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| RESEARCH ARTICLE

Leveraging Business Analytics to Enhance Supply Chain Resilience and Reduce Disruptions in Critical U.S. Industries

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| ABSTRACT
The growing complexity of world supply chains, alongside the growing demand instability and uncertainty in operations has intensified the necessity to use data-driven solutions that help to build resilience and minimize disruptions in critical sectors. The study analyses the potential of using business analytics to enhance supply chain resilience in America by basing on the DataCo Smart Supply Chain Dataset as the empirical evidence. The data, which is over 180,000 records at the transaction level, offers detailed information about logistics operation, consumer behavior, the use of payment modes, product categories and delivery performance. This type of multidimensional information provides a one of a kind chance to observe the correlation between delivery delays, operational risks, the change in demand, and frauds. The predictive modeling, clustering methods, and statistical analysis methods have been used to determine the important factors leading to supply chain fragility in the study. In particular, the demand forecasting, risk classification of late-delivery, and fraudulent orders are predicted with the help of machine learning models like Gradient Boosting, Random Forest, Logistic Regression, and LightGBM. These models allow finding the patterns that can be overlooked by traditional means of analysis, such as the correlation between the geographic distribution of the customers, the channel of payment, and the shipping delays. Moreover, clustering algorithms like K-Means and DBSCAN can give more information regarding a behavioral pattern of fraud and the inconsistencies of its operations. This study includes explainability tools, such as LIME and FairML, which makes the behavior of models more transparent such that predictive insights can be interpreted and made operationally feasible. The findings indicate that the key variables of critical concern include shipping mode, type of transaction, demand cycle seasonality and customer location that contribute greatly to resilience and risk. This study is a part of an increasing literature on digital supply chain transformation because it proves how business analytics facilitate proactive decision-making, operational planning optimization, and disruption relief in the U.S. industries. The results have strategic implications on supply chain managers, policymakers, and organizations that strive to develop flexible, information-driven, and resilient supply chain systems.

| KEYWORDS

Supply Chain Resilience, Business Analytics, Machine Learning Models, Demand Forecasting, Fraud Detection and Operational Risk Management

| ARTICLE INFORMATION

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1. Introduction
A. Background

Global supply chains nowadays are functioning in a very interdependent yet more uncertain environment that has seen the rapid change of technology, changing geopolitical situations and the higher expectation of consumers. U.S. critical infrastructure sectors like healthcare, pharmaceuticals, electronics, and transportation, defense, food distribution, and retail come under constant suspicion of disruption that would disrupt business continuity and stability of the national economy [1]. Incidents like pandemics, natural disasters, supplier failures, congestion at ports, labor shortages, cyberattacks, inflationary pressures, and changing consumer demand have increased the fragility of the supply chain. These interruptions tend to cause delays in production, stock outs, higher logistics, less customer satisfaction and poor competitive positioning. With the growth of the supply chains around the world and the use of complex networks of distributors, suppliers, manufacturers and service providers, the risk exposure increases in the same measure. The conventional supply chain management systems that are largely based on past information, decision-making that is manual and problem solving that is reactive are no longer enough to deal with the scale and occurrence of contemporary disruption. The recent increase in the size of big data, automation, cloud computing, and machine learning is an opportunity that organizations can use to analyze real-time data, identify anomalies early, and react proactively to threats to operations [2]. The supply chain resilience has therefore been of focal attention among industry practitioners and policymakers who are trying to achieve reliability and continuity in the event of uncertainty. As digital supply chains have emerged, it has become necessary with the increased supply of data in large quantities that structured and unstructured data can be harnessed to discover vulnerabilities, predict disruptions, and develop adaptive systems that can maintain performance even in conditions of complexity and dynamism.

B. Significance of Supply Chain Resilience

The resilience of supply chains has become one of the most important capabilities of the organization functioning in the environment characterized by high rates of disruptions, growing uncertainty, and rising levels of reliance on operations [3]. . It is the capacity of an organization to predict possible risks, to endure disruptions, to react to processes in times of crisis and to heal quickly to resume normal operations. The disruption in critical industries in the U.S. where economic stability, health and population, and national security are greatly affected by the industry can have a ripple effect and impact production systems, consumer markets and vital systems of service delivery. Thus, resilience is a crucial factor in mitigating vulnerability to a range of unpredictable risks like cyber attacks, supplier failures, and bottlenecks in the logistical chain, pandemics, and geopolitical conflicts. The resiliency of the supply chain not only reduces economic losses but also offers a high level of reliability of services, guarding relationships with the clients, and enhancing the competitive edge. The supply chain systems used to be traditional, that is, they tend to run on very limited visibility, siloed data and slow response mechanisms, which are not effective in detecting early warning signals or responding to alterations in the environment. The future supply chain resilience needs to be real time, dynamic planning, flexible sourcing and predictive intelligence. Machine learning, digital tracking, and automation support business analytics and give organizations the options to evaluate risk trends, forecast outcomes, and optimize their choices regarding procurement, production, transportation, and inventory management [4]. Agile supply chains make organizations more agile by ensuring better communication, cross-functional coordination, and data-driven strategy implementation. With disruptions in the frequency and magnitude ever increasing, the concept of supply chain resilience is not only necessary to sustain operations but also to guarantee organizational survival and sustainability in a volatile global environment.

