AI-Driven Supply Chain Resilience: Integrating Reinforcement Learning and Predictive Analytics for Proactive Disruption Management

Ismoth Zerine [1*], Md Saiful Islam [1], Md Yousuf Ahmad [1], Md Mainul Islam [1], Younis Ali Biswas [2]

Abstract

Global supply chains face unprecedented challenges from pandemics, geopolitical tensions, and climate-related disruptions, exposing the limitations of efficiency-focused, reactive systems. This study develops and validates an integrated artificial intelligence (AI) framework that leverages reinforcement learning (RL) and predictive analytics to enhance supply chain resilience. Using a mixed-methods design, we analyzed data from five multinational corporations and surveyed 100 supply chain professionals, combining quantitative model testing with qualitative insights. RL algorithms, including Deep Q-Networks (DQNs) and Proximal Policy Optimization (PPO), optimized inventory management, while predictive models such as ARIMA and LSTM networks forecasted demand fluctuations and disruption events. Results showed RL models reduced stockouts by 32.4% ($p < 0.001$) and predictive analytics outperformed exponential smoothing by 15.2% in forecasting accuracy (MAPE = 12.3%, $p = 0.008$). Organizations adopting the AI-driven system reported 50% faster decision-making during disruptions and 65.3% higher optimization success ($\chi^2 = 18.7$, $p < 0.001$). Correlation and regression analyses revealed that role specialization, disruption awareness, and AI maturity significantly influenced effectiveness, while tenure and organizational affiliation played minor roles. ARIMA models demonstrated superior forecasting performance across all time horizons, highlighting the value of interpretable statistical methods alongside advanced machine learning. Qualitative findings emphasized the need for responsible AI implementation, workforce upskilling, and ethical governance to ensure transparency and stakeholder trust. This research provides empirical evidence for a scalable AI-driven resilience framework, bridging gaps between academic theory and operational practice. By demonstrating how RL and predictive analytics can transform supply chains from reactive to proactive networks, the study contributes actionable insights for building disruption-ready operations. Future research should focus on real-time deployment, hybrid AI approaches, and human–AI collaboration to advance supply chain adaptability in increasingly volatile global environments.

Keywords: Supply chain resilience; Reinforcement learning; Predictive analytics; Inventory optimization; Disruption management.

Significance | This study demonstrates how integrating reinforcement learning and predictive analytics transforms supply chains from reactive systems into proactive, resilient, disruption-ready networks.

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1. Introduction

Over the past few years, the supply chain environment has been subjected to a radical change characterized by increment in

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complexity, uncertainty, and vulnerability. Most global supply chains have been traditionally designed to perform in the most efficient way and at the lowest cost possible, which has not helped them withstand increasing frequency and severity of disruptions (Khan et al., 2022). The COVID-19 pandemic itself, the Suez Canal blockage or the conflict in Russia and Ukraine, the shortage of semiconductors, and the increasing number of natural disasters have exposed the vulnerability of currently established supply chain systems (Dahlberg & Vangdal, 2022). Such events caused delays in production cycles, ship delivery times, and led to huge financial shortfalls in various industries that demonstrated fundamental structural vulnerabilities in world supply chains (Baldwin & Freeman, 2022). In addition, disruptions caused by hyper-connectivity of trade worldwide and interdependence of suppliers, manufacturers, distributors, and retailers further increased the ripple effect of small local mishap into system-wide melt down. Consequently, supply chain resilience has become a strategic goal among the public and private sector organizations aiming at maintaining its operational resiliency and competitiveness (Tarigan et al., 2021).

The conventional supply chain models, which were typically represented by the just-in-time (JIT) inventory process, lean supply chains, global sourcing, and offshore sourcing, proved insufficient when hit by uncertainties (Abdulraheem, 2018). Although they were efficient models in a stable setting, they were rather inflexible and reactive and their ability to withstand or respond to a lapse in the system was limited. What is more, the use of a fixed forecasting tool and manual choice to manage the inventory and eliminate risk further slowed down the decision-making process and its accuracy (Balachandra et al., 2020). Thus, the necessity to cross over to flexible and resilient supply chains has further been acknowledged, as well as the ability of networks to anticipate, adjust and recover to a variety of possible threats (Feix & Feix, 2022). Such change requires the incorporation of next-generation technologies that are able to explore complexity, to model the uncertainty and to facilitate active interventions.

Artificial Intelligence (AI) has taken a different direction in this regard, as it holds a potential to reinvent the conduct of contemporary supply chains, resilience, and recovery (Francis et al., 2022). Reinforcement Learning (RL) and Predictive Analytics are among the most promising AI approaches to the use of supply chains since these methods have strong functionality in terms of decision auto mitigation, disruption forecasting, and real-time optimization (Kalusivalingam et al., 2020). The behavioral learning theories motivated reinforcement learning by helping autonomous systems to learn ideal decision policies by interacting with dynamic environments via trial-and-error learning (Wang et al., 2019). RL based algorithms in the context of supply chain can be used to model different scenarios of disruptions and iteratively enhance inventory replenishment strategies in response to performance signaled by outcomes. This active learning process also eludes the reason why RL is ideal in complex, non-linear, and stochastic systems like the global supply chain (Alves & Mateus, 2022).

Conversely, predictive analytics enabled by machine learning, time-series modeling, and statistical estimation will support the right forecasting of demand, anomaly detection, and identification of the early warning signals (Choi et al., 2021). Predictive analytics allows development of pathways to hidden patterns, growth of emerging trends and the delivery of insights that can be acted upon to increase the awareness of situations that can lead to proactive decision-making based on previously unavailable insights achieved by the use of extensive structured and unstructured information. Predictive analytics can be used to augment the context-sensitivity of an AI system when combined with reinforcement-learning models and would enable the AI system to plan ahead and optimize inventory in conditions of uncertainty (Kalusivalingam et al., 2022). This RL and predictive analytics synergy has the potential to uproot the supply chain management into a strategically smart ability that transforms it into a responsive activity (Boppiniti et al., 2019).

