 2020, investigates how AI-powered predictive analytics can be applied to mitigate supply chain risks. This work investigates how predictive models powered by machine learning algorithms can foresee disruptions, optimize resource allocation, and provide proactive decision-making insights. Techniques used for the prediction of these risks include time series analysis, anomaly detection, and simulation modelling, among others, for demand fluctuations, supply shortages, natural disasters, and geopolitical uncertainties. It also puts light on practical implementations across retail sectors in developing risk assessment frameworks and early warning systems. For instance, time series analysis allows retailers to pinpoint patterns in their sales data, predict demand, and thereby adjust the levels of their inventories to avoid the problems of stockouts and overstocking, hence improving inventory optimization, reducing costs, and enhancing customer satisfaction.

Shobhana has discussed the increasing importance of supply chains in modern business and the growing investment in digital solutions to improve supply chain efficiency [15]. AI, being an imitation of human intelligence, is estimated to contribute $15.7 trillion to the global economy by 2030. The study has thrown light on big data, machine learning, cloud computing, blockchain, chatbots, and ChatGPT-all AI technologies that are remodelling industries by enhancing efficiency and customer satisfaction. Shobhana also touches on the advantages and disadvantages of AI in supply chains, focusing on how such technologies are changing the way business is done in all industries.

These studies put together complementary views on AI in supply chains. While Nimmagadda focuses on predictive analytics for risk management, Shobhana considers the overall contribution of AI to operational efficiency and customer satisfaction [16]. Both point out the potential of AI in optimizing resources and bringing better performance to supply chains [15]. Therefore, the study hypothesis that:
H2: *AI-powered predictive analytics has a positive and significant influence on supply chain efficiency during disruptions.*

AI-Based Optimization Algorithms and Supply Chain Efficiency During Disruptions
Badmus et al. assert that artificial intelligence (AI) algorithms have completely changed how companies run their operations, especially when it comes to demand forecasting, routing optimisation, and improving decision-making [17]. To precisely forecast future trends and behaviours, these algorithms apply sophisticated mathematical models to enormous volumes of data. Forbes reports that Okeleke et al. claim that AI algorithms examine economic indicators, market trends, client behaviour, and previous sales data [18]. AI can accurately forecast future demand by identifying trends and correlations in this data.

Modgil et al. explore how AI-driven supply chains develop resilience, especially in dynamic environments where disruptions can be extreme [19]. They prove that AI-orchestrated systems let supply chains identify risks, assess localization, and analyze failure modes, data trends, and "what-if" scenarios. These systems can simulate stress tests, address constraints, and reconfigure networks for greater flexibility. They also manage demand volatility, mitigate supply chain shocks, and activate operations for continuity with contingency management, demand management, and supply chain reconfiguration.

Samadhiya et al. discuss how AI technologies (AITs) enhance the resilience of healthcare supply chains by facilitating better adoption and collaboration [20]. The study, which was conducted in the Indian healthcare sector and analysed using PLS-SEM, revealed that AITs allow HSCs to be more adaptive and cooperative, thus being responsive to disruptions. On the other hand, it was found that SCD does not moderate the relationship between the adoption of HSC and HSCR, although it does moderate the relationship between the cooperation of HSC and HSCR. These findings from the studies epitomize how AI-powered adaptability and collaboration enable health stakeholders to cope with operational disruptions.

Taken together, the two studies underline the complementary ways in which AI can enhance supply chain resilience: whereas Modgil et al. (2022) concentrate on how AI can adapt to very extreme disruptions, Samadhiya et al. show how AITs underpin adaptability and cooperation within the healthcare sector in mitigating operational disruption [19,20]. Therefore, the study hypothesis that:
H3: *AI-Based Optimization Algorithms have a positive and significant influence on supply chain efficiency during disruptions.*

Methodology

The study specifically uses a quantitative descriptive research design, with this design, the study collected quantifiable information for statistical analysis of the population sample. The study population includes Businesses in Pittsburgh, Pennsylvania. According to Ran and Hafer assert that Pennsylvania is home to 1.1 million businesses and employs 2.5 million individuals about half of the state's private workforce [21]. The study sample was calculated using the rule of thumb of 10 where the number of items on the questionnaires is multiplied by 10 as recommended by [22]. Therefore required sample size is 190 (19*10) since the study has 16 items but Richard asserts that an addition of 20% is required when using the rule of thumb of 10, therefore the sample size is 228 Businesses in Pittsburgh Pennsylvania were the sample size [23]. The respondents were selected purposively. The firm selected include firms that have integrated artificial intelligence in their operations.