C. Business Analytics in the Contemporary Supply Chains

Modern supply chains use business analytics to transform big data of operational information into actionable information to support strategic planning, risk reduction and optimization of performance. Since supply chains produce enormous amounts of real-time data in the form of orders, shipments, customer interactions, supplier activities, and digital platforms, analytics offers the mechanisms necessary to extract meaning of this complexity and aid evidenced-based decision-making [5]. Additional analytics, including predictive modeling, clustering, data mining, anomaly detection, and machine learning, can assist an organization to unearth latent trends regarding demand fluctuations, delivery delays, fraud, inventory imbalances and customer preferences. Such insights enable supply chain managers to predict the state of things ahead, spot bottlenecks and rectify them before they get out of control, and plan operations in advance. Predictive analytics will be able to predict delays or inconveniences to allow companies to reroute freight, adjust timeframes, or change inventory. Prescriptive analytics assists in making decisions by providing suggestions to the best course of action in areas such as sourcing, production planning and logistics. Also, business analytics improves supply chain transparency and visibility by consolidating data that is collected at various touchpoints into dashboards and performance indices. Other tools like LIME, SHAP, and FairML, also make the analytical models interpretable and ethically accountable, which is necessary to ensure managerial trust and accountability. With the increased risks involved by supply chains due to fraud, cybersecurity threats, and operational deviations, fraud detection systems based on analytics can be used to detect anomalies and protect transactions [6]. In sum, business analytics will enable organizations to change the paradigm of managing supply chains in a reactive manner to proactive management to enhance efficiency, resilience, and responsiveness in a more dynamic global economy.

D. Problem Statement

Although the access to digital tools and massive supply chain data is increasing, there are several critical industries in the United States to face substantial disruption because of the lack of visibility, the slow detection of risks, as well as, the insufficient utilization of predictive analytics. The conventional supply chains are unable to predict operational breakdowns, detect fraud or predict demand thus causing delays, extra expenses and low reliability in the services offered [7]. Despite the fact that business analytics can be used to achieve strong predictive, optimization, and anomaly detection capabilities, there is still no extensive application of this tool to supply chain resilience strategies. This study discusses the issue of how high-level analytics and machine learning could be utilized efficiently to identify disruptions, evaluate risks, and increase resilience throughout the supply chain with the help of real-world information.

E. Objective of Study

The purpose of the study is to analyze the potential of business analytics in improving supply chain resiliency and mitigating disruptions in the key sectors of the U.S. economy. Major the objectives of this studies are

- To examine the important supply chain variables that cause operational disruption.
- To come up with predictive models to predict the demand and the likelihood of delivery.
- To detect patterns of fraud with the help of clustering and classification algorithms.
- To assess the effect of analytics on supply chain transparency and responsiveness [8].
- To identify the important variables that affect resilience and operational performance.
- To offer evidence-based recommendations to enhance supply chain resilience.

F. Research Questions

In this study, the author explains how business analytics may predict disruptions, identify risks, and enhance resilience in supply chains of U.S. industries.

Following the questions are guides to this study that are mentioned below:

1. What are the most important causes of supply chain disruptions?
2. What are the opportunities of predictive analytics to enhance demand forecasting and fraud detection?
3. What is the business analytics contribution to resiliency and operational decision-making?

G. Significance of Study

This study is important in that it provides solutions to the expanding demand of resilient and data-driven supply chains in the critical sectors in the United States that are experiencing rising disruptions [9]. With organizations trying to cope with the vagaries of demand, supply uncertainty, delays in transportation and risks associated with frauds, business analytics are offering a revolutionary solution to enhance the visibility of operations and decision making. This research shows how analytics can identify potential factors of disruption antecedents, streamline the logistics operations, and assist in proactive response plans by exploiting predictive modeling, clustering algorithms, and risk analysis. The results can provide important lessons to supply chain professionals who aim to achieve efficiency, lower costs, and continuity under uncertain environments. To policy makers, the research shows the significance of digital transformation in securing the national supply chain and the continuity of access to necessary products and services. To the researchers, the research is a contribution to the academic discussion as it combines real-life information with the sophistication of analytics, providing empirical data on the worth of analytics-based resilience. Moreover, companies that follow these findings will be able to enhance their competitive edge through increasing their adaptability, minimizing their vulnerabilities in the operations, and adopting smarter and data-driven strategies [10]. Finally, this research can be used to develop stronger, agile, and resilient supply chains that would be more able to navigate the uncertainties of the contemporary global setting.

2. Literature Review

A. Supply Chain Resilience Adaptation in Contemporary Industries

The idea of supply chain resilience has developed to be more proactive, rather than a reactive, understanding of ways to recover in the face of uncertainty, and to be prepared to handle it [11]. The supply chains in modern world markets are challenged by multi-dimensional disruptions of natural disasters and geopolitical upheavals as well as economic instabilities and cyber threats.

