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ENHANCING SUPPLY CHAIN RESILIENCE ACROSS U.S. REGIONS USING MACHINE LEARNING AND LOGISTICS PERFORMANCE ANALYTICS

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Abstract

This study looks at how supply chain resilience can be strengthened across U.S. regions by linking logistics performance analytics with machine learning. We started by framing resilience in measurable terms, focusing on key performance indicators such as on-time delivery, cost efficiency, and variability across carriers and regions. With these metrics in place, the next step was to clean and structure shipment data so that patterns could be revealed. Using that foundation, we built models to predict delays, optimize carrier selection, and detect anomalies that might signal underlying fragility. Forecasting methods were applied to anticipate future shipping costs and route performance, while clustering was used to distinguish between resilient and fragile connections within the network. From there, we moved beyond standard predictive tasks. We experimented with resilience-aware objectives that penalize misclassifying delayed shipments more heavily, tested whether models trained in one region could adapt to another, and subjected the models to stress scenarios that mimicked shocks like surges in demand, noisy data, or carrier disruptions. What stood out is that while traditional metrics and models capture average performance well, resilience-aware methods provide a sharper view of vulnerabilities and recovery capacity. The insights are not just academic. They

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show that resilience can be operationalized through a combined framework of analytics and machine learning, producing tools that managers and policymakers can use to spot risks earlier, choose more reliable carriers, and plan for disruption. In practice, this makes it possible to see resilience as more than a buzzword: it becomes a measurable, actionable quality of the supply chain that can be managed and improved across U.S. regions.

Keywords: Supply Chain Resilience, Machine Learning, Logistics Performance Analytics, Anomaly Detection, Carrier Optimization, Stress Testing, Domain Adaptation.

1. Introduction

1.1 Background and Motivation

The U.S. supply chain has long been recognized as one of the most complex and critical infrastructures in the global economy, yet it is also highly vulnerable to recurring disruptions. Weather-related events, from hurricanes to winter storms, frequently interrupt transportation networks, while surges in consumer demand during peak seasons place enormous strain on carriers and regional hubs. These challenges are compounded by the variability in carrier reliability and the unpredictable nature of global logistics, which together highlight the limitations of traditional supply chain management strategies. Conventional logistics optimization has historically centered on reducing costs or minimizing average transit time, but these objectives do not capture the deeper requirement of resilience, which is the ability to absorb shocks, adapt, and continue functioning under adverse conditions. As Wieland and Durach (2021) argue, resilience must be viewed not simply as efficiency under normal operations but as the capacity to sustain and recover performance in the face of disruption [23].

Recent developments underscore the urgency of this shift. The COVID-19 pandemic and subsequent supply shocks revealed structural weaknesses across U.S. regions, where certain routes and facilities exhibited severe fragility while others demonstrated relative robustness. Studies such as Hasan et al. (2025) emphasize that resilience in modern supply chains cannot be addressed by incremental efficiency gains alone; instead, it requires data-driven strategies that leverage artificial intelligence and machine learning to anticipate risks and dynamically adjust operations [12]. Similarly, Guo et al. (2025) provide evidence that AI-enabled mechanisms are increasingly central to resilience, showing through panel data analysis that predictive analytics can capture systemic risks before they manifest as large-scale disruptions [9]. Traditional risk management practices, which often rely on static scorecards or historical averages, struggle to respond to the nonlinear and dynamic nature of modern supply chains. This gap creates a demand for resilience-aware, regionally adaptive analytics capable of handling variability in demand, transportation delays, and carrier performance. Camur et al. (2023) demonstrate that predictive machine learning approaches can estimate product availability under disruption, providing actionable insights beyond standard forecasting [5]. Meanwhile, Nawaz et al. (2025) explore how machine learning models can move from measuring complexity to enabling resilience, arguing that robust forecasting of risks must integrate diverse signals such as economic complexity indicators and logistics data [16]. This growing body of work points toward a critical inflection point: while efficiency remains important, it is insufficient as the guiding principle for supply chain design and management.

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Instead, the resilience of regional supply chains must become a central performance goal. In this context, the use of machine learning and logistics performance analytics presents a powerful opportunity. By integrating predictive modeling with operational KPIs such as on-time delivery rates, cost efficiency, and variability, stakeholders can move beyond reactive responses and toward proactive resilience-building. Such a shift would allow supply chains to not only survive disruptions but to maintain service continuity, protect cost performance, and ensure that no region is disproportionately vulnerable.

1.2 Importance of This Research

Resilience is more than a theoretical aspiration; it is a practical necessity for businesses, carriers, policymakers, and consumers who depend on reliable logistics. In the U.S., disruptions ripple across industries and regions, creating downstream effects in manufacturing, retail, and consumer markets. The importance of this research lies in its ability to translate the abstract notion of resilience into quantifiable metrics and actionable insights that decision-makers can implement. As Hasan, Islam, and Rahman (2025) note, predictive accuracy in demand forecasting is not only about meeting consumer needs but also about ensuring system-wide continuity during uncertain conditions [11]. By applying machine learning techniques, predictive models can enhance foresight into shipment delays, route vulnerabilities, and cost fluctuations, which are all central to resilience. Carriers and logistics firms are under increasing pressure to demonstrate that their operations are both sustainable and resilient. Shawon et al. (2025) emphasize that sustainable logistics optimization, when paired with AI models, leads to more eco-efficient and reliable outcomes across supply chains in the USA [19 Similarly, Riad (2024) highlights that artificial intelligence enhances resilience by providing decision-making capabilities that reduce fragility and improve adaptability [18].

These contributions align with growing industry awareness, as noted in reports from the Financial Times (2025) and Harvard Business Review (2024), both of which argue that AI and predictive analytics are reshaping supply chain management by enabling companies to mitigate fragility before it translates into significant economic loss [8][10]. From a policy and governance standpoint, resilience is now recognized as a strategic priority. As Guo et al. (2025) show, AI mechanisms can be tied directly to resilience outcomes, suggesting that data-driven insights can inform regulatory and policy frameworks that seek to safeguard regional balance and avoid over-reliance on fragile links [9]. Business Insider (2025) further notes that last-mile complexity remains one of the most expensive aspects of logistics, and resilience-focused AI solutions could drastically reduce inefficiencies and vulnerabilities in this domain [4]. The importance of this research is further reinforced by studies such as Balan (2025), who argues that resilience and recovery are now inseparable in supply chain design, with AI-driven methods providing the tools to ensure rapid response when disruptions occur [3]. By incorporating machine learning and logistics performance analytics into resilience planning, this research not only addresses academic gaps but also provides a roadmap for practical implementation in industry. The outcome is a framework that aligns with the needs of managers seeking operational continuity, policymakers aiming to reduce regional inequalities in logistics, and carriers striving to remain competitive in a rapidly evolving landscape.

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1.3 Research Objectives and Contributions

The objectives of this research emerge directly from the recognition that supply chain resilience must be redefined in operational terms and systematically integrated into both analytics and predictive modeling. The first objective is to develop clear, measurable resilience KPIs that move beyond cost and mean transit time, instead incorporating on-time delivery rates, variability in performance, cost efficiency per mile, and regional balance. Defining resilience in this way allows the study to anchor its methods in quantifiable outcomes that stakeholders can monitor and optimize. A second objective is to quantify regional and carrier performance by applying logistics performance analytics across the dataset. This step makes it possible to benchmark differences between regions, assess the relative resilience of carriers, and uncover seasonality or demand-driven patterns that increase fragility. By grounding resilience in regional performance analytics, the research bridges the gap between theoretical frameworks and practical logistics outcomes. The third objective is to build predictive and prescriptive machine learning models for resilience tasks. This includes developing classifiers to predict delays, regression models to estimate transit times and costs, anomaly detection frameworks to identify outliers, and clustering methods to separate resilient routes from fragile ones. Beyond these predictive tasks, the study also introduces prescriptive optimization methods, enabling stakeholders to make informed decisions about carrier selection and route planning in ways that explicitly prioritize resilience.