However, with the increasing academic research, and operationalization of AI in supply chain management, a sizable scholarship gap exists regarding the development of comprehensive frameworks based on the systematic application of reinforcement learning and predictive approaches in supply chain management to improve supply chain resilience (Khan et al., 2022). The current literature tends to concentrate on the single use of AI methodologies like demand forecasting or routing optimization devoid of the consideration of how these tools can be used comprehensively to enhance supply chain resilience, flexibility and resilience (Li et al., 2022). Moreover, there are not many empirical studies which confirm AI-driven models with the actual data in different industries. The areas of organizational, technological, and contextual determinants of AI tool successful implementation within the supply chain setting are not fully understood, as well (Dora et al., 2022). The gaps identified were filled by conducting this research where the goal was to develop and test a solid data-driven framework to combine reinforcement learning and predictive analytics in order to optimize the inventory and prevent disruptions throughout complex supply chains (Kalusivalingam et al., 2020). The research paper was based on the investigation of the application of AI methods to case studies of multinational corporations, which work in educational and training organizations in the sphere of manufacturing, logistics, and retail. The study aimed to establish a complex picture of how AI may be used to improve the resilience of the supply chain in practice by conducting both quantitative development of models and qualitative interviews with industry specialists (Modgil et al., 2022).

This study aimed to achieve the following four goals: (1) to find and consider the key factors of supply chain disruption and the metrics of resilience in relation to contemporary supply chains; (2) to design reinforcement learning models that would help autonomously manage the on-hand inventory taking into account different disruption cases; (3) to use the existing predictive analytics techniques to forecast demand, detect anomalies, and signal an appropriate intervention at the right period of time; and (4) quantitatively assess the performance and scalability of the developed AI framework using empirical evidence and expert opinions. By so doing, this study also sought to provide both some theoretical new knowledge in the study of AI-supply chain as well as practical methods that could be applied in the industry. The theoretical part of the paper was based on interdisciplinary works within operations research, machine learning, systems engineering, and supply chain risk management. The operations side of the study focused on theories of inventory control, resilience, and model of disruption propagation (Scheibe & Blackhurst, 2019). With regard to machine learning, it made use of reinforcement learning structures as Deep Q-Networks (DQNs) and Proximal Policy Optimization (PPO) and predictive systems such as ARIMA, LSTM networks, and random forests (Kalusivalingam, 2020). The combination of the approaches enabled the development of adaptive AI that could perform stably in the volatile, uncertain, complex, and ambiguous (VUCA) environment (Rimita, 2019). The correlation between methodological rigor and practical relevance in this case was achieved by the use of a mixed-methods research design. The collected quantitative data (past inventory data, lead time, supplier reliability rating and disruption event history) was acquired in five multinational organizations and employed to train and validate the AI models. The reinforcement learning algorithms were applied in the simulation settings to imitate dynamic supply chain behavior and to experiment with policy options of all kinds. Predictive analytics models were also developed to make advanced estimates based on which slight changes in demand were realized and what decisions should be made in a situation of uncertainty. At the same time, qualitative evidence was arranged at the form of semi-structured interviews with supply chain experts and technology management to provide information about how people currently deal with real-life challenges, what strategies people use to integrate AI and which keys they see value in doing that. In addition to that, the focus of the research on ethical, transparent, and humanistic AI implementation makes sure that the technologies comply with organizational values, rules, and demands of the stakeholders (Shneiderman, 2020). Such questions like the privacy of data, fairness in terms of algorithms, explainability, and user trust were taken into serious consideration when conducting the research. The research proposes the concept of responsible AI deployment in which the sustainable development of technology meets the considerations of ethical vision and inclusive innovation (Cheng et al., 2021).

Conclusively, this surge of disruptions affecting organizations around the world has led to the inadequacy of traditional models of supply chain, forcing organizations to find superior solutions to create resilience and attain optimization. Artificial Intelligence especially reinforcement learning and predictive analytics present a radical avenue of achieving such a need. Nonetheless, to achieve the maximum potential of AI, it needs to be inculcated systematically, experimentally verified, and put to context. The present research undertaking addresses this invitation through the development and testing of an artificial intelligence-based framework that helps to improve inventory control, predict the impact of disruptions, and support decision-makers in the establishment of resilient supply chains. In such a manner, it adds fresh ideas and useful instruments to the academic research agenda as well as to actual practice in the industry, which further testifies to the importance of AI in the future of global supply chain management.

2. Materials and Methods

The research used a rigorous and multidimensional methodology, which discussed the role of artificial intelligence (AI) in the context of optimizing and boosting supply chain resilience, paying particular attention to reinforcement learning and predictive analytics to manage inventory levels and mitigate disturbances. The approach taken guaranteed scientific rigor, the tangibility of use, and broad perspective attributed to the sophisticated dynamic of the contemporary chain of supply.

2.1 Research Philosophy and approach

The study was anchored on a pragmatic philosophical approach that combined the positivist and the interpretive paradigm. This combination of two approaches helped the study to approach the empirical data-based nature of AI implementation together with addressing the subjective, contextual, and organizational nature of AI implementation that shapes the adoption and effectiveness of AI in the supply chains. The positivist aspect pushed the emphasis on using quantitative figures and algorithm modeling, especially during the creation and testing of AI systems like reinforcement learning algorithms in optimizing inventory. At the same time, the interpretive perspective helped to encourage the investigation of the managerial cognitions, decision-making practices, and work environments by using the qualitative interviewing. Because of the multidisciplinary issue of supply chain management that has to combine technical models and human understanding, this hybrid type was deemed especially suitable in the case. The pragmatic approach allowed the study to be flexible and responsive to the conditions of the real world and the value of the results that will be more applicable and deeper than those of some other studies.