The researcher uses data collection instruments to gain relevant information from the respondents, who are SME owners or managers, from whom they will learn to enrich the study.

The primary source of the data is collected in this study through questionnaires. Bearing in mind the analysis mission, information is obtained directly from primary sources. A formal questionnaire is used as the key data collection tool for the study. The questionnaire has five sections, the first section has questions on the firm characteristics, the second part has questions on AI-driven Demand Forecasting adapted from Verma and Kumari et al. the third section has AI-powered Predictive Analytics questions also adapted from, the fourth section has questions on AI-Based Optimization Algorithms which were adapted from Samadhiya et al. and the final section has questions on supply chain efficiency during disruptions also adapted from Katsaliaki et al and Kaul and Khurana [15,16, 20,24-27].

A Google form of the questionnaires was distributed to the firm through email and a cover letter indicating the ethical considerations which include Informed Consent, Confidentiality and Transparency. This implies that data will be anonymized to protect the identity of participants and organizations and all data sources and methodologies will be clearly stated to ensure replicability and transparency.

Cronbach's alpha is used in Statistical Package for the Social Sciences (SPSS) to determine the reliability of the research instrument and factor analysis was used to examine the internal structure of a test to see whether items group together as expected, which helps establish construct validity. To produce the data analysis based on questions from the study and goals, the researchers are using statistical tools called SPSS. For ease of analysis, the data collected were sorted, classified, and tabulated. The data analysis is consisted in particular of descriptive statistics. The data processing findings are then analyzed, inferences made, and submitted.

Empirical Result

Firms' Characteristics

Table 1 presents the firms' characteristics which were considered as control variables. These include firm size, economic sector and firm age. The study revealed that By firm size, the most common are firms with 100-499 employees, at 39.9%, followed by firms with less than 50 employees at 18.9%, and between 50-99 employees at 24.1%.

Table 1: Firms' Characteristics

Particular	Frequency	Percent
Firm Size Less than 50	43	18.9
50-99	55	24.1
100-499	91	39.9
500 or more	39	17.1
Total	**228**	**100.0**
Economic Sector Services Sector	56	24.6
Manufacturing Sector	95	41.7
Trade	50	21.9
others	27	11.8
Total	**228**	**100.0**
Firm Age Below 20 years	42	18.4
20 - 39 years	62	27.2
40 - 59 years	63	27.6
60 or more	61	26.8
Total	**228**	**100.0**

Source: Field Work (2024).

The largest size category of firms, defined as those with 500 or more employees, accounts for 17.1% of the total sample. Economic sectors of the firm include the Manufacturing Sector at 41.7%, followed by the Services Sector at 24.6%. The Trade sector is represented at 21.9%, with the remaining 11.8% classified under other sectors. Firm age further classifies this into firms being between 40 to 59 years of age, totaling 27.6% and between 20 to 39 years, being 27.2%. Out of the total firms, 26.8% are aged 60 years or more and 18.4% are less than 20 years old.

Reliable Tests and Validity Tests

The validity and reliability analysis are presented in this section and cover the exploratory factor analysis, the Cronbach alpha test, and model fitness indices. The reliability test was done using Cronbach Alpha is SPSS as indicated in the methodology in chapter 3 of this research and the results are presented in Table 2.

Table 2: Reliability Test

S/N	Variables	Cronbach's Alpha	N of Items	AVE	CR
1	Demand Forecasting	0.749	4	0.53	0.82
2	Predictive Analytics	0.889	4	0.5	0.79
3	Optimization Algorithms	0.805	4	0.61	0.81
4	Supply Chain Efficiency	0.793	4	0.56	0.79

Source: Field Work (2024).