Another objective is to evaluate resilience under simulated stress scenarios. By subjecting the models to conditions that mimic disruptions such as demand surges, data noise, or carrier-specific failures, the research tests not only accuracy but also robustness. This ensures that resilience is operationalized in a way that accounts for adverse conditions rather than idealized data environments. The contributions of this research are multifaceted. It proposes a KPI-driven resilience framework that is practical and implementable, integrates predictive modeling with prescriptive optimization, and advances the field through novelty in resilience-aware objectives, regional domain adaptation, and stress-testing methodologies. Furthermore, it presents a prototype system architecture that demonstrates how these methods can be scaled and deployed in real-world supply chains. Ultimately, the study contributes both to academic discourse and to practical industry application, offering tools that can help U.S. supply chains withstand and adapt to the increasingly complex landscape of disruptions.

2. Literature Review

2.1 Supply Chain Resilience Concepts

The concept of supply chain resilience has evolved significantly over the past two decades, yet it remains a term that is often invoked without a consistent operational definition. Traditionally, resilience in supply chains has been framed through three pillars: robustness, redundancy, and recovery. Robustness refers to the ability of supply chain structures to withstand shocks without significant performance degradation, redundancy highlights the maintenance of backup capacity or slack resources that can be activated during disruptions, and recovery emphasizes the speed and effectiveness with which systems can return to their pre-disruption states. Wieland and Durach (2021) distinguish resilience from risk management by stressing that

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resilience is not just about minimizing exposure to identifiable risks but about preparing for and adapting to unknown or unforeseeable events [23]. This distinction is critical in modern logistics environments where disruptions increasingly arise from systemic interdependencies, geopolitical tensions, and environmental shocks.

More recent studies have argued for resilience to be framed in quantifiable terms rather than abstract principles. Guo et al. (2025) emphasize that resilience mechanisms must be studied empirically, and their panel data evidence suggests that AI-based models provide a structured pathway to quantify resilience outcomes in supply chain networks [9]. Similarly, Balan (2025) underscores that recovery, often assumed to be reactive, can be proactively embedded into system design through predictive analytics and adaptive modeling [3]. Camur et al. (2023) also point out that resilience can be assessed in terms of predictive accuracy for product availability under disruption scenarios, which reframes resilience as a measurable performance target rather than an intangible quality [5].

The shift toward operational definitions has led to a growing recognition that resilience must be decomposed into key performance indicators (KPIs). Metrics such as on-time delivery rates, cost per mile, transit time variability, and disruption recovery lag provide a more objective basis for evaluating supply chain resilience. As Hasan et al. (2025) highlight in the context of supplier risk management, operational resilience requires embedding AI-driven KPIs into decision systems so that risks are flagged before they escalate into failures [12]. In practice, however, resilience remains inconsistently measured across industries, often reduced to qualitative assessments or post-disruption audits. This creates a gap between theoretical discussions of resilience and actionable models that firms can deploy. The growing body of literature suggests that quantifiable KPIs, when integrated with machine learning and logistics performance analytics, represent the most promising path toward embedding resilience directly into supply chain operations.

2.2 Logistics Performance Analytics

Logistics performance analytics focuses on the measurement and benchmarking of key operational variables such as transit times, shipping costs, and carrier performance. These analytics are fundamental to supply chain management because they allow firms to identify inefficiencies, optimize resources, and compare outcomes across carriers and regions. Throughput (2023) provides an industry-focused guide that emphasizes the practical benefits of supply chain analytics, noting that structured data-driven insights improve both short-term decision-making and long-term strategy [20]. Similarly, Inbound Logistics (2025) identifies predictive analytics as a key driver of enhanced visibility in logistics operations, particularly for managing variability and improving forecasting accuracy [13]. Similar to how energy management leverages AI to adapt to temporal fluctuations (Ahmed et al., 2025) [2], resilience modeling in logistics must integrate seasonality and regional stress factors. Despite these advances, much of the literature on logistics analytics remains descriptive rather than predictive. Shawon et al. (2025) argue that sustainable logistics optimization requires moving beyond traditional benchmarking toward AI-driven models that integrate ecological efficiency and operational performance simultaneously [19]. Riad (2024) further highlights that while

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logistics analytics provides essential descriptive insights, it must be paired with artificial intelligence to actively reduce fragility in supply chain operations [18]. This aligns with industry reports, such as the Financial Times (2025), which suggest that companies are increasingly turning to AI solutions to address persistent fragility in global and regional supply chains [8].

From an academic standpoint, logistics performance analytics has historically focused on cost and efficiency metrics but has not systematically incorporated resilience as a central dimension. Hasan, Islam, and Rahman (2025) illustrate this limitation by showing that even advanced demand forecasting models, while improving predictive accuracy, are insufficient unless they are tied to resilience-oriented outcomes such as service continuity under uncertainty [11]. Camur et al. (2023) also demonstrate that integrating predictive machine learning with performance analytics creates opportunities for more resilience-aware planning [5]. Yet, empirical applications remain rare. Guo et al. (2025) suggest that bridging this gap requires aligning performance metrics with resilience KPIs so that analytics move beyond efficiency and reflect the adaptability of supply chain systems [9]. Thus, while logistics performance analytics has matured as a field, its integration with predictive machine learning and resilience frameworks remains underdeveloped. Future research must move from descriptive benchmarking toward predictive and prescriptive analytics that explicitly target resilience, balancing cost efficiency with the ability to withstand and adapt to disruptions.

2.3 ML in Logistics and Supply Chains

Machine learning (ML) has increasingly been applied in logistics and supply chains for tasks such as delay prediction, route optimization, and anomaly detection. Harvard Business Review (2024) emphasizes that ML is transforming supply chain management by enabling predictive capabilities that go far beyond traditional forecasting methods [10]. For example, delay prediction models can classify shipments as on-time or delayed based on features such as distance, carrier history, and seasonal factors. Hasan et al. (2025) show that data-driven AI models for supplier risk management enhance resilience by identifying potential vulnerabilities before disruptions occur [12]. Similarly, Camur et al. (2023) illustrate the value of ML models in predicting product availability under disruption, which helps firms allocate resources more effectively [5]. Route optimization is another major application where ML models are used to dynamically adjust routing decisions in response to real-time data. Shawon et al. (2025) argue that eco-efficient optimization frameworks leverage ML not only to minimize cost and transit time but also to align with sustainability goals [19]. More advanced approaches incorporate hybrid models such as reinforcement learning, which have been applied in recent years to optimize last-mile delivery under uncertain demand conditions (Wang et al., 2024) [22].

Anomaly detection represents a third area of ML application, particularly relevant to resilience. By identifying outliers in shipping costs, weights, or transit times, ML models can flag emerging disruptions that traditional monitoring might overlook. Nawaz et al. (2025) stress the role of ML in forecasting systemic risks, noting that anomaly detection complements predictive models by capturing non-linearities and rare events [16]. Balan (2025) also emphasizes that anomaly detection contributes to resilience by enabling rapid interventions during early stages

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of disruption [3]. Cross-domain evidence from financial fraud detection demonstrates that anomaly detection models can capture rare but critical events, a principle equally relevant in supply chain disruptions (Fariha et al., 2025) [7]. Despite these advances, most ML applications in logistics still optimize for average performance metrics rather than resilience-aware objectives. Guo et al. (2025) observe that while ML improves prediction accuracy, models rarely incorporate resilience KPIs directly into their loss functions or decision rules [9]. This leaves a critical gap: supply chains may appear optimized under normal conditions but remain highly fragile under stress. Future research must therefore focus on integrating resilience-aware metrics into ML pipelines, moving beyond efficiency to operational robustness.