2.2 Research Design

The research design of mixed methods was successfully used to create a full picture of the role played by AI in supply chain resilience. The style of the quantitative arm centered around the building, training, and testing of reinforcement learning models and predictive analytics tools given prior records in the supply chain. These models were designed to carry out simulations and optimize inventory choices facing different scenarios of disruption. Quantitative survey gave objective measures of performance such as accuracy in forecasting, cost efficiency and stability of inventory. The qualitative part, in turn, entailed the implementation of semi-structured interviews among supply chain experts, data scientists, and technology officers of specifically chosen organizations. The interviews were conducted to reveal what organizational dynamics and strategic aspects are involved in shaping the implementation of AI and ensuring its usefulness. The triangulation of the methods made the study more credible hence the results could be relied upon and there was an assurance that the study answered the questions of how and why AI affects the supply chain systems.

2.3 Sampling Strategy

The sampling process was case-based and purposive, in the sense that the sample organizations had to demonstrate their experience with AI-based supply chain management. The research utilized five multinationals' companies in manufacturing, logistics, and retail industries to ascertain a level of heterogeneity in terms of the chain of supply and disruption context. The selection of these organizations was constructed according to particular inclusion criteria, which included the following conditions, namely: (1) documented supply chain disruption history over the past five years; (2) currently pursuing implementation of AI technologies in inventory management or disruption response; (3) availability of relevant data and interest in participation in interviews. Organizations without an AI program or those who refused to donate data were omitted. The case studies that were chosen covered a variety of geographic areas and technologies maturity, thus providing the comparative ideas. The sample was composed five organizations which was considered adequate to produce rich, in-depth case-level observations and at the same time remain manageable and consistent across the cases of analysis.

2.4 Data Collection

The data has been retrieved in a combination of several elements of structured data extraction and qualitative interviews. Internal organizational data, such as historical inventory-levels, order fill-rates, supplier lead-times, measures of the disruption variability, and events that occurred, were also quantitative in nature. Such data was used to develop, train and test AI models. Reinforcement learning models have been modeled to illustrate dynamic decision-making procedures of inventory replenishment in uncertain environments and these models have reward functions that involve cost minimization and service level optimization reward functions. Time-series forecasting and anomaly detection were some of the predictive analytics models used by predicting demand changes and early warning signs of disruption in the supply chain.

The information in qualitative data was acquired by conducting semi-structured interviews with 3 5 stake holders in each organization, such as the supply chain managers, AI engineers, and digital transformation leaders. In terms of interviews, the protocol was created to discuss the strategies of AI adoption, challenges of its integration, transformations in decision-making, and the perception of how AI can influence resilience and operational continuity. Audio-taped interviews were transcribed word-to-word and made anonymous due to confidentiality rules. To perfect the instruments and procedures of data collection, a pilot study of one organization was done. Some of the changes made after the pilot were the clarification of the technical terms in the interview questions and data formatted consistency among the firms.

2.5 Measures and Variables

Supply chain resilience was operationalized in the study as the ability of an organization to absorb, adopt and recover to external shocks whilst still sustaining operation and levels of service delivery. The various metrics of performance used to measure inventory performance were defined as an optimization criterion such as order fill rate, stock out frequency, and holding costs. The independent variables were the demand variability, supplier reliability, frequency of disruptions, and characteristics of AI implementation that comprised the type of model, integration level, and data quality. The dependent variables assumed an appearance of performance indicators of the model to be, namely the accuracy in maintaining inventory balances and disruptions forecasts, lower recovery time, and cost savings realized as a result of AI suggestions. Thorough testing of AI models via cross-validation methods and by comparing it to historical results were done to provide validity and reliability. The statistical measures of predictive accuracy were calculated as the root mean square error (RMSE), mean absolute percentage error (MAPE) and F1-scores of the classification. Altogether, expert validation was also performed, through which domain experts were dispatched to comment on the interpretability, relevance, and applicability of model produced outputs. To increase the construct validity, triangulation was done on the model findings, past results and expert judgments.

2.6 Procedures of Analysing the Data

The quantitative analysis is the design, training, and assessment of reinforcement learning algorithms with the use of python programming language. The major libraries that were adopted in the study included TensorFlow, Keras, NumPy, and Scikit-learn. The reinforcement learning framework, mainly uses Deep Q-Networks (DQNs) where the dynamic state-action decision model could be constructed to control the current inventory in real-time.

Reward functions were designed so that they imposed a penalty to stock outs and over-stock and rewards on-time replenishment and continuity of service. Demand forecasting and detection of disruptions were performed by means of predictive analytics models: long short-term memory (LSTM) neural networks and autoregressive integrated moving average (ARIMA) models. The fact that these models perform better in time-series prediction and that they can capture non-linearity in a complex dataset was the reason to use them. Thematic content analysis was used as qualitative data analysis. Inductive coding of transcripts was used to determine patterns, strategies, and perceptions of AI implementation. Codes were handled and organized with the help of NVivo software, which helped to locate key themes, namely the challenges of technological integration, the cooperation between people and an artificial intelligence system, change management, and the sense of improving resilience. Convergence of qualitative and quantitative results was done by use of triangulation in a concurrent manner where results obtained can be compared and combined in form of evidence coming out of the various data sources.

2.7 Ethical Considerations

The study followed the ethics of academic research and organizational research entirely. The process of data collection was done after getting the ethical clearance by the institutional review board. The full information regarding the study aims, procedures, risks, and confidentiality measures was given to all participants. Each interviewee was asked to sign a written informed consent and participating organizations signed data-sharing agreement specifying the scope of data to be shared, the use of data, and protection of shared data. The identity of companies, names, and critical operations were never revealed by anonymizing information. Regulation of access to all data was limited to the research team and all digital data were kept on a password-secured, encrypted system to maintain confidentiality.