The findings show that every variable exhibits respectable levels of validity and reliability:
Cronbach's Alpha values for Demand Forecasting, Predictive Analytics, and Optimisation Algorithms are 0.749, 0.53, and 0.82, respectively; 0.889, 0.5, and 0.79 for Predictive Analytics; 0.805, 0.61, and 0.81 for Optimisation Algorithms; and 0.793, 0.56, and 0.79 for Supply Chain Efficiency. These values indicate good internal consistency and moderate to strong convergent validity across the variables.

Exploratory Factor Analysis
Table 3 presents the results of two important statistical tests used to assess the suitability of the data for Factor Analysis: the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity. These tests check whether the data is appropriate for identifying underlying factors and whether correlations among variables are sufficient to justify the use of factor analysis.

Table 3: Bartlett's test of Sphericity and KMO

Particulars		Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.759
Bartlett's Test of Sphericity	Approx. Chi-Square	3571.64
	df	231.000
	Sig.	0.000

Source: Field Work (2024).

Kaiser-Meyer-Olkin's measure of sampling adequacy is 0.759, which is above the common threshold recommendation of 0.6, hence, the sample is adequate to conduct factor analysis. Additionally, Bartlett's Test of Sphericity yielded an approximately Chi-Square value of 3571.64 with 231 degrees of freedom and a significance level of 0.000, highly significant ($p < 0.05$), indicating that the correlation matrix is not an identity matrix and that factor analysis is appropriate to study the data. Such findings confirm the assumptions underlying factor analysis in the dataset.

Table 4 shows the factors extracted for important variables about AI-driven technologies and their effect on supply chain efficiency during interruptions. These factors include supply chain efficiency during disruptions, AI-powered predictive analytics, AI-driven demand forecasting, and AI-based optimisation algorithms. Together with the factor loadings for each item inside each construct, the Total Variance Explained (TVE) for each variable is given. The TVE shows the total percentage of variation in the data that the factor explains, whereas the factor loadings show how strongly each item and its matching variable are related.

The results obtained show that all the variables are significantly extracted, showing each of the AI-related constructs to be very important in explaining supply chain performance during disruptions. AI-driven demand forecasting has an explained variance of 81.2%, while its individual items have high loadings, for instance, DEF2 with 0.936. AI-powered predictive analytics explained about 75.9%, while its item like PRA4 is highly loaded to 0.820. For example, AI-Based Optimization Algorithms are explained by 78.3% of the variance, with all items loading well, such as OPA1 at 0.853. Finally, 67.2% of the variance explains Supply Chain Efficiency During Disruptions, and the highly influential item is SCED4 at 0.855. On the whole, these results point out that AI technologies will significantly enhance a supply chain's efficiency, adaptiveness, and resilience during disruptions.

Table 4: Communalities

S/N	Particular/ Variables	Extraction	TVE
	AI-driven Demand Forecasting		81.2 %
DEF1	AI-driven demand forecasting provides accurate predictions for future demand.	0.8280	
DEF2	AI models help reduce errors in demand forecasting.	0.9360	
DEF3	The integration of AI in demand forecasting helps optimize inventory levels.	0.8130	
DEF4	AI-driven forecasting improves decision-making during periods of uncertainty.	0.6700	
	AI-powered Predictive Analytics		75.9 %
PRA1	AI-powered predictive analytics help anticipate supply chain disruptions.	0.8110	
PRA2	Predictive analytics allow for proactive risk management in supply chains.	0.7060	
PRA3	AI-based predictive analytics improve the speed of response to disruptions.	0.7000	
PRA4	Predictive analytics help optimize resource allocation during disruptions.	0.8200	
	AI-Based Optimization Algorithms		78.3 %
OPA1	AI-based optimization algorithms improve supply chain efficiency.	0.8530	
OPA2	Optimization algorithms help minimize logistics and transportation costs.	0.7170	
OPA3	AI-based optimization supports real-time decision-making during disruptions.	0.7820	
OPA4	AI algorithms help optimize inventory and reduce wastage during disruptions.	0.7780	
	Supply Chain Efficiency During Disruptions		67.2 %
SCED1	AI enhances the overall efficiency of supply chains during disruptions.	0.5190	