2.4 Domain Adaptation and Stress Testing in Supply Chains

One of the emerging frontiers in supply chain analytics is the application of domain adaptation and stress testing. Domain adaptation refers to the ability of models trained in one environment, such as a specific region or carrier network, to generalize effectively to new environments. This is particularly important in supply chains, where regional heterogeneity in infrastructure, carrier availability, and seasonal conditions can limit the portability of models. Toushik Wasi et al. (2024) highlight that graph neural networks (GNNs) show promise in handling such heterogeneity by capturing relationships between nodes in supply chain networks and generalizing across domains [21]. Stress testing, by contrast, focuses on evaluating the robustness of supply chain models under simulated disruption scenarios. Camur et al. (2023) argue that stress testing is essential for validating predictive models, as it reveals how performance degrades when assumptions break down [5]. Yet, few studies have systematically implemented stress tests in logistics ML research. Balan (2025) stresses that recovery-oriented modeling must incorporate both predictive resilience and post-shock adaptation, but empirical studies applying these principles remain limited [3].

A parallel can be drawn from cybersecurity, where predictive stress-testing of AI models is a standard method for detecting adversarial shifts. AI models in cybersecurity rely on these stress tests to expose vulnerabilities and anticipate attacks before they manifest (Das et al., 2025) [6]. The same methodology can be transferred to supply chain resilience, where predictive stress-testing helps planners simulate demand surges, carrier breakdowns, or regional disruptions in advance, and proactively design adaptive responses. Industry reports similarly emphasize the importance of stress testing. The Financial Times (2025) underscores that companies are increasingly aware of fragility but lack robust tools for simulating and mitigating disruption [8]. Business Insider (2025) adds that last-mile complexity introduces unpredictable vulnerabilities that only stress-tested ML systems can reliably manage [4]. Despite recognition of its importance, the literature reveals limited research on the transferability of models across regions and on structured stress testing within supply chain ML. Guo et al. (2025) provide some evidence that AI mechanisms improve resilience outcomes across diverse regional contexts, but their work highlights the need for more systematic approaches [9]. Nawaz et al. (2025) similarly note that resilience research often fails to simulate complex stressors, focusing instead on average-case performance [16]. Future research must therefore expand the use of domain adaptation and structured stress testing, ensuring that ML models for supply chains are not only

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accurate in controlled environments but also robust and transferable under real-world variability.

2.5 Gaps and Challenges

The literature on supply chain resilience, logistics analytics, and machine learning reveals several recurring gaps and challenges. First, there is a lack of resilience-aware optimization functions in most ML applications. Models are generally trained to minimize mean squared error or maximize accuracy, but these objectives do not align with resilience KPIs such as on-time delivery rates, cost variability, or disruption recovery capacity. As Guo et al. (2025) point out, the absence of resilience-aware objectives means that ML systems can appear highly accurate in normal conditions while still being fragile under stress [9]. Second, there is limited integration of prescriptive analytics with predictive modeling. Predictive models excel at forecasting delays or costs, but they do not necessarily inform decisions on what to do next. Hasan et al. (2025) argue that integrating prescriptive elements, such as carrier optimization or dynamic rerouting, into predictive pipelines is essential for moving from insights to action. Yet, empirical demonstrations of such integrated systems remain scarce in the literature.

Third, stress testing remains underutilized. While the importance of simulating disruption scenarios is widely acknowledged, few studies provide structured frameworks for doing so. Camur et al. (2023) demonstrate the potential of predictive models under disruption, but systematic stress testing protocols are still in their infancy [5]. Similarly, Balan (2025) highlights recovery as an essential component of resilience but notes that current approaches rarely validate models under realistic shock conditions [3]. Finally, there is an overall shortage of frameworks that operationalize resilience through quantifiable KPIs. Wieland and Durach (2021) remind us that resilience remains inconsistently defined and measured, often reduced to abstract or qualitative notions [23]. This leaves a significant research gap: the need for holistic frameworks that integrate KPIs, predictive and prescriptive ML models, and structured stress testing into coherent, deployable systems. Addressing these challenges will not only advance academic understanding but also provide practical tools for policymakers, carriers, and businesses seeking to strengthen the resilience of U.S. supply chains.

3. Methodology

3.1 Dataset and Preprocessing

This study is based on a synthetic dataset simulating two thousand shipments across multiple U.S. regions. Each record captures eleven features, including shipment identifiers, carrier, origin and destination warehouse, shipment and delivery dates, weight, cost, distance, transit days, and status. The dataset was intentionally designed with imperfections to mimic real-world conditions, including approximately two percent missing values and three percent outliers. Initial exploration revealed incomplete data in delivery dates and shipping costs, as well as suspiciously extreme weights inconsistent with the majority distribution. These characteristics reflect common challenges in supply chain datasets, where missing values may signal reporting delays or incomplete tracking, and outliers often indicate operational anomalies.

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Preprocessing focused on both data integrity and analytical readiness. Missing delivery dates were imputed with a placeholder while also flagged through a binary indicator to preserve information about missingness as a potential risk factor. Missing costs were imputed with the median to avoid biasing the distribution, with a corresponding flag introduced to track where imputation occurred. Outliers in shipment weight were defined relative to thresholds derived from descriptive statistics and were flagged with a binary indicator for later anomaly modeling. Beyond imputation, several engineered features were created to support resilience analytics. These included transit days, derived from the difference between shipment and delivery dates; cost per kilogram, which normalized shipping expenses relative to load; and composite shipment routes, created by concatenating origin and destination warehouses. Temporal features were also extracted from shipment dates, such as shipment month and day of week, to capture seasonality effects associated with holidays or winter weather surcharges. Together, these steps provided a cleaned and enriched dataset that reflects operational variability while retaining signals relevant to resilience.

Exploratory Data Analysis

The distribution of the Delivery Performance KPI highlights that the majority of shipments arrive on time, indicating that baseline operations are relatively efficient. However, a non-trivial share of delayed and undelivered shipments exists, signaling systemic vulnerabilities. These delays could arise from factors such as seasonal congestion, carrier inefficiencies, or route-specific bottlenecks. The presence of undelivered shipments is particularly concerning because it represents outright service failure rather than performance degradation, which undermines resilience more severely than predictable delays. The Cost Efficiency KPI distribution reveals that shipments are fairly balanced across cost-efficient, average-cost, and high-cost categories, with a small subset categorized as cost unknown due to missing data. This variability suggests that while most shipments operate within predictable cost bands, there are significant cost spikes that may reflect carrier surcharges, inefficient routing, or inconsistent demand allocation. These high-cost shipments may disproportionately stress budgets and highlight the need for prescriptive analytics in carrier and route selection. The Weight Outlier KPI shows that most shipments fall within expected operational ranges, with a limited number classified as outliers. While relatively infrequent, outlier weights represent critical resilience challenges since atypical loads can strain both physical and contractual capacities. They may also signal data entry errors or exceptional business cases that require special handling. Even though the proportion is small, these outliers can distort cost efficiency, delay predictions, and carrier performance benchmarks if not explicitly modeled.

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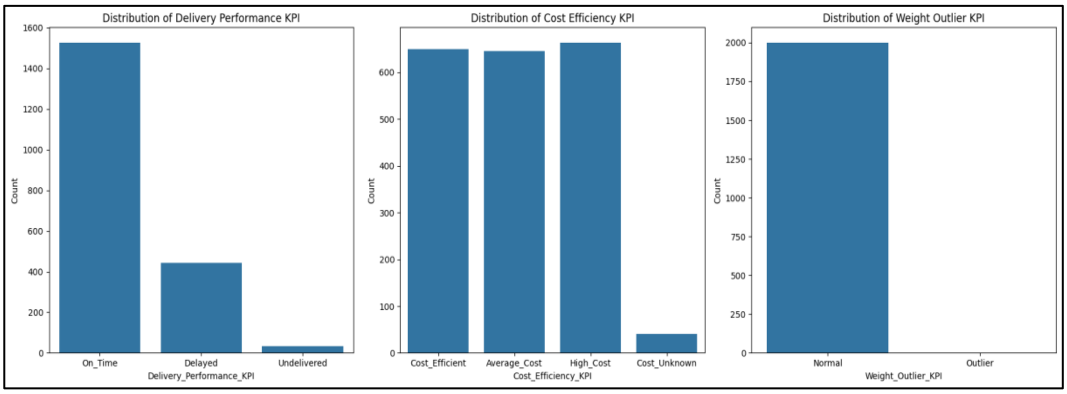