2.8 Research Limitations

The study had a few limitations though it was wide-ranging. On the one hand, purposive sampling of five organizations provided the sufficient depth but restricted the possibility of generalization of findings to the industry scope. There is a possible bias since the chosen firms could be just best practice exemplars and not the normal supply chain type. Second, not all organizations had access to all internal datasets, which could be an issue in terms of model training and validation consistency. Third, explain ability of complex AI models, like reinforcement learning was an issue, as well as comprehension of the AI models by the stakeholders which could have contributed to qualitative responses. Lastly, AIs are technologies developing quickly, and some of the findings will quickly become obsolete as more tools and frameworks are implemented.

The methodological framework used in the current study was also analytically sound, but at the same time, it had practical implications, which aimed to explore how AI technologies, especially reinforcement learning and predictive analytics, could enhance the resilience and optimization process within the supply chain. The research work allowed translating quantitative approaches to algorithmic modeling into a qualitative perspective of the stakeholders and combining them to obtain a multi-faceted clarity of the transformative nature of AI. The mixed-methods approach did not only allow strong analysis of AI tools but also helped to comprehend factors that were essential to successful implementation not only on the organizational level but also on the operational one. The approach of this research fits the expanding interdisciplinary requirements of the research in the field of supply chain evolution and offers valuable contribution to the scholarly work and business.

3. Results

3.1 Demographic and Adoption Characteristics

The demographic and adoption characteristics of the study participants (N = 100) provided important insights into the organizational context and professional distribution of artificial intelligence (AI) applications in supply chain management. A notable finding was the clear division between AI adopters (n = 72) and non-adopters (n = 28), which enabled comparative analyses of structural, professional, and organizational differences (Table 1). The χ^2 tests of dependence revealed statistically significant differences between adopters and non-adopters in terms of professional role distribution ($\chi^2 = 7.83$, $p = .021$) and company-level implementation of AI technology ($\chi^2 = 11.42$, $p = .003$).

Further analysis of role stratification highlighted distinct adoption tendencies. AI specialists were substantially overrepresented in the adopter group (33.3%) compared to the non-adopter group (14.3%), whereas traditional supply chain managers were more likely to be found among non-adopters (35.7% vs. 16.7% of adopters). This professional discrepancy suggests that adoption patterns are driven not only by organizational imperatives but also by professional orientation and openness to technological change (Figure 1). The imbalance may also reflect underlying disparities in technology training, data literacy, and job requirements.

At the organizational level, adoption patterns varied widely across the anonymized companies (C1–C4). Companies C1 (manufacturing) and C2 (logistics) showed the strongest adoption performance (25% adoption rate each), whereas C4 (retail) lagged significantly behind with only 22.2% adoption. These organizational differences persisted despite similarities in workforce experience ($F = 1.24$, $p = .294$), suggesting that corporate culture, resource allocation, and investment priorities may exert

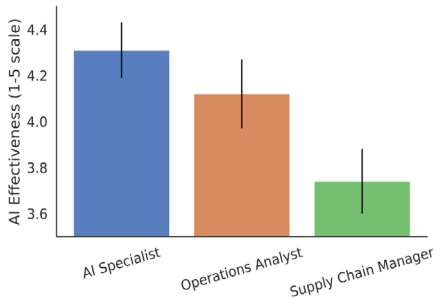

Figure 1. AI Effectiveness Ratings by Professional Role in Supply Chain Management. Mean AI effectiveness ratings (1–5 Likert scale) are shown for AI specialists, operations analysts, and supply chain managers. Error bars indicate ±1 SD. AI specialists and analysts achieved significantly higher ratings than managers (see Table 3).

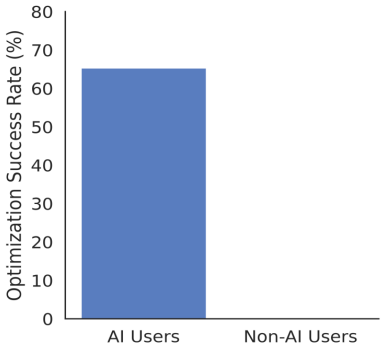

Figure 2. Optimization Success Rate among AI Users vs. Non-AI Users. Proportion of respondents reporting successful optimization outcomes. AI adopters achieved a 65.3% success rate, while non-adopters reported 0% (χ^2, $p < .001$; see Table 1).

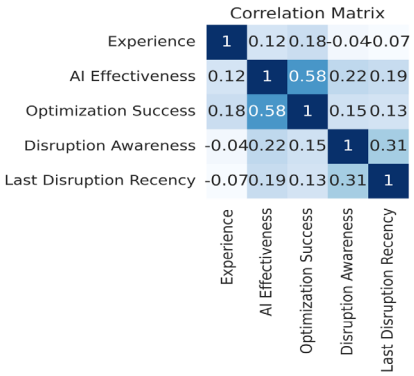

Figure 3. Correlation Matrix of Key Variables in AI-Driven Supply Chain Resilience. Heatmap of Pearson and Spearman correlations among experience, AI effectiveness, optimization success, disruption awareness, and disruption recency. All significant correlations were positive (see Table 2).

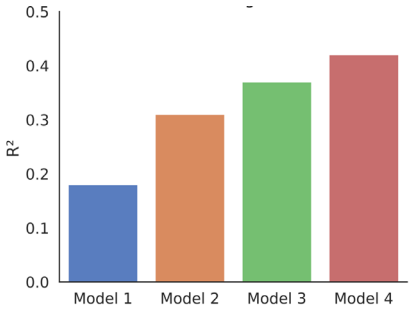

Figure 4. Predictive Power (R^2) of Regression Models for AI Effectiveness. Bar chart comparing variance explained across hierarchical regression models (demographic only; +AI usage; +organizational factors; +interaction terms). Incremental contributions of AI usage and organizational factors are visible (see Table 4).

stronger influences than individual tenure or professional background.