This has changed resiliency thinking into incorporation of strategic flexibility, strong planning, and visibility of operations. Contemporary resilience models emphasize that there is a necessity to increase the robustness of a system, continue with operational continuity and ensure fast realignment of the resources in case of disruptions. Risk identification mechanisms, redundancy and flexible sourcing structures have played a major role in this development. Furthermore, digitalization has increased the speed of resilience creation because it has made it possible to track the resilience in real-time, make predictions and plan scenarios. Organizations can now identify signals of issues in advance and take appropriate action before disruption through the use of big data technologies, IoT-based sensing devices and automated reporting tools. Resilience has also been broadened to the concept of adaptive capacity in which the focus is on the continued learning, analyzing after the disruption and integrating the innovative processes. Moreover, companies are recognizing that resilience goes far beyond operational adaptations and involves wide-ranging strategic alignment in the areas of procurement, logistics, inventory, and customer service [12]. The collaborative relationships with suppliers, transparency at multi-tier levels and information sharing networks also enhance resilience through the coordinated efforts along the supply chain. Due to the increased frequency and complexity of disruptions, resilience has evolved to become an initiative that is not only cost-based but most importantly, a point of competitive advantage. Good resilience measures can make organizations sustain their services, retain confidence as well as protect their future sustainability. In general, the development of supply chain resilience can be characterized by an increased focus on risk mitigation in advance, responsiveness of systems, and decisions based on data as the key elements of navigating through the unpredictable global landscape.

B. *Digitalization and Data-driven Supply Chain management*

The digital transformation has changed supply chain management in a remarkable way; it has made supply chain management be more automated, more visible, and decisions are made based on data. Contemporary supply chains produce immense amounts of organized and unorganized data across a number of platforms, such as enterprise systems, digital transactions, logistics tracking mechanisms, and networks of customer interaction [13]. The adoption of digital tools, including cloud computing, IoT, blockchain, and sophisticated analytics, has allowed moving data between the nodes of the supply chain without complications, enhancing its transparency and operational alignment. These technologies enable organizations to gather real-time data about the levels of inventory, the status of production, the transportation pathways, and the environmental conditions, and help make quicker and more precise decisions. Digitalization could also improve collaboration between suppliers, manufacturers, distributors and retailers via automated mechanisms of information sharing, decrease delays and alleviate disruptions. Supply chain management that is based on data can help the organization detect vulnerabilities in performance, anticipate risks in operations, and streamline resource distribution with the help of algorithmic intelligence. Digital dashboards, simulators and automated reporting allow decision-makers to obtain actionable information that would be challenging to obtain with the use of manual techniques. Robotics and smart manufacturing systems also assist in efficiency in operations since repetitive activities are automated, and the human error is minimized. The digital procurement systems enhance the sourcing strategies through reviewing the performance of the suppliers and detecting possible vulnerability. In the meantime, blockchain technologies provide impartiality and increase the confidence in transactions. Digital transformation can help facilitate a smooth coordination of supply chains with the rise of globalization in connectedness that minimizes the reliance of manual implementations. It also aids in predictive maintenance, route optimization and demand sensing that enhance supply chain resilience [14]. Digital transformation is, therefore, very important in accelerating efficiency, minimization of operational uncertainty and creation of adaptive supply chain systems capable of responding efficiently to changes in market and environmental scenarios. In general, data-driven supply chain management is a transition to a traditional, reactive approach to dynamic, technology-intensive ecosystems that ensure long-term resilience and strategic competitiveness.

C. *Demand Forecasting and Predictive Analytics of Supply Chains*

Predictive analytics has emerged to be a key component in demand forecasting because of its capacity to use the past trends, behavioral patterns and come up with precise predictions into the future [15]. Conventional forecasting techniques are usually based on a linear trend and seasonal forecasting and are inadequate in dynamic markets where consumer behavior changes, supply and uncertainty of external conditions. In the modern predictive analytics, machine learning algorithms, time-series modeling, and statistical forecasting are employed to generate a more reliable demand prediction. These models capitalize on the extensive variety of variables like historical sales, product characteristics, seasonal, promotional activities and macroeconomic variables. Predictive analytics-based demand forecasting assists organizations to streamline inventory levels, decrease stockouts, lower excess holding expenses, and overall service delivery. Gradient Boosting, Random Forest, LSTM networks and regression-based machine learning models are popular in modeling nonlinear relationships and other complex interactions between data. The techniques are very effective in predicting both short-term and long-term demand both in the product lines and in geographical areas. Predictive analytics also facilitate real-time adaptive processes through continuous updating of predictions as new information continues to be available. In addition, demand forecasting models can utilize external data processes, like market trends, customer sentiments on online platforms, or environmental data which enhances accuracy. Predictive insights enable organizations to structure procurement, production anticipation, distribution, and workforce planning in accordance with the anticipated market needs [16]. This congruence plays a vital role in ensuring stability of the supply chain in situations of volatility or in disruptions that cannot be predicted. Other strategic decisions that are supported by data-driven forecasting include capacity planning, inventory locations, and coordination with suppliers. Consequently, predictive analytics enhances operational efficiency, responsiveness and resiliency through minimizing uncertainty in supply chain planning processes. Finally, sophisticated demand forecasting can enable organizations to stay competitive and have the ability to meet customer expectations and better ways of dealing with risks.