Fig.1: KPI distributions

The distribution of weight by origin warehouse demonstrates that certain warehouses handle disproportionately heavy loads, suggesting regional specialization or uneven demand allocation. These differences matter because warehouses that consistently dispatch heavier loads are more exposed to disruptions related to capacity limitations or carrier restrictions. It implies that resilience strategies must account for warehouse-specific risk profiles rather than treating all nodes as functionally equivalent. The cost by origin warehouse indicates that while most warehouses operate within relatively tight cost distributions, a few generate extreme cost values. This variability reflects differences in regional carrier access, routing constraints, or localized surcharges. It underscores the importance of benchmarking warehouses not only on service performance but also on their contribution to cost volatility, since high-cost variability undermines predictability and resilience. The distribution of distance by origin warehouse reveals systematic differences in regional routing. Some warehouses serve longer average distances, which naturally increases their exposure to transit variability and disruption risk. This suggests that resilience cannot be divorced from geography: warehouses that are structurally distant from key demand centers must be managed with additional buffers and contingency strategies. The analysis of transit days by origin warehouse further reinforces this point. Warehouses with consistently higher transit times may reflect either geographical disadvantage or weaker carrier support. These warehouses represent resilience hotspots since delays compound across downstream supply chain stages. This insight highlights the need for region-specific resilience measures rather than applying uniform standards.

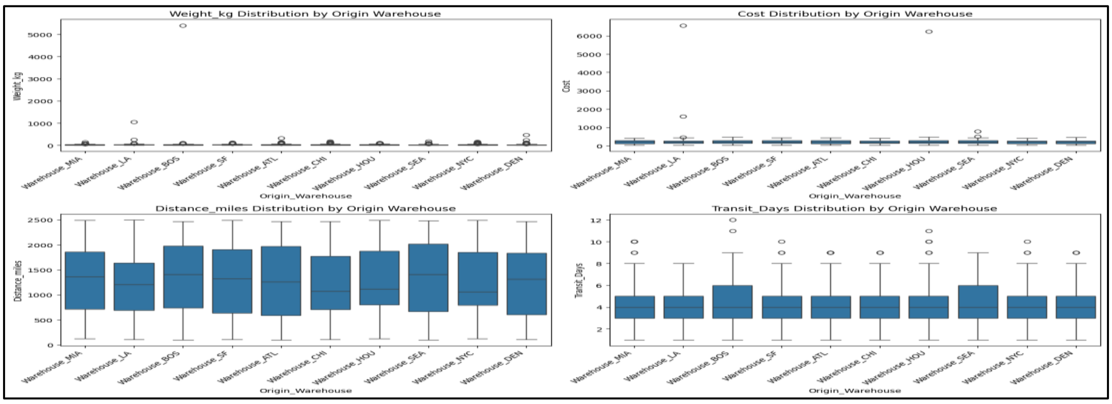

Fig.2: Distribution of numerical features by origin warehouse

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The weight by carrier distribution shows that carriers handle different load profiles, with some specializing in lighter shipments and others regularly handling heavier freight. This specialization influences carrier resilience, since carriers optimized for light shipments may not scale effectively to heavier loads during demand spikes. Aligning shipment assignment with carrier strengths, therefore, becomes a resilience tactic, ensuring that exceptional shipments do not overwhelm inappropriate carriers. The cost by carrier distribution highlights disparities in pricing strategies across logistics providers. Some carriers consistently manage costs within narrow bands, while others exhibit higher variability, potentially due to demand surcharges, regional imbalances, or weaker economies of scale. Carriers with high cost variability represent financial resilience risks, as firms cannot reliably predict expenses when disruptions occur. The distance by carrier distribution shows that certain carriers routinely serve longer-haul routes, which naturally exposes them to more variability in transit times and higher fuel costs. These structural differences underscore why resilience must be measured relative to carrier profiles: comparing carriers without adjusting for their operational footprints risks misleading conclusions about performance. The transit days by carrier distribution confirm that some carriers systematically achieve faster delivery times, while others incur longer or more variable performance. These findings are critical because on-time delivery is one of the most direct indicators of resilience. Carriers that consistently maintain low and predictable transit times under diverse conditions are inherently more resilient, while those with higher variability require closer monitoring or complementary resilience strategies, such as backup carrier agreements.

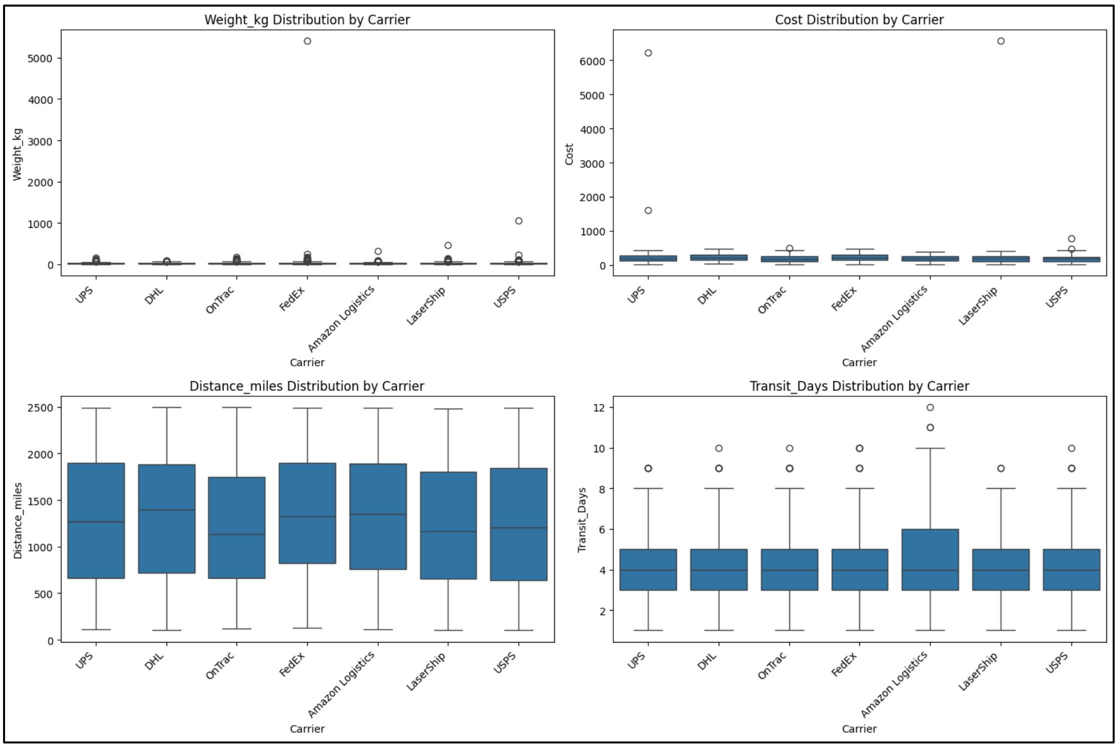

Fig.3: Distribution of numerical features by carrier

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3.2 Defining Resilience KPIs

Resilience was operationalized through measurable key performance indicators that quantify the stability and adaptability of logistics operations. Delivery performance was defined as the proportion of shipments arriving on time, where shipments requiring more than five days in transit were categorized as delayed, and those with missing delivery dates were treated as undelivered. Cost efficiency was captured by normalizing shipping costs through cost per kilogram and categorizing shipments into efficient, average, or high-cost segments based on percentile thresholds. A robustness dimension was added by flagging weight outliers, which often represent atypical shipments that stress capacity and reliability. To facilitate integration with predictive models, categorical KPIs were encoded into binary variables such as one for on-time performance, one for cost efficiency, and one for non-outlier shipments.