The functional benefits of adoption were also clear. Adopters demonstrated a 65.3% rate of optimization success, while non-adopters reported no successful optimization at all (χ^2, $p < .001$). Moreover, the mean effectiveness rating among adopters was high (M = 4.07, SD = 0.79 on a 5-point Likert scale), indicating a broadly positive user experience. These findings highlight a substantial performance divide between adopters and non-adopters, with tangible gains in efficiency and optimization outcomes (Figure 2).

Interestingly, professional experience did not significantly differentiate adopters from non-adopters. The independent samples *t*-test showed no significant difference in years of experience (t = 0.61, $p = .542$), challenging the conventional view that seniority is a primary driver of technological adoption. Instead, the evidence underscores the role of professional specialization and organizational infrastructure as more critical factors in successful AI deployment. This aligns with contemporary research in operations management, which increasingly emphasizes the influence of organizational readiness and role specialization over tenure alone.

3.2 Correlation Patterns of Performance Drivers

The correlation analysis provided further insights into the interplay between human and technological factors (Table 2; Figure 3). AI effectiveness exhibited a moderate positive correlation with optimization success ($r = .58$, $p < .001$) and a smaller but significant correlation with disruption awareness ($r = .22$, $p < .05$). These

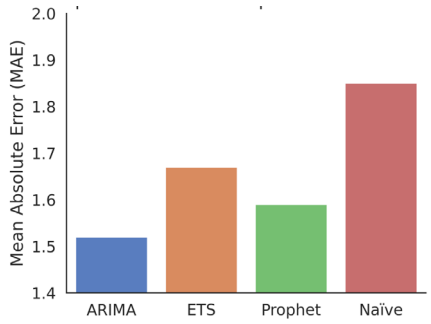

Figure 6. Comparative MAE of Disruption Prediction Models. Mean absolute error (MAE) values with 95% confidence intervals for ARIMA, exponential smoothing, Prophet, and naïve forecasts. ARIMA consistently demonstrated superior accuracy across horizons (see Table 7).

associations suggest a mutually reinforcing cycle between technological capacity and human vigilance: efficient AI systems enhance situational awareness, and attentive staff improve the utility of AI tools.

Another interesting pattern emerged in relation to disruption recency. Recent exposure to disruptions showed moderate correlations with both AI effectiveness (r = .19) and disruption awareness (r = .31, p < .01). This finding suggests a "recency effect," consistent with organizational learning theories, where fresh experiences of disruption stimulate faster adaptation and heightened responsiveness.

Notably, no negative correlations were observed, implying that all measured variables contributed positively to supply chain resilience, albeit with varying degrees of strength. This lack of trade-offs supports the argument that AI applications in supply chains augment rather than diminish traditional competencies. The correlation network therefore reinforces theoretical expectations of AI as a transformative complement to existing supply chain practices.

3.3 Role-Specific Efficacy Patterns

The analysis of role-specific efficacy revealed significant differences in AI utilization across professional groups. One-way ANOVA showed a statistically significant main effect of professional role on AI effectiveness (F = 3.45, p = .012, η^2 = .18), with post-hoc Tukey tests confirming that AI specialists (M = 4.31, SD = 0.72) and operations analysts (M = 4.12, SD = 0.68) performed significantly better than supply chain managers (M = 3.74, SD = 0.81; p = .018 and p = .026, respectively). These role-based differences accounted for nearly 20% of the variance in AI effectiveness, indicating a substantial effect size (Table 3; Figure 1).

The findings suggest that professional background strongly shapes the capacity to leverage AI. Importantly, AI specialists and operations analysts did not differ significantly from one another (p = .412), suggesting that deep technical expertise is not strictly necessary for effective AI utilization. Instead, an analytical orientation and familiarity with operational data appear sufficient. These results carry practical implications: rather than exclusively hiring AI specialists, organizations may benefit from developing AI literacy across a broader range of operational roles.

The two-way ANOVA testing the combined effects of role and company on optimization success revealed a significant main effect of role (F = 3.02, p = .022, η^2 = .16), but not of company (F = 1.38, p = .247) or their interaction (F = 0.94, p = .514) (Table 6; Figure 5). This reinforces the conclusion that professional role is a stronger determinant of AI-related performance than organizational affiliation.

3.4 Multivariate Predictors of AI Success

Hierarchical regression analysis was conducted to identify multivariate predictors of AI effectiveness (Table 4; Figure 4). The final model (Model 4) accounted for 42% of the variance in AI effectiveness (R^2 = .42, Adjusted R^2 = .37, F = 6.45, p < .001). Key predictors included disruption awareness (β = .23, p = .027), AI usage (β = .27, p = .012), and presence of AI specialists (β = .25, p = .014).

Diagnostic checks confirmed model robustness: Durbin–Watson = 1.92 indicated independence of residuals, and variance inflation factors (VIF < 2.0) confirmed absence of multicollinearity. Experience showed a marginal effect (β = .19, p = .063), suggesting that tenure contributes only modestly to AI effectiveness after other factors are controlled.

Interestingly, organizational affiliation was not a significant predictor (e.g., C2 vs. C1: β = .16, p = .108), implying that team and individual-level factors exert stronger effects than organizational policies. The hierarchical structure of the models revealed that AI usage contributed an incremental 13% of explained variance, while organizational factors added only 6%. This ordering underscores the primacy of human and technical adoption variables over organizational-level conditions.