D. *Anomaly Detection and Supply Chain Fraud*

Fraud detection and anomaly identification are both gaining relevance in the area of supply chain management as digital transactions and e-commerce activities continue to increase throughout the world. False orders, payment manipulations, identity misrepresentation, return fraud, and tampering of data are some of the fraudulent activities that have a high financial and operational risk [17]. The rule-based detection systems that are typically used to detect fraud are usually not effective in detecting emerging fraud patterns because it is rigid and relies on predefined conditions. In order to overcome such weaknesses, the supply chain processes have embraced machine learning-driven fraud detection algorithms that can process large volumes of data to detect anomalies, behavioral anomalies, and outliers. The methods employ classification algorithms, clustering methods, and anomaly detection models to distinguish regular transactions and suspicious transactions. Purchase methods, order value, risk of delivery, customer behavior, shipping patterns as well as geographic inconsistency are many of the features that are usually subjected to identify the likelihood of fraud. Random Forest, Gradient Boosting, Support Vector machines and neural network machine learning algorithms have shown high effectiveness in identifying the complex fraud schemes that adapt with the change of time. The clustering algorithms such as K-Means and DBSCAN also improve the process of analyzing the fraud by clustering transactions based on their similarities and finding anomalies that may indicate what is not normal. Analytics-enabled fraud detection systems can help in saving a lot of money through preventing financial losses, safeguarding consumer confidence and ensuring supply chain integrity. Besides, the explainability tools also make sure that the detecting models are transparent and that the investigators can comprehend the reasons why specific transactions were flagged. Real time anomaly is also important as it helps reduce the operational disruption since it helps organizations to counter unauthorized activities promptly [18]. These innovations contribute towards making supply chains resilient by avoiding fraud-based delays, chargebacks, and distorted inventory. With the further development of digital platforms, it is becoming more and more necessary to apply analytics-based fraud detection to secure supply chain operations and guarantee the safety of supply chain procedures, as well as their accuracy and reliability throughout the entire operational cycle.

E. *Machine Learning in Supply Chain Strengthening*

Machine learning has become highly relevant in resilience enhancement of the supply chain in terms of predictive intelligence, automated decision-making, and operational visibility. The modern supply chains produce intricate data sets comprising logistics records, customer data, product data, shipment tracking data and performance indicators. It is possible to feed this large amount of data into machine learning models to reveal hidden links, forecast upcoming disruptions and assist in strategic planning [19]. The classification models are used to detect fraud, delivery risks and sort anomalies in the operations. Regression models can be used to predict the demand, lead time and any changes in costs so that an organization can optimize the procurement, production and distribution decisions. The clustering algorithms are used to identify customers groups, fraud patterns, and product groupings that are the reasons behind the customization of strategy and risk evaluation. The reinforcement learning helps to make dynamic decisions that optimize routing, inventory allocation, and scheduling as the conditions change. Machine learning also supplements early-warning systems as it helps to recognize abnormal patterns that can predict disruption and take preventive measures by organizations. Sensor-driven predictive maintenance allows preventing equipment failure, which may influence the production and delivery operations. Moreover, machine learning is useful to simulate scenarios and conduct stress-tests, which allow supply chains to learn how various disruptions work and which mitigation strategies are most effective. Machine learning and combination of various technologies such as IoT, cloud platform and automation enhances real-time visibility and responsiveness [20]. Explainable AI models provide transparency, which makes the outputs of machine learning understandable to supply chain managers. All these features are contributing to resilience since it is more adaptive, more accurate, and less reliant on a manual decision-making process. Machine learning enables organizations to stay efficient in volatile situations and offers the basis to have resilient, data-driven, and intelligent supply chain systems.

F. *Empirical Study*

In the article a digital supply chain twin to manage the disruption risks and resilience in the era of Industry 4.0 by Dmitry Ivanov and Alexandre Dolgui, the authors present the idea of a digital supply chain twin as a real-time computerized model to increase visibility, risk prediction, and resilience of the global networks of supply. The paper highlights the implementation of digital twins in the combination of model-based and data-driven models in order to simulate operational conditions, assess the effects of disruptions, and assist with the proactive and reactive decision-making. The authors emphasize that the COVID-19 pandemic revealed that global supply chains were too vulnerable and that it is critical that they be monitored in real-time, have end-to-end visibility and model scenarios quickly. Digital supply chain twins can also help an organization map network structures, analyze both past and real-time disruption data, and predict the risks of operations more accurately. This is in line with the goals of current supply chain analytics, where predictive modeling, simulation, and advanced data visualization can play a role in the improvement of resilience strategies [1]. The article offers theoretical and practical backgrounds that could be used in relation to the present research paper to strengthen the idea that the combination of digital technologies, predictive analytics, and dynamic modeling could reduce disruption and enhance continuity in vital U.S. industries.

In the article titled Leveraging supply chain disruption orientation to achieve resilience: the role of supply chain risk management practices and analytics capability by Hua Liu and Shaobo Wei, the authors discuss the effectiveness of disruption orientation and analytics capability in enhancing the supply chain resilience together. In the study, it is argued that a significant disruption orientation in organization with awareness, preparedness and proactive identification of potential disruption leads to higher resilience in case internal and external risk management practices are implemented effectively. The authors emphasize that risk management may serve as a key mediator, which would help a firm to transform the awareness of disruption into adaptive reactions and sound operational strategies [2]. These results also indicate that there is a strong moderating effect of analytics capability; companies that have more developed analytics tools, predictive modeling, and real-time data processing are in a better place to detect weaknesses, assess risks, and undertake timely interventions. The positive impact of disruption orientation is magnified by high analytics ability especially in improving internal process controls, as well as external collaboration with suppliers and logistic partners. This work can be considered very relevant in terms of the current research since it highlights the strategic value of incorporating the business analytics into the framework of resilience building. It supports the notion that empirically based observations, paired with organized risk management routines, can greatly improve the capacity of the supply chains to forecast, endure, and recuperate because of the disruptions.