SCED2	AI helps the supply chain quickly adapt to unforeseen disruptions.	0.6670	
SCED3	AI-based systems improve supply chain resilience under crisis conditions.	0.6470	
SCED4	AI helps maintain continuous supply chain operations during disruptions.	0.8550	

Source: Field Work (2024).

Multiple Regression Analysis

The study's objectives were fulfilled by using regression analysis. Multiple regression analysis is a model that establishes the link between the control variables (Firm Size, Economic Sector and Firm Age) independent variables (Demand Forecasting, Predictive Analytics and Optimization Algorithms) and dependent variables (Supply Chain Efficiency). The result is presented in Table 5.

Table 5: Multiple Regression Analysis

Variable	Model 1	Model 2
Economic Sector	0.442***	0.0490***
	(0.010)	(0.0160)
Firm Size	-0.029**	-0.0400***
	(0.012)	(0.0050)
Firm Age	0.0390*	0.0140
	(0.0200)	(0.0090)
AI -driven Demand Forecasting		0.7710*** (0.0330)
AI -powered Predictive Analytics		0.0910*** (0.0150)
AI-Based Optimization Algorithms		0.0830*** (0.0180)
(Constant)	2.001***	0.7920***
	(0.083)	(0.0740)
R	.743a	.789b
R Square	0.788	0.878
Durbin-Watson		2.055
Sig.	0.000	0.000

Note: N = 228, ***p** < .05. ****p** < .01. *****p** < .001 and Standard errors are in parentheses.

Dependent Variable: Supply Chain Efficiency During Disruptions

According to Table 5, two models are presented. Model 1 investigates the effects of economic sector, firm size, and firm age on supply chain efficiency. Model 2 adds AI-related variables: AI-driven Demand Forecasting, AI-powered Predictive Analytics, and AI-Based Optimization Algorithms. Table 5 provides standardized regression coefficients, standard errors, R-squared, and significance for all the variables.

The results of Model 1 indicate that the economic sector is positively and significantly related to supply chain efficiency at $\beta = 0.442$ and $p < 0.001$, whereas firm size negatively but significantly influences efficiency at $\beta = -0.029$ and $p < 0.01$. Firm age has a positive influence on efficiency at $\beta = 0.039$ and $p < 0.05$, though weaker compared to the economic sector and firm size.

Thus, in Model 2, adding the AI-driven variables increased the explanatory power of this model: R^2 was equal to 0.878 in contrast to the smaller one (0.788 in Model 1). Accordingly, the results of the three AI variables also proved to have a strong positive effect on the supply chain efficiency during disruptions, with AI-driven Demand Forecasting ($\beta = 0.771$, $p < 0.001$), AI-powered Predictive Analytics ($\beta = 0.091$, $p < 0.001$), and AI-Based Optimization Algorithms ($\beta = 0.083$, $p < 0.001$). These cases show a Durbin-Watson statistic of 2.055, meaning that there is no significant autocorrelation in the residuals; thus, the regression models are reliable. The results are all significant, with Model 2 explaining a greater degree of variance in supply chain efficiency and therefore showing the important role of AI technologies in enhancing supply chain resilience in cases of disruption.

Discussion

Results in Table 5 show that AI-driven technologies significantly affect supply chain efficiency during disruptions. In Model 2, AI-driven demand forecasting has the highest value, indicating the improvement of supply chain efficiency through the correct forecast of demand during disruption. AI-powered predictive Analytics also correlate positively and significantly with efficiency hence contributing to enhanced supply chain resilience by anticipation of prospective disruptions. Finally, AI-Based Optimization Algorithms have a positive effect , that underpins real-time decision-making and enhancement of supply chain flexibility in case of disruption. Overall, the results emphasize how essential AI technologies are in improving performance in supply chains since the significance of all the variables in the various roles performed is less than 0.001.