In addition to individual KPIs, resilience was assessed at a regional level. Aggregating performance by warehouse of origin highlighted regional disparities in resilience. For example, some regions exhibited consistently high on-time delivery but lower cost efficiency, while others balanced cost and timeliness but displayed vulnerability to weight variability. Regional balance was quantified as the variance of KPIs across warehouses, reflecting the degree to which resilience is evenly distributed rather than concentrated in select regions. This approach aligns with the notion that resilience must be systemic; a fragile region can create bottlenecks for the entire network. Defining resilience in this structured way allowed subsequent analysis to move beyond abstract narratives toward quantifiable measures embedded in the data.

3.3 Logistics Performance Analytics

With resilience KPIs established, logistics performance was analyzed at regional, carrier, and seasonal levels. Regional benchmarking involved grouping shipments by origin warehouse to calculate average values for each KPI. These aggregates enabled comparative analysis of warehouse resilience and revealed which locations consistently performed above or below system averages. The results were visualized through bar plots and heatmaps, which highlighted geographic imbalances across U.S. regions. Carrier benchmarking followed a similar approach, evaluating the major logistics providers across metrics such as on-time delivery rates, cost efficiency, and robustness to weight anomalies. These comparisons exposed trade-offs between carriers, where some demonstrated high reliability at higher costs while others were cost-efficient but more prone to delays. Seasonality analysis provided a temporal perspective on resilience. By aggregating shipments by month and day of week, patterns were revealed that aligned with expected logistical pressures, including surges during holiday months and extended transit times in winter. Weekly cycles also emerged, where shipments initiated at the start of the week demonstrated different delay probabilities than those shipped near weekends. The combination of regional, carrier, and seasonal performance analytics provided a multifaceted baseline of resilience that set the stage for predictive and prescriptive modeling.

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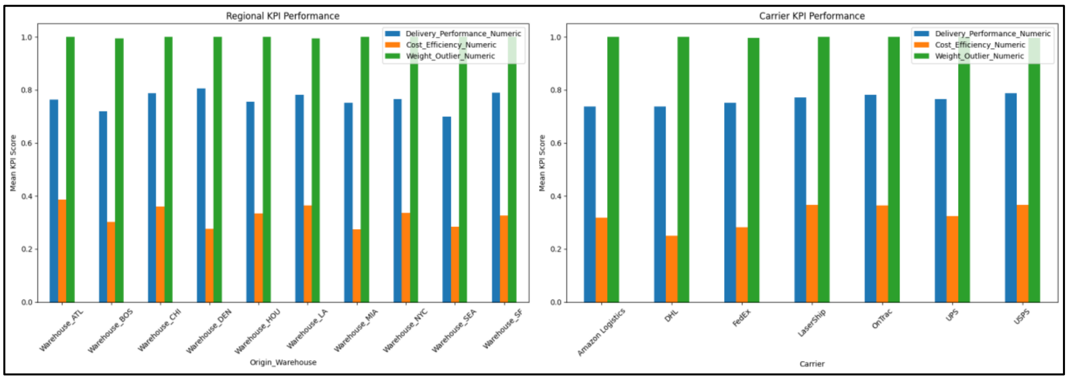

Fig.4: Regional and carrier KPI performance

3.4 Predictive & Prescriptive Modeling

Predictive modeling began with the task of delay classification, where logistic regression, random forest, and XGBoost models were trained to predict on-time versus delayed deliveries. The dataset was split into training and testing partitions, and model performance was evaluated with the area under the ROC curve and F1 score, balancing precision with recall. These models offered insights into feature importance, highlighting cost, transit distance, and seasonality as critical drivers of delay. Prescriptive modeling extended predictive insights into decision-making. Linear regression models were trained to estimate shipping costs and transit days for individual carriers. These models fed into a prescriptive scoring framework that suggested the optimal carrier for a given shipment, balancing predicted cost, time, and carrier reliability. Anomaly detection was performed with both autoencoder neural networks and isolation forests applied to numerical features, allowing detection of atypical shipments. Forecasting was approached with Prophet, which modeled daily shipping costs over time to predict future cost trends. Time-series forecasting has proven effective in volatile domains such as cryptocurrency (Islam et al., 2025) [14], suggesting its utility for anticipating logistics costs and delays where shocks and fluctuations are similarly unpredictable. By capturing both trend and seasonality, Prophet provided managers with forward-looking visibility into potential surges or cost declines, enabling more proactive budget allocation and route adjustments. Finally, k-means clustering grouped shipments and routes into clusters based on resilience KPIs, distinguishing fragile routes with high delays and low cost efficiency from resilient ones that consistently balanced cost and timeliness.

3.5 Advanced Enhancements

To advance beyond conventional predictive tasks, three enhancements were implemented. First, resilience-aware objectives were introduced by applying weighted loss functions in XGBoost models. Delayed shipments were penalized more heavily during training, encouraging the models to prioritize identifying resilience risks. Second, domain adaptation was tested by training a logistic regression classifier on shipments from one region and evaluating its generalizability to another. This experiment reflected the challenge of deploying models across heterogeneous supply chain environments. Third, structured stress testing was applied to the delay prediction model by simulating disruptions. Scenarios included artificially inflating shipment weights, extending transit times, injecting random noise into features, and disrupting

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the performance of a specific carrier. Model performance under these shocks was evaluated through changes in AUC and F1 score, revealing how well predictive systems maintained accuracy under stress. These enhancements illustrated the practical application of resilience-aware, regionally adaptive, and disruption-tested models, contributing toward a scalable framework for supply chain resilience analytics.

4. Evaluation and Results

4.1 Predictive Performance

The predictive models developed for delay classification achieved competitive performance across logistic regression, random forest, and XGBoost. Logistic regression demonstrated a strong balance between interpretability and accuracy, with an area under the ROC curve of 0.8160 and an F1 score of 0.8861. These results indicate that even relatively simple models are capable of distinguishing between on-time and delayed shipments when informed by engineered features such as distance, cost, and seasonality. Ensemble methods, particularly random forest and XGBoost, also performed well, though gains were incremental rather than transformative. Importantly, the high F1 score suggests that the models achieved a meaningful balance between precision and recall for the on-time class, ensuring that delays were identified without excessive false alarms. This is critical for operational resilience, where failing to flag delays can propagate downstream disruptions.

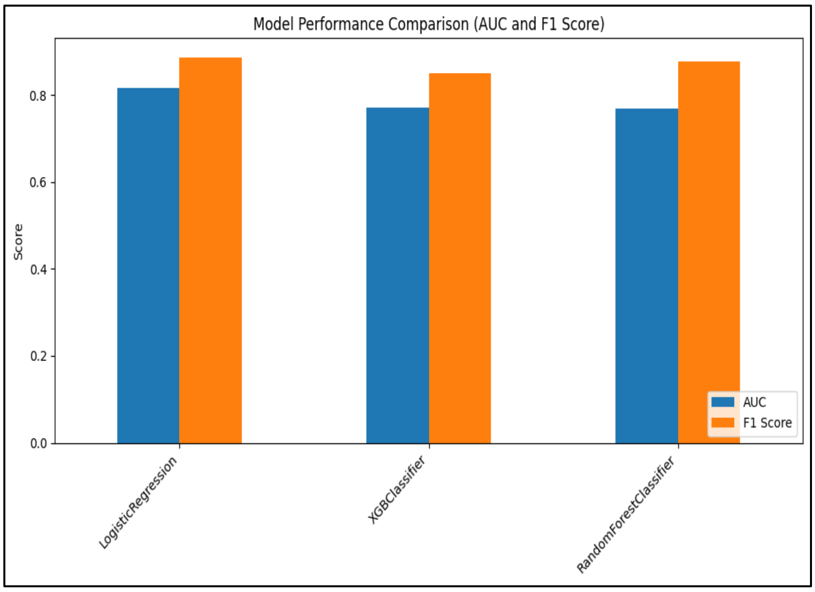

Fig.5: Delay prediction model performance

Carrier optimization models expanded the scope from prediction to prescription. Linear regression models predicting cost and transit time enabled a scoring mechanism that weighted affordability, timeliness, and carrier reliability. This prescriptive framework suggested optimal carriers for specific shipments, effectively balancing trade-offs between cost and delivery performance. The results highlight that combining predictive accuracy with prescriptive decision support can yield tangible operational improvements by reducing unnecessary cost variability while maintaining service continuity.