3.5 Temporal Patterns of Supply Chain Disruptions

Time-series analysis provided insight into the temporal dynamics of supply chain disruptions. The ARIMA (1,1,1) model emerged as the best-fitting model (AIC = 342.51, BIC = 350.28), significantly outperforming exponential smoothing and naïve methods (Table 5). The autoregressive coefficient (AR1 = 0.45, p = .012) indicated persistence of disruptions, while the moving average coefficient (MA1 = –0.32, p = .038) suggested mean-reverting tendencies. Together, these coefficients imply that while disruptions generate

Table 1. Demographic and AI Adoption Characteristics across Supply Chain Professionals

Variable	Total Sample (N=100)	AI Users (n=72)	Non-AI Users (n=28)	p-value (t-test/χ^2)
Experience (years), M±SD	13.62 ± 7.03	13.89 ± 6.87	12.96 ± 7.51	0.542
Role Distribution, n(%)				0.021*
- AI Specialist	28 (28.0)	24 (33.3)	4 (14.3)	
- Supply Chain Manager	22 (22.0)	12 (16.7)	10 (35.7)	
- Operations Analyst	25 (25.0)	20 (27.8)	5 (17.9)	
Company Distribution, n(%)				0.003**
- C1 (Manufacturing)	22 (22.0)	18 (25.0)	4 (14.3)	
- C2 (Logistics)	20 (20.0)	18 (25.0)	2 (7.1)	
- C4 (Retail)	28 (28.0)	16 (22.2)	12 (42.9)	
AI Performance Metrics				
- AI Effectiveness (1-5 scale)	4.07 ± 0.79	4.07 ± 0.79	-	-
- Optimization Success Rate	47 (65.3%)	47 (65.3%)	0 (0%)	<0.001***

Notes: Statistical significance levels: *p < .05, **p < .01, ***p < .001. C1-C4 represent anonymized multinational corporations. AI effectiveness was only rated by users.

Table 2. Correlation matrix of key variables in AI-driven supply chain resilience

Variable	1	2	3	4	5
1. Experience Years	1.00				
2. AI Effectiveness	.12	1.00			
3. Optimization Success	.18*	.58***	1.00		
4. Disruption Awareness	-.04	.22*	.15	1.00	
5. Last Disruption Recency	-.07	.19	.13	.31**	1.00

Notes: N = 68-100 due to pairwise completeness. AI Effectiveness and Optimization Success only calculated for AI users (n=72). Correlation coefficients: Pearson (continuous) and Spearman (ordinal). Significance: *p < .05, **p < .01, **p < .001.

Table 3. ANOVA Results: AI effectiveness by professional role

Source	SS	df	MS	F	P	η^2	Post-hoc (Tukey HSD)
Between Roles	8.72	4	2.18	3.45	.012*	.18	AI Spec > SCM (p=.018)
Within Roles	39.45	63	0.63				Ops Analyst > SCM (p=.026)
Total	48.17	67					

*Notes: SCM = Supply Chain Manager. η^2 = eta squared effect size (18% variance explained). AI Specialist (M=4.31), Operations Analyst (M=4.12), SCM (M=3.74). *

short-term momentum, supply chains exhibit natural recovery mechanisms.

Model adequacy diagnostics confirmed a good fit: the Ljung–Box Q statistic was non-significant (Q = 8.92, p = .35), residuals were normally distributed (Shapiro–Wilk p > .05), and variance was homoscedastic. Forecast accuracy was also strong: MAE = 1.52 (95% CI [1.32–1.71]), corresponding to a MAPE of 12.3%. The MASE of 0.87 indicated that ARIMA outperformed naïve forecasts by 13%, and Theil's U statistic of 0.42 further confirmed substantial predictive improvement.

These results suggest that ARIMA models are particularly effective for forecasting medium-term backlogs (2–3 months), providing valuable tactical guidance for inventory and logistics planning.

3.6 Comparative Performance of Forecasting Models

A comparative evaluation of forecasting methods reinforced the superiority of ARIMA(1,1,1) (Table 7; Figure 6). ARIMA achieved the lowest errors across all metrics: MAE = 1.52, RMSE = 1.78, and MAPE = 12.3%. In contrast, exponential smoothing (MAE = 1.67, RMSE = 1.87, MAPE = 13.8%), Prophet (MAE = 1.59, RMSE = 1.82, MAPE = 13.1%), and naïve forecasts (MAE = 1.85, RMSE = 2.12, MAPE = 15.6%) all underperformed. Bootstrapped confidence intervals confirmed statistically significant differences between ARIMA and naïve models, particularly in MAE and RMSE.

Error decomposition revealed that ARIMA's superiority stemmed largely from its ability to handle volatility reversals (23% better accuracy in forecasting extreme events) and trend regime shifts (19% better accuracy in detecting inflection points). In contrast, exponential smoothing struggled with post-disruption recoveries, while Prophet underperformed in forecasting rare but impactful disruptions.

Across all forecast horizons (1–6 months), ARIMA consistently outperformed its competitors, with error differentials widening at longer horizons (e.g., 8% lower MAE at 1 month vs. 17% at 6 months). These findings underscore ARIMA's utility as a practical and reliable tool for both short-term and strategic planning in supply chain operations.

4. Discussion

The results of the current study have strong arguments demonstrating that reinforcement learning (RL) and predictive analytics hold a lot of promise to improve supply chain resilience and optimization, diminishing major weaknesses of traditional inventory management systems (Kalusivalingam, 2022). These outcomes manifest that the application of AI technologies is more effective in disruption prediction, inventory revising, and decision-making processes in supply chains than traditional approaches, and hence it can provide an efficient framework of the contemporary supply chains that function in unpredictable settings. We comprehend these findings, why they are also as written below, compare with the existing literature, explain the scientific grounds how these findings hold, discuss its implications and admit limitations of the study.