Hypothesis H1

The obtained results support H1, since the dispersion in the supply chain, in case of disruptions, is significantly and highly positively influenced by AI-driven demand forecasting. AI-driven Demand Forecasting has a regression coefficient of 0.771 and a p-value < 0.001, meaning this AI-driven method for the creation of forecasts is indeed highly effective at improving supply chain operations upon disruption. This corroborates Muthukalyani and Shobhana, who have identified how AI-driven demand forecasting outperforms conventional methods because of handling huge volumes of data, identifying complicated patterns, and responding to any fluctuation in market conditions [14,15]. With enhanced accuracy in predictions, AI makes it possible to optimize inventory, predict changes in demand in advance, and minimize errors valuable in times of disruption to the supply chain.

Moreover, Rane et al. point out that AI technologies, such as predictive analytics, become highly instrumental in the early identification of risks related to transportation delays [7]. By predicting these disruptions in advance, businesses can adjust schedules or routes before major issues arise, thus keeping supply chain operations smoother. AI-driven Demand Forecasting thus becomes an important contributor to improving the overall efficiency of supply chains in times of unpredictable disruptions.

Hypothesis H2

AI-powered Predictive Analytics positively influences supply chain efficiency in the case of disruptions. This hypothesis is confirmed by the results of this study. The regression coefficient for AI-powered Predictive Analytics is 0.091 ($p < 0.001$), indicating a significant relationship between predictive analytics and supply chain efficiency. This means that the ability of AI to analyse vast amounts of data, predict future disruptions, and optimize resources is important in building resilience within supply chains.

These findings align with Nimmagadda 2020, who noticed that predictive models could highlight a group of possible risks like fluctuation in demand and supply, geopolitical uncertainties, etc. AI-powered predictive analytics allows companies to adapt their inventories, transportation routes, and disruption planning so as to maintain effective and responsive supply chains. According to Kumari et al., AI-driven predictive analytics enhance decision-making by predicting disruptions even before their occurrence, thus allowing interventions to take place in advance to prevent causes or mitigate adverse effects [25]. Predictive analytics increase the resilience of supply chains against disruptions while making them more efficient.

Hypothesis H3

Finally, H3 has shown that AI-Based Optimization Algorithms are beneficial to Supply Chain Efficiency even at times of disruption. These results prove the hypothesis in Table 5 with a regression coefficient of 0.083 ($p < 0.001$), indicating the positive contribution of optimization algorithms to the efficient running of a supply chain, especially during disruptions. This finding consequently supports the work of Badmus et al. who had stated that AI-based optimization algorithms transform supply chain operations by equipping firms with optimized decision-making and resource allocation capabilities in real time [17]. For example, AI algorithms may suggest alternative routes, sources of supply, or production schedules, all of which will directly improve flexibility and responsiveness during disruptions.

The findings also validate Modgil et al. who show how AI systems dynamically reconfigure supply chains to keep the operations running during extreme disruptions using optimization techniques. Similarly, Samadhiya et al. illustrate how AI enables increased collaboration in supply chains for enhanced adaptability of the supply chain toward its responses in case of operational disruptions. Thus, AI optimization algorithms form the backbone of supply chain flexibility, which becomes so vital in cases of disruptions [19,20].

Appendix A: Correlation Analysis

		1	2	3	4	5	6	7
1=DEF	Pearson Correlation	1						
	Sig. (2-tailed)							
	N	228						
2=PRA	Pearson Correlation	.774**	1					
	Sig. (2-tailed)	0.000						
	N	228	228					
3=OPA	Pearson Correlation	.199**	.208**	1				
	Sig. (2-tailed)	0.002	0.001					
	N	228	228	228				
4=SCED	Pearson Correlation	.783**	.727**	.204**	1			
	Sig. (2-tailed)	0.000	0.000	0.001				
	N	228	228	228	228			
5=SEC	Pearson Correlation	.501**	.710**	.172**	.640**	1		
	Sig. (2-tailed)	0.000	0.000	0.006	0.000			
	N	228	228	228	228	228		
6=SIZ	Pearson Correlation	.720**	.688**	.177**	.626**	.692**	1	
	Sig. (2-tailed)	0.000	0.000	0.005	0.000	0.000		
	N	228	228	228	228	228	228	
7=AGE	Pearson Correlation	0.038	0.022	-0.019	-0.036	0.018	0.042	1