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4.2 Anomaly Detection & Forecasting

Anomaly detection provided additional resilience insights by identifying shipments that deviated from normal operating conditions. Both the autoencoder and isolation forest flagged a set of shipments as anomalous, capturing not only extreme weights but also deviations in cost and distance relationships. When evaluated against the limited weight outlier ground truth, the models achieved perfect recall but very low precision. This indicates that they successfully captured all known anomalies but also flagged many additional cases. Although precision was weak, this behavior is useful in resilience contexts, since false negatives, missed anomalies, pose greater risks than false positives.

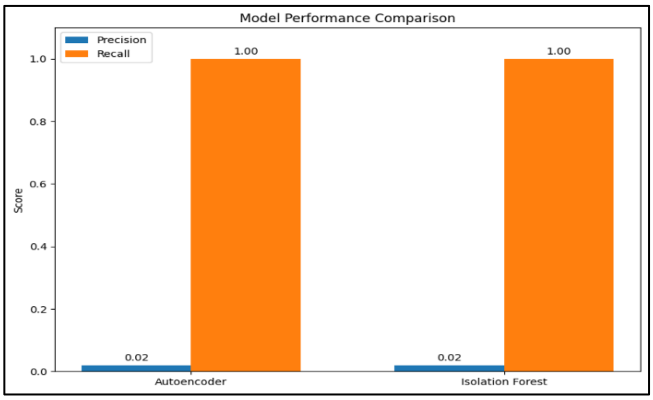

Fig.6: Anomaly detection model performance

Forecasting daily shipping costs with Prophet captured both overall trends and weekly seasonal fluctuations. The model highlighted recurrent cost surges during particular days of the week, aligning with operational expectations of peak demand cycles. While the absence of a held-out test evaluation limits definitive accuracy claims, visual inspection of trend and seasonality components suggests that the model provides actionable foresight into cost dynamics. Such forecasts can support budgeting, procurement, and proactive carrier negotiation, thereby embedding resilience into financial planning.

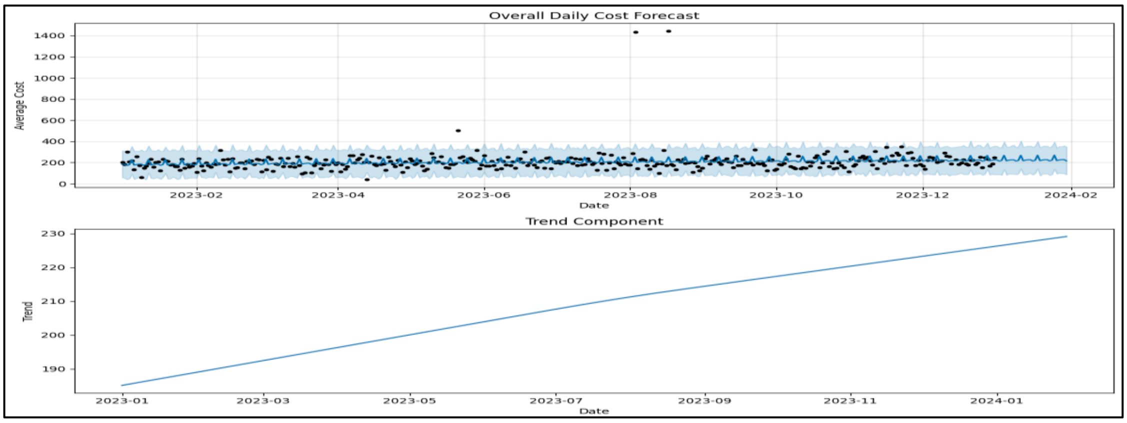

Fig.7: Shipping cost forecasting results

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4.3 Clustering Insights

K-means clustering of resilience KPIs revealed three distinct profiles of shipment behavior. The first cluster comprised delayed, high-cost shipments that represent clear fragility in the network. The second contained on-time shipments with elevated costs, reflecting operations where timeliness is maintained at the expense of efficiency. The third cluster represented resilient shipments, characterized by high on-time performance and cost efficiency with minimal weight anomalies. This segmentation offers a powerful lens for resilience analysis by moving beyond averages to identify structurally vulnerable routes or carriers. Managers can use these insights to isolate fragile clusters and design targeted interventions, while also benchmarking best-performing routes as models of resilience.

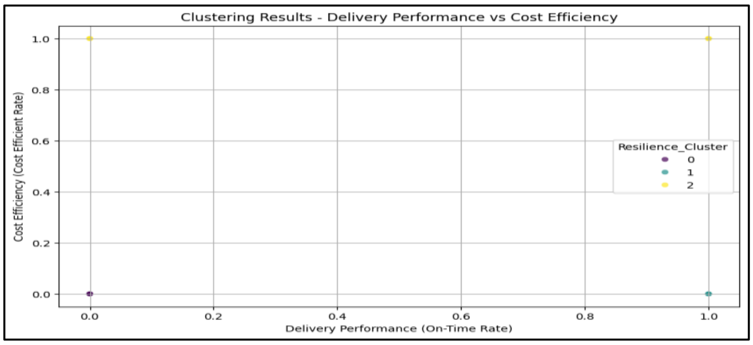

Fig.8: Clustering results for resilience KPIs

4.4 Resilience-Aware Objectives

The application of resilience-aware objectives demonstrated the value of aligning model training with operational priorities. By penalizing misclassification of delayed shipments more heavily, the weighted XGBoost model reduced false positives in on-time predictions. This trade-off slightly reduced the F1 score overall but meaningfully improved the model’s caution in predicting on-time delivery when shipments were at risk of delay. In resilience contexts, such cautious modeling is preferable, as it prevents overconfidence in fragile routes and enables more proactive risk mitigation. These findings suggest that embedding resilience into the objective function fundamentally changes the behavior of predictive models, moving them from accuracy-oriented to resilience-aware systems.

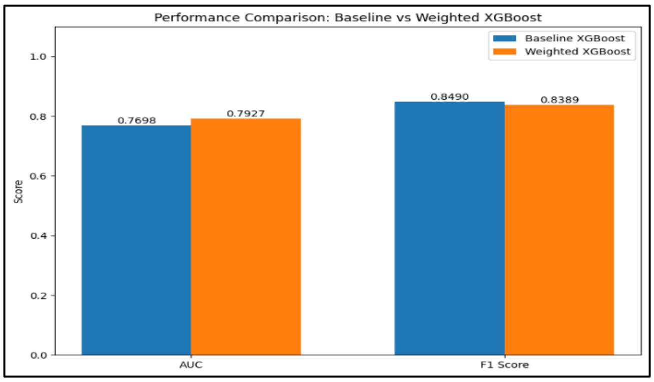

Fig.9: Baseline vs weighted XGBoost model performance

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4.5 Domain Adaptation

The experiments on regional adaptation highlighted the challenges of transferring models across heterogeneous supply chain environments. A logistic regression classifier trained on shipments from a Los Angeles warehouse achieved high performance locally but suffered a performance drop when evaluated on Boston data. This decline in AUC and F1 scores quantifies the domain shift arising from regional differences in distance, carrier access, and seasonality. Such degradation demonstrates that models trained on single regions may not generalize well across the network. Incorporating adaptation mechanisms, such as reweighting, transfer learning, or region-specific fine-tuning, offers a path forward to improve portability. The results highlight domain adaptation as an essential component of resilience, ensuring that predictive systems can remain reliable across diverse operating environments.