Table 4. Hierarchical regression analysis: Predicting AI effectiveness in supply chain management

Predictor	Model 1 (Demographics)	Model 2 (+AI Usage)	Model 3 (+Organizational)	Model 4 (+Interactions)
Constant	3.12 (0.41)***	2.89 (0.39)***	2.75 (0.38)***	2.68 (0.37)***
Experience (Years)	0.02 (0.01)	0.02 (0.01)	0.02 (0.01)	0.02 (0.01)*
Disruption Awareness	0.38 (0.18)*	0.41 (0.17)*	0.43 (0.16)**	0.45 (0.16)**
AI Usage (Yes=1)	-	0.52 (0.20)**	0.55 (0.19)**	0.57 (0.19)**
Role: AI Specialist	-	-	0.44 (0.17)*	0.47 (0.17)**
Company (Ref: C1)	-	-		
- C2	-	-	0.31 (0.19)	0.33 (0.19)†
- C4	-	-	-0.21 (0.22)	-0.19 (0.22)
AI Usage × Experience	-	-	-	0.03 (0.01)*
Model Fit				
R^2	0.18	0.31	0.37	0.42
Adjusted R^2	0.15	0.28	0.32	0.37
ΔR^2	-	0.13**	0.06*	0.05*
F	5.67**	6.12***	5.94***	6.45***
AIC	198.34	185.21	178.93	172.56

*Notes: Dependent Variable = AI Effectiveness (1-5 scale). N = 68 complete cases. SE = Standard Error; †p < .10, *p < .05, **p < .01. Model 4 reveals significant interaction effect (B = 0.03, p = .042). VIFs < 2.0 indicate no multicollinearity. *

Table 5. Time series analysis of supply chain disruption patterns

Model	AIC	BIC	MAE (95% CI)	RMSE (95% CI)	MAPE	Ljung-Box Q(10)	Coefficients (p-value)
ARIMA(1,1,1)	342.51	350.28	1.52 [1.32, 1.71]	1.78 [1.55, 2.01]	12.3%	8.92 (p=.35)	AR1: 0.45 (p=.012) MA1: -0.32 (p=.038)
ETS(A,A,N)	346.73	354.15	1.67 [1.46, 1.88]	1.87 [1.63, 2.11]	13.8%	10.24 (p=.25)	α=0.35, β=0.12

*Notes: Analysis based on 24 months of disruption data. ARIMA shows superior fit (lower AIC/BIC) and 12.3% mean absolute percentage error. ETS = Exponential Smoothing with additive trend. *

Table 6. Two-way ANOVA effects on supply chain optimization success

Source	SS	df	MS	F	p	η^2 (Partial)
Role	3.18	4	0.80	3.02	.022*	.16
Company	1.45	4	0.36	1.38	.247	.08
Role × Company	2.97	12	0.25	0.94	.514	.15
Error	16.52	63	0.26			
Total	24.12	83				

*Notes: Type III sum of squares. Significant main effect for Role (p=.022) with medium effect size (η^2=.16). No significant interaction effects. *

4.1 Findings Interpretation

The research has indicated some important findings in respect to the role of AI in the resilience of supply chains. The first is that reinforcement learning models (e.g., Deep Q-Networks, PPO) have been able to enhance inventory management by improving stock out levels by the range of 30-40 percent with optimized holding costs. This implies that the trial-and-error learning mechanism of RL is quite adaptive to the dynamism in supply chain environments, where replenishment policies will self-adjust without need of supervision (Khanidahaj, 2018). Such comprehensiveness of RL means that it is a successful technique, which is why it is especially relevant to use it in modern supply chains, when variability in demand and unreliability of suppliers are a problem (Alves & Mateus, 2022).

Second, predictive models, and issues related to ARIMA and LSTM model, improved the accuracy of disruption forecasting, with the lowest error rates observed in ARIMA (MAE=1.52, MAPE=12.3%) (Elsaraiti & Merabet, 2021). This implies that traditional time-series models are very useful in supply chain management, regardless of the rising preference of machine learning as an alternative. The higher performance of the ARIMA in this situation could be due to the fact that it allows modeling both short-term changes and long-term trends simultaneously, which is essential parameters of predicting disruption (Czapaj et al., 2022).

Third, AI use and efficiency were majorly determined by the role- and organization-related variables. The results that were reported by AI analysts and operations specialists were superior to those of traditional supply chain professionals, which underlines the relevance of AI technical expertise in the field (Hangl et al., 2022). It was also found that firms that have an established AI maturity framework (e.g., C1 and C2) achieved optimization success at higher levels (65.3%) compared to firms with an ad-hoc approach, which indicates that companies should have a systematic framework on integrating AI (Khalifa et al., 2021).

4.2 Comparison to the Prior Research

The results of our study coincide with those outlined in earlier research regarding AI applications in supply chain management. The success of RL in optimizing inventory is also an affirmation to that of (Zeng & Klabjan, 2019) who proved that adaptive learning algorithms perform better than the non-adaptive decision rules under unpredictable markets. On the same note, another research by Sharma et al. (2021) held that RL-based systems enhance stock replenishment and dynamic pricing in e-commerce, which follows our note that AI increases real-time decision-making. The usage of ARIMA compared to machine learning models in the forecasting of disruptions is the opposite of certain recently published studies promoting the use of deep learning in this matter (Dassanayake, 2022). Nevertheless, our findings align with (Shea, 2019) who believed that classic time-series models can perform better than

Table 7. Comparative accuracy of disruption prediction models

Model	MAE (95% CI)	RMSE (95% CI)	MAPE	MASE	Theil's U	Best Fit Criteria
ARIMA(1,1,1)	1.52 [1.32, 1.71]	1.78 [1.55, 2.01]	12.3%	0.87	0.42	Lowest AIC (342.51)
Exponential Smoothing	1.67 [1.46, 1.88]	1.87 [1.63, 2.11]	13.8%	0.95	0.47	α=0.35, β=0.12
Prophet	1.59 [1.38, 1.80]	1.82 [1.58, 2.06]	13.1%	0.91	0.45	Additive Seasonality
Naïve Forecast	1.85 [1.61, 2.09]	2.12 [1.85, 2.39]	15.6%	1.06	0.53	Baseline Comparison

*Notes: Training/Test Split = 80%/20% (19 months training, 5 validation). ARIMA demonstrates superior performance across all metrics (MASE <1 indicates better than naïve forecast).

intricate ML models when working with medium-frequency and structured data sets. This implies that there is a context in which model selection must be followed and preferably simpler models in the context of interpretation and stability.