	Sig. (2-tailed)	0.546	0.735	0.768	0.57	0.777	0.508	
	N	228	228	228	228	228	228	

Appendix B: Hypothesis Table

S/N	Hypothesis	Result	Status
H1	AI-driven Demand Forecasting has a positive and significant influence on Supply Chain Efficiency during Disruptions.	Coefficient = 0.771, p < 0.001	Accepted
H2	AI-powered Predictive Analytics has a positive and significant influence on Supply Chain Efficiency during Disruptions.	Coefficient = 0.091, p < 0.001	Accepted
H3	AI-based Optimization Algorithms have a positive and significant influence on Supply Chain Efficiency during Disruptions.	Coefficient = 0.083, p < 0.001	Accepted

Conclusions

The results of the multiple regression analysis indicate that AI-driven technologies significantly enhance Supply Chain Efficiency, Resilience, and Flexibility during disruptions. More precisely, AI-driven Demand Forecasting is very important in enhancing efficiency by providing accurate demand predictions with minimal forecasting errors. AI-Powered Predictive Analytics: It enables a firm to proactively anticipate disruptions and take necessary actions in advance, thus contributing to supply chain resilience . AI-Based Optimization Algorithms: These algorithms facilitate real-time decision-making by a firm in case of disruptions and optimize resource allocation, thus enhancing supply chain flexibility. These results underline the transformative power of AI technologies in rendering supply chains more adaptable, resilient, and efficient in the face of unexpected disruptions.

Recommendations

Based on the study findings the following recommendations are made By following these recommendations, businesses can strengthen their supply chain operations, reduce vulnerabilities to disruptions, and ensure long-term efficiency and resilience.

The organization should adopt AI-driven demand forecasting tools that will enhance the preciseness of demand forecasts, reduce errors in demand estimates, and optimize inventory management. This will guarantee increased efficiency at times of uncertainty and disruption within the supply chain. Companies should focus on integrating AI-powered predictive analytics into the supply chain to enhance their ability to foresee and hedge against impending disruptions. This will help with resilience and enable better agility toward up-and-coming
risks.

Implement AI-based optimization algorithms to help improve decision-making in real time. AI-based optimization algorithms can be used by firms to optimize resource allocation, transportation, and inventory management in case of disruptions that can keep companies flexible while lowering their costs. Enable collaboration among cross-functional teams within IT, supply chain, and operations to unlock maximum value from these AI technologies. These steps ensure effective implementation, integration, and an uplift of the overall supply chain performance through AI tools.

Continuous Monitoring and Improvement: It is vital that organizations periodically evaluate and make improvements to their AI systems. As the technology behind AI continues to evolve, ongoing assessment will ensure that the solutions perform optimally and remain relevant to the dynamic nature of supply chains.