The article by Rafiqus Salehin Khan, Md Riad Mahamud Sirazy, Rahul Das, and Sharifur Rahman is called An AI and ML-Enabled Framework of Proactive Risk Mitigation and Resilience Optimization in Global Supply Chains During National Emergencies, where the authors suggest the very general framework of using the capabilities of artificial intelligence and machine learning in order to increase the resilience of supply chain in the face of the country-wide disasters. Their model combines the four elements needed, such as Emergency Threat Detection, Dynamic Impact Simulation, Adaptive Response Engineering, and Resilience monitoring to help in real-time risk evaluation and quick adaptation to operations [3]. The paper underlines the significance of integrating multi-source data related to the internet of things, satellite images, social media intelligence, and the government alerts in order to detect the initial disturbances and forecast the propagating effects through multiple-level networks. The authors emphasize that AI methods, such as reinforcement learning, graph neural networks, and simulation modeling can dynamically reconstruct logistics routes, prioritize the allocation of resources, and guarantee the fast delivery of the necessary products in case of a crisis. Notably, supply chain traceability and sustained resilience assessment is promoted by blockchain-driven transparency and smart monitoring. The article is extremely pertinent to the current study as it shows that AI-based analytics can be used to transform operational reaction to predictive disruption, the continuity of the supply chain under emergencies, and it fits perfectly well in the objective of utilizing analytics to improve resilience in the critical industries of the United States.

In the article by Shivam Gupta, Surajit Bag, Sachin Modgil, Ana Beatriz Lopes de Sousa Jabbour, and Ajay Kumar called Examining the influence of big data analytics and additive manufacturing on supply chain risk control and resilience: An empirical study, the authors explore the role of advanced digital technologies in ensuring the development of supply chain risk control and resilience. This paper uses a contingent perspective of resources to investigate the role of big data analytics (BDA) and additive manufacturing (AM) in defining the capabilities of organizations to handle disruptions in complex and vulnerable supply chains. Based on the survey sample information of 190 companies, and PLS-SEM analyses, the research concludes that BDA substantially enhances risk intelligence by helping to detect, monitor, and interpret disruption signals better. Instead, additive manufacturing enhances readiness and smart risk management by means of dynamic and real-time production [4]. The authors point out that BDA and AM assist organizations to minimize ripple effects and the cascading impact of disruptions in multi-tier networks by enabling organizations to make decisions more quickly and responsive. These results are very relevant to the goals of the current study as they prove that data-driven technologies and advanced analytics are a key factor to consider to increase supply chain resilience. The research supports the need to embark on digital and analytical solutions to predict disruptions and reduce operational risk, as well as maintain continuity in most essential industrial sectors.

In the article entitled The role of big data analytics capabilities in strengthening supply chain resilience and firm performance: a dynamic capability view by Mohamad Bahrami and Sajjad Shokouhyar, the authors examine how big data analytics capability (BDAC) enhances supply chain resilience and, ultimately, organizational performance. Based on the dynamic capability perspective, this paper suggests that BDAC enhances the capacity of firms to sense, interpret, and respond to disruptions, based on the quality of information in the supply chain, the visibility of operations, and the accuracy of decisions. Based on the survey data on senior executives within the IT department and partial least squares modeling, the authors prove that BDAC does not have a direct positive effect on the business performance but has a positive effect through the constant of increasing the supply chain resilience as a mediator. Results indicate that innovativeness in problem solving and data-based adaptation generated through analytics potentials help the firms to respond more quickly to disruptions and sustain continuum during turbulent environments [5]. The study determines risk management culture as one of the important moderators which enhances the positive association between resilience and performance. This study is extremely pertinent to the current one as it shows that analytics-based insights backed by organizational culture and dynamic capabilities enhance the resilience of the supply chain- which is a necessity in the life of minimizing disruptions and maintaining the efficiency of operations in the most demanding industries in the U.S.

3. Methodology

This study will use a data-driven approach that combines a quantitative analysis, predictive modeling, and machine learning to investigate the value of business analytics in improving the resiliency of a supply chain in vulnerable industries in the United States [21]. This methodology is a sequential process that starts with data acquisition of the DataCo Smart Supply Chain dataset, preprocessing, feature engineering, model development, model evaluation, and model interpretation. Both structured and unstructured is examined to determine patterns associated with the delays in the delivery process, demand variability, and frauds and operational risks. Several analytical tools, such as descriptive analysis, classification algorithms, time-series forecasting and risk prediction models are used to reveal insights. Such a scientific methodology would guarantee the correct, reproducible results and allow creating the actionable measures aimed at enhancing the resilience of the supply chain and minimizing the disruptions.