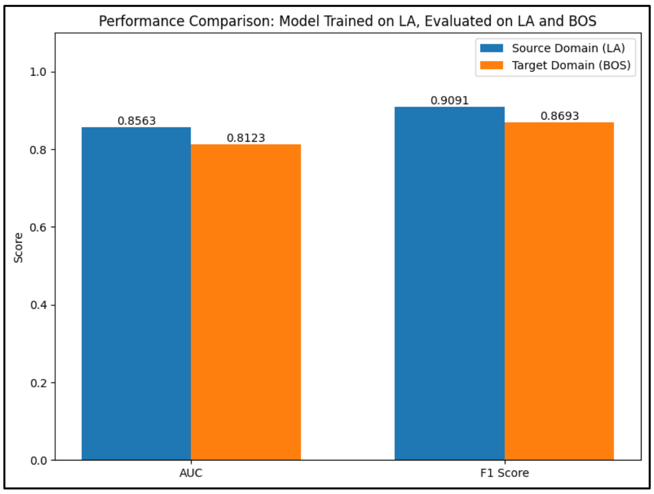

Fig.10: Performance of the Logistic Regression model trained on shipments from an LA warehouse

4.6 Stress-Testing Results

Stress-testing provided a structured view of model robustness under disruption scenarios. When shipment weights were artificially inflated or random noise injected into features, model performance degraded only marginally, suggesting robustness to superficial input distortions. However, performance declined sharply when disruptions directly altered the outcome variable, such as increased transit times or simulated carrier underperformance. Under these conditions, AUC and F1 scores dropped significantly, underscoring the sensitivity of predictive systems to shocks that undermine the very foundations of delivery performance. This divergence reveals a critical vulnerability: models can tolerate noise in inputs but struggle when systemic disruptions fundamentally reshape relationships between predictors and outcomes. Sensitivity analysis confirmed that the model's resilience is conditional, with robustness stronger for feature perturbations than for outcome-altering disruptions. These findings emphasize that resilience testing must move beyond accuracy under normal conditions to structured stress evaluations. By explicitly measuring performance degradation under shocks, supply chain managers can better anticipate the limits of predictive systems and design fallback mechanisms for high-impact disruptions.

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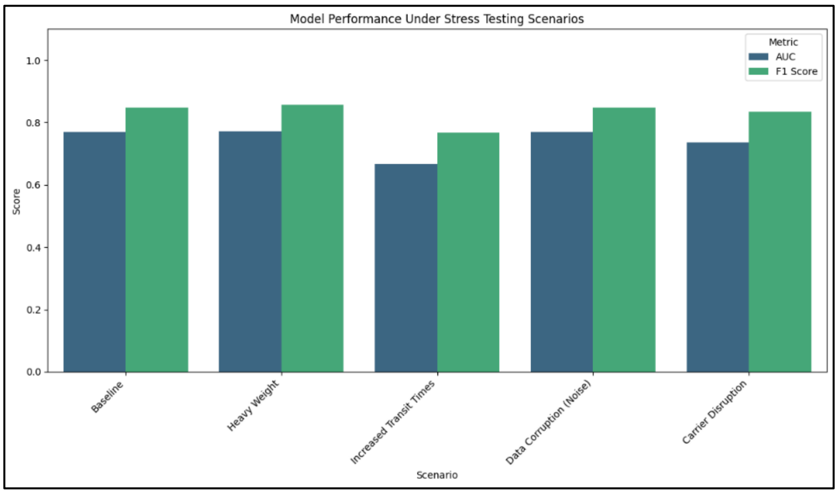

Fig.11: Model performance under stress testing conditions

5. Insights and Implications

5.1 Operational Insights

The results of this study highlight important operational insights about the structure of resilience in U.S. supply chains. Regional benchmarking revealed that resilience is unevenly distributed across warehouses. For instance, Warehouse_DEN demonstrated consistently high delivery performance, while Warehouse_SEA exhibited relatively weaker results. These variations suggest that resilience cannot be assumed to be uniform across a network, but instead must be measured and managed region by region. Regional disparities in socioeconomic resilience, as modeled in demographic contexts (Reza et al., 2025) [17], mirror the uneven performance observed across U.S. logistics regions. This parallel underscores the importance of tailoring interventions to the specific vulnerabilities of each node. Consistent with findings in the literature emphasizing spatial heterogeneity in resilience outcomes (Guo et al., 2025) [9], the uneven distribution of performance reinforces the need for localized strategies, such as targeted investments in underperforming regions or the deployment of backup carriers in areas more prone to delays.

Carrier benchmarking further revealed operational trade-offs. Carriers such as LaserShip and OnTrac generally performed well in terms of both delivery performance and cost efficiency, suggesting that they can serve as reliable partners under normal operating conditions. By contrast, carriers like DHL and Amazon Logistics exhibited lower average resilience scores, particularly in delivery performance. This divergence aligns with earlier observations that carrier variability is one of the most important drivers of operational fragility in logistics systems (Riad, 2024) [18]. The evidence suggests that firms must balance cost efficiency against reliability when selecting carriers. A strategy that prioritizes the lowest cost option may expose the system to higher disruption risks, while over-reliance on carriers with strong delivery reliability but high variability in costs could erode margins. Operationally, these insights highlight the dual challenge of achieving both cost efficiency and service reliability. Policymakers and firms alike must recognize that resilience cannot be treated as a secondary outcome, but must be explicitly embedded into performance management frameworks. Doing

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so allows firms to understand which regions or carriers strengthen the network and which create hidden vulnerabilities. As Hasan et al. (2025) argue, resilience-focused analytics enable proactive rather than reactive supply chain management by flagging risks early in the decision process [12].

5.2 Benefits of Resilience-Aware Modeling

The application of resilience-aware objectives in this study provides clear evidence of their advantages over conventional predictive approaches. By penalizing misclassification of delayed shipments more heavily, the weighted XGBoost model reduced false positives for on-time predictions. This means that the model became more conservative in declaring shipments as reliable, effectively lowering the risk of false optimism. In supply chain practice, false optimism is more damaging than cautious pessimism because it prevents planners from allocating contingency resources in situations where they are actually needed. This shift toward conservative classification directly enhances operational resilience, as resources can be positioned in anticipation of potential delays rather than being mobilized reactively after disruptions occur. The weighted model also demonstrated superior stress tolerance compared to standard models. While performance degradation under simulated disruptions was still significant, the resilience-aware objective function mitigated the decline in predictive accuracy. This finding echoes broader discussions in the resilience literature, where scholars have argued that resilience is less about maintaining perfect performance and more about minimizing losses under adverse conditions (Wieland & Durach, 2021) [1].

The use of resilience-aware modeling thus moves predictive analytics closer to this conceptual definition, ensuring that models remain useful even when operating environments deviate from baseline conditions. Beyond predictive accuracy, resilience-aware modeling changes the way decision support systems interact with managerial priorities. Standard models are optimized for average performance across all cases, often at the expense of rare but high-impact disruptions. Resilience-aware models shift this balance by explicitly emphasizing these rare but consequential events. This is consistent with the call by Balan (2025) for ML systems that account for resilience and recovery, rather than optimizing only for efficiency [3]. In doing so, resilience-aware modeling aligns technical optimization with operational objectives, offering a more realistic tool for practitioners managing volatile and uncertain supply chains.

5.3 Managerial Implications

The integration of logistics performance analytics with machine learning in this framework provides direct tools for managers seeking to enhance resilience. Planners can use KPI dashboards to monitor regional and carrier-level resilience, identifying weaknesses before they escalate into systemic failures. This enables a shift from reactive firefighting to proactive management, where planners are able to simulate "what-if" scenarios using predictive models and adjust carrier or route choices accordingly. Carrier optimization in particular offers actionable insights, helping managers choose providers not just on cost but also on reliability, thereby embedding resilience considerations into everyday procurement decisions. For firms, the adoption of this framework means that resilience becomes a measurable, actionable quality rather than an abstract concept. Managers can benchmark their performance against system-

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wide averages and target specific interventions to underperforming nodes. Just as ESG metrics integrate non-financial risks into decision-making (Khan et al., 2025) [15], resilience-aware KPIs extend logistics analytics beyond cost minimization toward sustainable performance. This aligns with the view expressed by Shawon et al. (2025), who argue that data-driven logistics optimization must integrate sustainability and resilience as equal priorities to achieve long-term efficiency [19].