References

1. Barasa E, Mbau R, Gilson L. What is resilience and how can it be nurtured? A systematic review of empirical literature on organizational resilience. International Journal of Health Policy and Management. 2018. 7: 491.
2. Waters D. Supply chain risk management: vulnerability and resilience in logistics. Kogan Page Publishers. 2011.
3. Deshpande S, Hudnurkar M, Rathod U. An exploratory study into manufacturing supply chain vulnerability and its drivers. Benchmarking: An International Journal. 2023. 30: 23-49.
4. Katsaliaki K, Galetsi P, Kumar S. Supply chain disruptions and resilience: A major review and future research agenda. Annals of Operations Research. 2022.
5. Kaul D, Khurana R. AI-driven optimization models for e-commerce supply chain operations: Demand prediction, inventory management, and delivery time reduction with cost efficiency considerations. International Journal of Social Analytics. 2022. 7: 59-77.
6. Cortes-Murcia DL, Guerrero WJ, Montoya-Torres JR. Supply chain management, game-changing technologies, and physical internet: A systematic metareview of literature. IEEE Access. 2022. 10: 61721-61743.
7. Rane N, Choudhary S, Rane J. Artificial intelligence for enhancing resilience. Journal of Applied Artificial Intelligence. 2024. 5: 1-33.
8. Odulaja BA, Oke TT, Eleogu T, Abdul AA, Daraojimba HO. Resilience in the face of uncertainty: A review on the impact of supply chain volatility amid ongoing geopolitical disruptions. International Journal of Applied Research in Social Sciences. 2023. 5: 463-486.
9. Sawik T. Stochastic optimization of supply chain resilience under ripple effect: A COVID-19 pandemic related study. Omega. 2022. 109: 102596.
10. Eyo-Udo N. Leveraging artificial intelligence for enhanced supply chain optimization. Open Access Research Journal of Multidisciplinary Studies. 2024. 7: 001015.
11. Teece DJ. Explicating dynamic capabilities: The nature and microfoundations of sustainable enterprise performance. Strategic Management Journal. 2007. 28: 1319-1350.
12. Rane N, Choudhary S, Rane J. Artificial intelligence for enhancing resilience. Journal of Applied Artificial

Intelligence. 2024. 5: 1-33.

13. Shobhana N. AI-powered supply chains towards greater efficiency. Complex AI Dynamics and Interactions in Management. 2024.
14. Muthukalyani AR. Unlocking accurate demand forecasting in retail supply chains with AI-driven predictive analytics. Information Technology and Management. 2023. 14: 48-57.
15. Shobhana N. AI-powered supply chains towards greater efficiency. Complex AI Dynamics and Interactions in Management. 2024.
16. Nimmagadda VSP. AI-powered predictive analytics for retail supply chain risk management: Advanced techniques, applications, and real-world case studies. Distributed Learning and Broad Applications in Scientific Research. 2020. 6: 152-194.
17. Badmus O, Rajput SA, Arogundade JB, Williams M. AI-driven business analytics and decision making. World Journal of Advanced Research and Reviews. 2024. 24: 616-633.
18. Okeleke PA, Ajiga D, Folorunsho SO, Ezeigweneme C. Predictive analytics for market trends using AI: A study in consumer behavior. International Journal of Engineering Research Updates. 2024. 7: 36-49.
19. Modgil S, Gupta S, Stekelorum R, Laguir I. AI technologies and their impact on supply chain resilience during COVID-19. International Journal of Physical Distribution & Logistics Management. 2022. 52: 130-149.
20. Samadhiya A, Yadav S, Kumar A, Majumdar A, Luthra S, et al. The influence of artificial intelligence techniques on disruption management: Does supply chain dynamism matter? Technology in Society. 2023. 75: 102394.
21. Ran B, Hafer J. Reversing population decline in rural Pennsylvania. Rural Policy-The Research Bulletin of the Center for Rural Pennsylvania. 2023. 2: 1.
22. Van Belle G. Statistical rules of thumb. John Wiley & Sons. 2011.
23. Richard W. Intellectual and emotional intelligence, organizational culture and auditors' professionalism. GRIN Verlag. 2024.
24. Verma P. Transforming supply chains through AI: Demand forecasting, inventory management, and dynamic optimization. Integrated Journal of Science and Technology. 2024.
25. Kumari TL, Bambuwala S, Rajalakshmi M. AI-driven solutions for supply chain management. Journal of Informatics Education and Research. 2024.
26. Katsaliaki K, Galetsi P, Kumar S. Supply chain disruptions and resilience: A major review and future research agenda. Annals of Operations Research. 2022.
27. Ghodake SP, Malkar VR, Santosh K, Jabasheela L, Abdufattokhov S, et al. Enhancing supply chain management efficiency: A data-driven approach using predictive analytics and machine learning algorithms. International Journal of Advanced Computer Science & Applications. 2024.