A. *Research Design*

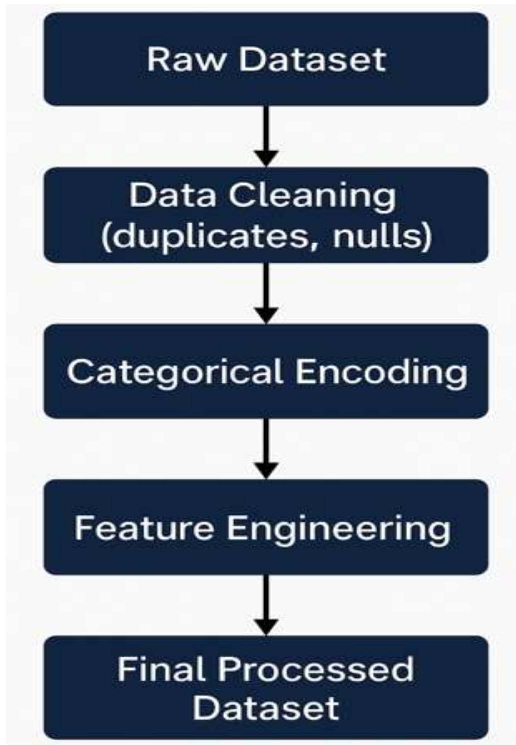
The research design of the current study will involve machine learning, predictive modeling, and exploratory data analysis as the quantitative research design to examine the potential of business analytics to increase the resilience of supply chains and lessen the effect of operational disruptions [22]. There is a design focus on objective measuring, statistical validity, and reproducibility of the analytical processes. It uses a data-driven method to process large-scale transactional, logistical and behavioral data that has been obtained through the DataCo Smart Supply Chain dataset. The design will allow identifying patterns which deal with delivery delays, tendencies of fraud and fluctuations in demand between product categories and customer segments. The study is done in a systematic working process that begins with data extraction, in which both structured and unstructured data are gathered. Data preprocessing is then undertaken and this involves cleaning, missing values, format conversion, and data consistency. Different derived variables like shipping delays, delivery variance and aggregated demand indicators are then created using feature engineering. The second step is model development, during which classification, forecasting, and risk prediction models are learned with the help of suitable algorithms. This is followed by model evaluation which involves the use of statistical performance measures to evaluate accuracy, interpretability and generalizability. Lastly, analysis interpretation aligns the results of the analysis with practical implications of supply chain resilience [23]. Such a research design allows conducting research in a systematic manner, predicting, and forming a reasonable base to elaborate on the strategies to be implemented to reduce disruption of the supply chain.

B. *Data Particulars and Sources*

The research is based on the use of the DataCo Smart Supply Chain Dataset, which is a rich dataset with a total of more than 180,000 transaction-level entries that reflect the real-life supply chain performances in various spheres. The data will contain comprehensive data regarding logistics operations, customer segments, and transactional values, and product types, channels of payment, delivery performance, and indicators of fraud [24]. It is constructed to integrate both structured information, e.g. delivery dates, sales data, quantity of order, shipping time, and categorical variables, as well as unstructured clickstream information, which allows performing multifaceted study of customer behaviour and digital interaction behaviour. The main variables to be used in this study are Days for Shipment (Real), Days for Shipment (Scheduled), Delivery Status, Late Delivery Risk, Payment Type, Product Price, Order Profit, Category Name and Customer City. These characteristics facilitate end to end analysis in regards to demand prediction, fraud detection and prediction of delivery risks. Data is publicly accessible and anonym zed, which guarantees the ethical disclosure and data integrity. It is diverse, detailed, and sizable, which allows applying it to machine learning tasks, predictive analytics, and research aimed at resilience. The data set allows us to investigate the trends of deliveries, the points of operation, and the risk issues that influence the key industries in the U.S.

C. *Preprocessing of Data and Engineering of Features*

Preprocessing of data is also crucial in data quality, consistency and modeling readiness. Preprocessing stage commences with eliminating duplicates, inconsistent dates, standardizing the numerical variables and addressing missing or incomplete values. Categorical variables, such as the status of delivery, type of payment, category of product, etc, are converted to numeric representations through the use of label encoding or one-hot encoding. Shipping times, price values, and profit of orders are investigated to reduce distortions in the training of a model [25]. This is done through feature engineering that is used to improve the performance of the model by creating new variables applicable to the analysis of resilience. Derived features will be the Shipment Delay (difference between scheduled and actual delivery days), Delivery Variance, Order Month, Seasonal Indicators, Risk Score, and Aggregated Sales Metrics. These learned attributes assist machine learning models in obtaining temporal habits, behavioral characteristics and operational deviations.