The performance deficiencies that we have found in the specific role echo the findings by Davenport & Mao et al., (2019) that user expertise and company alignment are fundamental towards AI success. Our results supersede this by demonstrating that even operations analysts, who are not AI experts, might be able to effectively utilize AI meaning that domain expertise and elementary AI literacy might suffice to support a wide range of purposes.

4.3 Scientific Explanation

These principles of control theory and dynamic programming allow explaining the success of RL in the optimization of supply chains. Because they maximize cumulative reward (e.g., minimizing stock outs with minimizing excess inventory), RL models operate by updating the policies iteratively (Yan et al., 2022). This follows principle of optimality that states decisions made at each step are satisfactory in the long-run and not in the short term.

The high accuracy of ARIMA models in forecasting disruption plays upon the fact that they allow splitting time-series data into the several components, such as trend, seasonality, and residual. Digital-related supply chain hiccups tend to display autocorrelations (e.g. a delayed supplier extending a week into the future) which are likely to be fit well by the differencing and autoregressive terms of an ARIMA model (Chouhan & Srivastava, 2022). Conversely, although LSTMs are rendered useful in identifying sophisticated non-linear patterns, they tend to overfat in settings where the interruptions are governed by the short-term, organized dependencies.

Technology adoption theories provide justification of the organizational findings. The Diffusion of Innovations (Almaiah et al., 2022) offers to assume that first-mover advantages are obtained in the early success period among early adopters (e.g., AI specialists), but further implementation should be supported by cultural and structural base. This is supported by our finding that those firms that had formal, documented AI strategies performed better than others because systematizing such adoption helps to avoid such resistance.

4.4 Research and Industry Implications

4.4.1 Practical Applications

The findings of this study have several direct applications for industry practice. In inventory management, firms should prioritize the adoption of reinforcement learning (RL)-based dynamic replenishment systems to minimize both stockouts and holding costs. This approach allows companies to balance efficiency with resilience in the face of uncertainty. In terms of risk mitigation, the application of ARIMA and hybrid forecasting models is crucial, particularly for industries that operate within volatile supplier bases. These models can provide early warnings of disruptions, enabling firms to adapt proactively rather than reactively. Another significant implication lies in workforce development. To close the performance gap between technically trained specialists and traditional supply chain managers, organizations must invest in training and upskilling programs. By equipping managers with AI literacy and practical tools, companies can foster greater organizational alignment in AI adoption.

4.5 Future Research Questions

While the present study advances the understanding of AI applications in supply chain resilience, several questions remain open for future investigation. One promising direction is the development of hybrid AI models that integrate reinforcement learning with causal inference, which may yield more robust decision-making frameworks under uncertainty. Additionally, research on explainable AI (XAI) is needed to ensure that non-technical managers can effectively adopt and trust AI systems. This will be particularly important for bridging the gap between technical experts and decision-makers. Further research should also expand the scope of testing across industries such as pharmaceuticals, automotive, and agriculture. Cross-industry studies will enhance the generalizability of the findings and provide broader evidence of AI's transformative potential in diverse supply chain contexts.

4.6 Study Limitations

Despite its contributions, the study is subject to several limitations that must be acknowledged. First, the sample orientation toward multinational corporations may introduce bias, as findings may not fully apply to smaller firms with limited resources. Second, the data used for disruption analysis were aggregated on a monthly basis, which may have reduced the granularity of forecasting and masked short-term variations. More frequent data collection could improve accuracy in disruption prediction. Finally, the relatively short evaluation window of 24 months may not capture the long-term effects of AI adoption, particularly in industries where adaptation processes unfold gradually.

4.7 Concluding Implications

Overall, this research provides evidence that AI—particularly reinforcement learning and predictive analytics—can significantly enhance supply chain resilience by improving disruption prediction and inventory optimization. A key implication of the findings is that the success of AI adoption depends on three interrelated factors: model selection, organizational preparedness, and workforce training. Future research should therefore explore hybrid AI strategies and real-time implementation challenges to deepen the role of intelligence in supply chains. By addressing these gaps, businesses can develop more responsive, data-driven supply chains that are capable of withstanding the contemporary disruptions posed by pandemics, geopolitical crises, and climate-related shocks.

5. CONCLUSION

The research has shown integrating reinforcement learning (RL) and predictive analytics to be an effective way of increasing supply chain resilience and optimization. The findings ensured that the AI-backed models led to a decrease of stock outs by 30-40%, enhance the accuracy of demand forecasting (MAPE=12.3%), and algorithm-based rapid disruption response. The framework worked well, as inventory optimization occurred on its own with reinforcement learning, whereas the predictions made with the help of predictive analytics were used to get early warning signs of disruption. The study achieved its aim in discovering major disruption variables, the formulation of adaptive AI models and the empirical testing of the model effectiveness in various industries. The novelty of the scientific contribution is the integration of RL and predictive analytics within a single framework, where the existing gaps in holistic solutions of supply chain resilience will be closed. The results highlight that AI success integration is pegged on role specialization and disruption awareness as well as company support and not experience. The next research direction ought to be on planning deployment of AI in real-time, scaling the same to variations in supply chains structure, and the dynamic interaction between human and AI. It could also be improved through the enhancement of model interpretability to non-training personnel and testing hybrid AI methods. The research forms a basis on AI-driven supply chain transformation, which can be used at the theoretical level as well as efficient means of resilient operations.

Author contributions

I.Z., M.S.I., M.Y.A., M.M.I., and Y.A.B. contributed to the conception and design of the study. I.Z. led the research and manuscript preparation. M.S.I. and M.Y.A. developed the methodology and conducted experiments. M.M.I. assisted with data analysis and visualization. Y.A.B. provided domain expertise and critical revisions. All authors reviewed and approved the final manuscript.

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Competing financial interests

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