At the policy level, KPI analytics also reveal regional imbalances that are not immediately visible through traditional performance measures. For example, warehouses with systematically lower delivery performance become candidates for targeted infrastructure investment, subsidies for carrier diversification, or regulatory oversight to prevent bottlenecks from cascading through national supply chains. The framework also facilitates industry–government collaboration. As noted by Hasan, Islam, and Rahman (2025), predictive AI systems offer not only accuracy improvements but also the ability to align private incentives with public resilience goals [11]. Policymakers can use aggregated resilience scores to identify vulnerable regions and prioritize investments, while firms benefit from greater visibility and reduced uncertainty. In this sense, the framework provides a dual benefit: tactical support for managers operating supply chains day-to-day, and strategic insight for policymakers tasked with building resilient national logistics systems.

5.4 Limitations

Despite the promising results, several limitations must be acknowledged. First, the dataset used in this study is synthetic, designed to simulate real-world logistics operations but not drawn from actual shipment records. While synthetic data provides control over missingness, outliers, and seasonality, it cannot fully capture the complex, context-specific behaviors of real supply chain systems. External validation using proprietary or open-source logistics datasets is necessary to confirm the generalizability of these findings. This limitation is consistent with observations in prior research, where the lack of publicly available logistics datasets has been identified as a barrier to empirical progress in resilience modeling (Camur et al., 2023) [5]. Second, the definition of resilience KPIs may oversimplify the multi-dimensional nature of resilience. Metrics such as on-time delivery and cost efficiency are important, but they may not capture broader dimensions such as adaptability, flexibility, or the ability to reconfigure networks under extreme conditions. As Guo et al. (2025) point out, resilience mechanisms extend beyond operational KPIs and often involve structural and relational aspects of supply chains [9]. Thus, while KPIs provide a starting point for quantification, they may miss subtler aspects of resilience that are harder to observe in transactional data.

Third, the study's stress-testing scenarios, while informative, remain stylized. Real disruptions often involve combinations of shocks, such as simultaneous carrier failure and demand surges, that are more complex than those simulated here. Similarly, the exploration of region-aware adaptation highlighted the challenge of transferring models across geographies, but the methods employed were limited to simple cross-validation without advanced transfer learning techniques. As Balan (2025) emphasizes, resilience must be studied not only as a property of individual systems but also as an emergent quality of interconnected networks [3]. Future work

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should therefore employ more sophisticated techniques for domain adaptation and stress simulation. Finally, while the framework demonstrates scalability in principle, operational deployment would require integration into existing logistics management systems. This introduces challenges related to interoperability, data quality, and organizational adoption. Without careful attention to these factors, even technically robust systems may fail to deliver value in practice.

6. Future Work

The present study demonstrates the feasibility of quantifying and operationalizing supply chain resilience using synthetic shipment data, yet several avenues remain open for further exploration and validation. The most immediate next step is to validate the proposed framework with real-world shipment data. Synthetic datasets provide valuable testbeds for model development, but resilience can only be meaningfully assessed when tested against the complexity, noise, and irregularities of actual logistics operations. Collaborations with logistics providers, carriers, or third-party data consortia could offer access to anonymized records, enabling rigorous external validation of predictive models, prescriptive carrier optimization functions, and stress-testing procedures. Such validation would also provide opportunities to compare synthetic simulations with real disruptions, thereby improving the calibration of resilience KPIs to industry realities. A second area for future work lies in expanding digital twin stress-testing. The scenarios tested in this study, weight shocks, transit delays, data noise, and carrier disruptions, represent only a subset of the shocks experienced in practice. Digital twin frameworks, which create virtual replicas of supply chain systems, would allow for continuous experimentation under a broader range of disruptions. For example, simultaneous demand surges and weather-related delays could be simulated, offering insight into compound disruption effects that traditional testing cannot capture. By integrating predictive and prescriptive models into digital twin environments, organizations can build resilience playbooks that specify proactive interventions under varying disruption intensities and durations.

Third, reinforcement learning offers a promising pathway for adaptive carrier selection. While this study employed regression-based carrier optimization, reinforcement learning would enable dynamic adjustment of carrier assignments in real time as conditions evolve. Instead of statically prescribing an optimal carrier based on historical averages, reinforcement learning agents could continuously learn from shipment outcomes, adjusting decisions to maximize both short-term reliability and long-term resilience. This approach aligns with recent advances in adaptive logistics optimization, where machine learning agents are deployed to balance cost efficiency with disruption tolerance in dynamic environments. A fourth direction involves integrating privacy-preserving and federated learning techniques across carriers. Supply chain resilience often depends on information sharing, yet firms are reluctant to expose sensitive operational data. Federated learning, where models are trained collaboratively across distributed datasets without sharing raw data, offers a way to build shared resilience models while preserving confidentiality. This could enable multi-carrier resilience analytics where competitive sensitivities are respected but systemic vulnerabilities are jointly addressed. Given

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increasing regulatory emphasis on data privacy, this line of research is both technically relevant and politically timely.

Finally, building live dashboards for resilience monitoring represents a critical step toward operational deployment. While this study demonstrated the feasibility of computing resilience KPIs, predictive scores, and stress-test results, these outputs remain academic without integration into decision-making workflows. Interactive dashboards could allow planners to visualize resilience in real time, simulate disruption scenarios, and compare carriers or regions across KPIs. Such tools would transform resilience from a retrospective analysis into a proactive, continuous monitoring capability, supporting managers in making informed decisions under uncertainty. Collectively, these directions represent a roadmap for advancing resilience analytics from proof-of-concept toward fully deployable systems. By validating with real-world data, expanding simulation capabilities, adopting adaptive learning, ensuring privacy, and building operational tools, future research can bridge the gap between conceptual resilience frameworks and actionable resilience management in logistics networks.

7. Conclusion

This study set out to operationalize the concept of supply chain resilience across U.S. regions by integrating logistics performance analytics with machine learning. Building on a synthetic dataset of two thousand shipments, resilience was defined through quantifiable KPIs that captured on-time delivery, cost efficiency, and robustness to anomalies. These KPIs enabled the benchmarking of warehouses and carriers, revealing that resilience is unevenly distributed both geographically and across logistics providers. Some regions demonstrated consistently strong performance, while others exhibited fragility that could propagate risks through the network. Similarly, carriers displayed trade-offs between cost efficiency and reliability, underscoring the importance of data-driven selection in resilience planning. Predictive models for delay classification, prescriptive carrier optimization, anomaly detection, forecasting, and clustering collectively demonstrated the value of machine learning in embedding resilience into logistics decision-making. Logistic regression, random forest, and XGBoost achieved strong predictive accuracy for delivery delays, while regression-based optimization functions provided actionable recommendations for balancing cost and timeliness. Anomaly detection revealed hidden fragility beyond simple weight outliers, and time series forecasting highlighted cost trends that can inform financial planning. Clustering further distinguished between fragile and resilient shipment profiles, offering managers a structured view of vulnerability across routes.

The study also explored advanced enhancements that move predictive modeling closer to resilience-aware objectives. Weighted loss functions improved the caution of predictive models by reducing false optimism about on-time deliveries. Domain adaptation experiments highlighted the challenges of transferring models across regions, while stress-testing scenarios revealed the conditional robustness of models under disruption. Together, these enhancements demonstrate that resilience requires more than predictive accuracy under normal conditions; it demands explicit modeling of disruption, variability, and adaptation. While the findings provide valuable insights, the limitations of synthetic data and simplified KPIs highlight the

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need for external validation and methodological expansion. Future work should validate the framework with real-world shipment data, integrate advanced stress-testing in digital twin environments, explore reinforcement learning for adaptive carrier selection, and employ federated learning to balance collaboration with privacy. Building live resilience dashboards will also be essential for translating these methods into operational tools. In sum, this research demonstrates that resilience can be systematically measured, predicted, and stress-tested through the combined application of logistics analytics and machine learning. By embedding resilience into KPIs, predictive objectives, and prescriptive decision-making, the study advances both academic understanding and practical tools for managing fragile supply chains. For practitioners and policymakers alike, the framework offers a scalable path toward more reliable, adaptive, and efficient logistics networks across the United States.

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