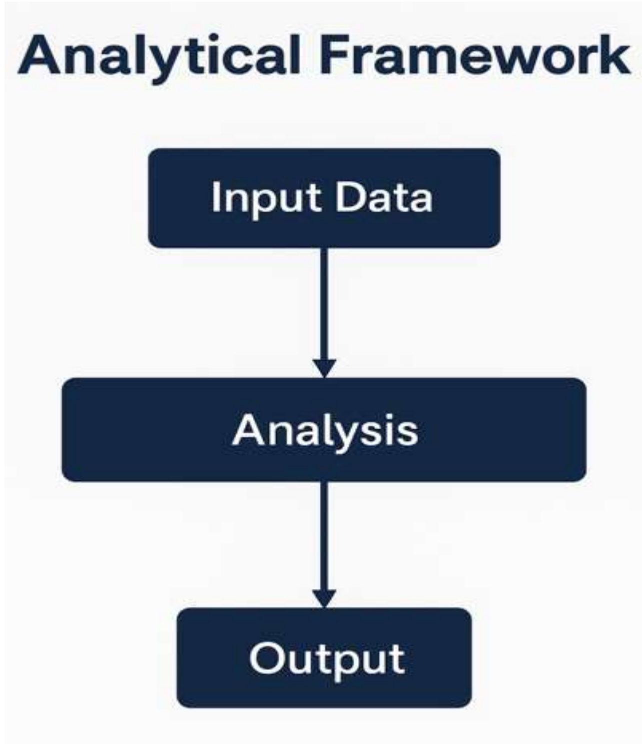


This flowchart display the sequential processing steps applied to prepare the dataset

The data preprocessing model provides the necessary steps that are necessary to convert the raw data of the supply chain into high-quality and analysis-ready data. It starts with loading the raw data and then proceeds to systematically clean the data to eliminate duplicates, deal with missing data sets and fix discrepancies. Categorical variables, including payment type or status of delivery, are coded in numbers to be interpreted by machine learning models. Areas of improvement are also made through feature engineering, which generates new variables, such as shipment delays and monthly order patterns. The resulting product is a standardized, structured and enriched dataset that is optimal in predictive modelling, risk analysis and resilience estimation.

D. *Setting up Analytical Framework and Model*

The analytical framework comprises three fundamental elements, such as demand prediction, fraud, and delivery risk prediction. All the components are using machine learning models that are specific to the analytical purpose [26]. Random Forest algorithms, Gradient Boosting and LSTM are applied to evaluate time series sales trends and forecast future demand levels to be used as demand forecasting. The classification models such as LightGBM, Support Vector Machines, Logistic Regression and ensemble voting are used to detect fraudulent or suspicious orders. Delivery risk prediction uses decision trees and boosting models to categorize deliveries as on time, late and advance to intervene and plan operations early. Each model is trained on an 8020 train test split and hyperparameters are optimized either via grid-search or AutoML to optimize the predictive accuracy and generalizability of the model. The analytical model is aimed at comprehensive analysis of a variety of dimensions of supply chain resilience.

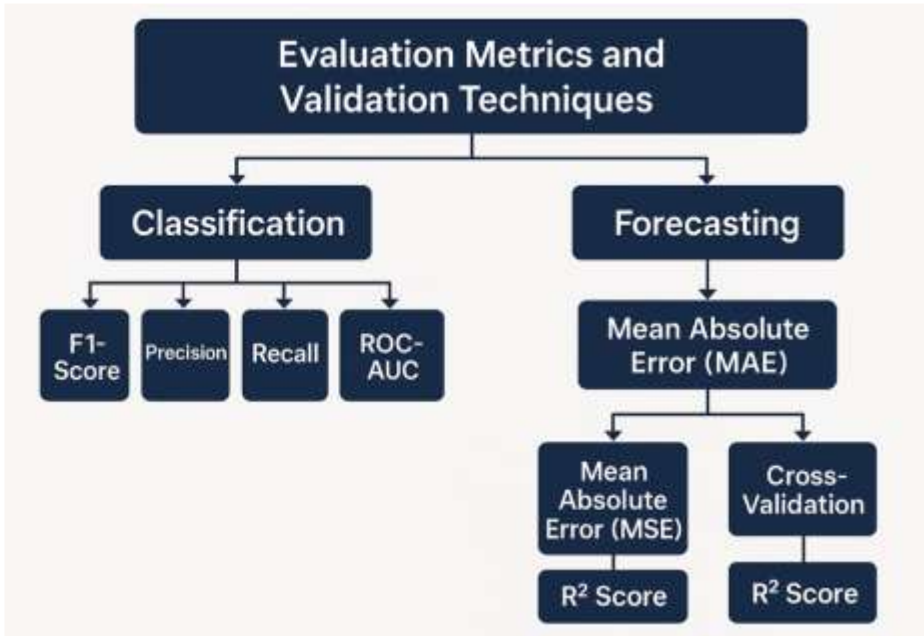


This flowchart shows how input data is analyzed to generate meaningful outputs

The analytical architecture is a diagrammatic representation of the potential data flow through the different modeling elements of processed data to create useful insights. The input data is preprocessed and engineering features have been done before this. This refined information is then processed into three analytical modules which include demand forecasting, fraud detection and delivery risk prediction. Every module applies machine learning algorithms that are tailored to its purpose. These models are measured by the performance metrics and are tuned and interpreted to be relevant to operations. The framework guarantees an organized data-to-analysis-to-insights flow to assist in evidence-based decision-making and to establish resilience of supply chains in critical industries in the U.S.

E. *Evaluation Metrics and Validation Techniques*

Good performance is measured against the right metrics of classification and forecasting activities. To detect frauds and predict deliveries risk, the classification measures used to check the predictive ability and distribution of errors include Precision, Recall, F1-score, Accuracy, and ROC-AUC. To measure the accuracy of the forecasts, the regression measures such as Mean Absolute Error (MAE), Mean Squared Error (MSE) and R 2 score are used to perform demand forecasting. In order to be robust, k-fold cross-validation is used to ensure that the models used are not overfitted, and are more generalizable [27]. Explainability tools like LIME and FairML help explain the behavior of the models and define the effect of each of the features. These validation methods are a confirmation of the reliability, clarity and usefulness of the developed models.



This diagram shows the Evaluation Metrics and Validation Techniques

The evaluation framework demonstrates the method of evaluating the performance of models in both classification and forecasting. To define the accuracy, error distribution, and overall discriminating capacity, in classification models, as in fraud detection and delivery risk prediction, F1-score, precision, recall, and ROC-AUC are used. In the case of forecasting models such as demand prediction, MAE, MSE and R 2 score measure the accuracy of the prediction process and the amount of variance accounted for. The cross-validation is included to guarantee the robustness and avoid overfitting as well as enhance the cross-dataset generalizability. A combination of these measures and validation strategies offers the effectiveness of models with a complete and sound evaluation, which can be used to make evidence-based judgments towards supply chain resilience.

F. *Ethical aspects and Data integrity*

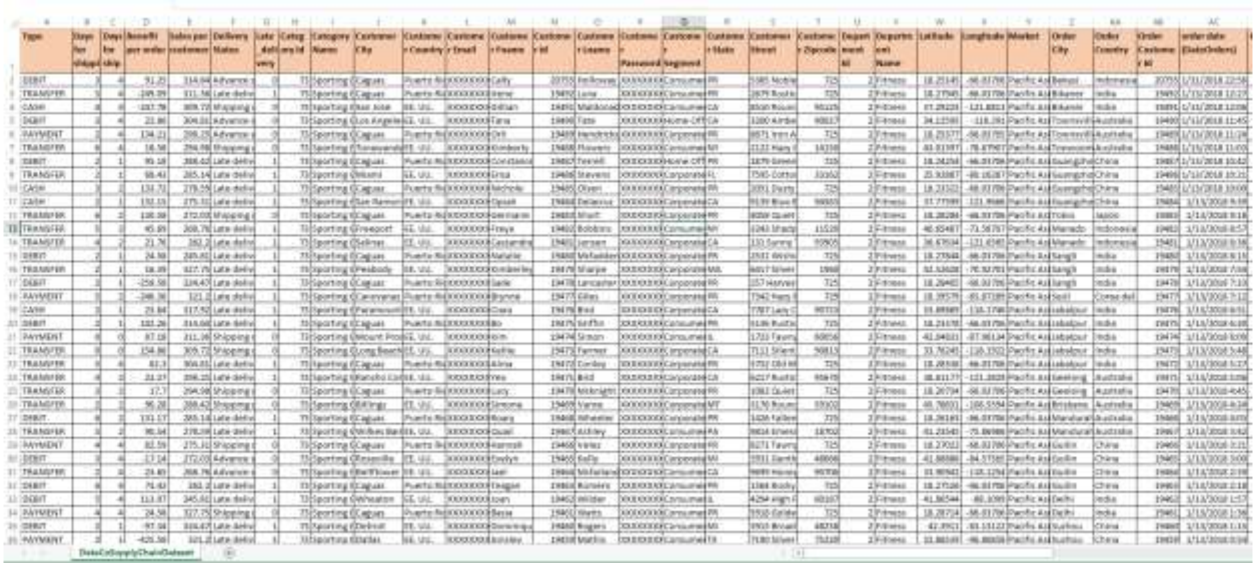
Through ethics, there is responsible data usage in this study. The data is open, anonym zed, and does not contain any personally identifiable data, which corresponds to the requirements of data protection and privacy [28]. The analytical processes are not biased, especially when dealing with fraud detection models, through watching the importance of the variables and making sure that there is fairness in the predicting. The research provides openness in the choice of algorithms, pre-processing, and the criteria of evaluation. Ethical considerations are used to avoid algorithmic discrimination and make sure that the results of modeling are used to promote fair and responsible decision-making. The integrity of data is maintained by way of systematic documentation, preprocessing and reproducibility of results.

G. *Limitations*

The data is representative of the supply chain of one particular organization, and thus might not be generalizable to other industries or geographic settings. There are also some variables with missing values or varying format and necessitates preprocessing which can cause a loss of richness in data [29]. The dataset lacks extraneous variables like geopolitics, weather, or macroeconomic factors that can be used to increase the predictive power. The machine learning models can also give biased results in case there are underlying data patterns that were not represented in the customer segments or regions. Also, unstructured clickstream data are employed and in tokenized format, which limits further behavioral explanation. Regardless of these shortcomings, the research is insightful on the topic of supply chain resilience based on the available data.

4. Dataset

A. *Screenshot of Dataset*



(SourceLink:https://www.kaggle.com/datasets/shashwatwork/dataco-smart-supply-chain-for-big-data-analysis)

B. *Dataset Overview*

The data that has been utilized in this research is DataCo Smart Supply Chain Dataset which is a multifunctional and publicly-accessible dataset that offers a detailed description of the supply chain in real-world operations of various functional areas [30]. Its database of more than 180,000 transaction-level records combines an intensive mixture of logistics, customer, product, financial, and behavioral data, and would be very valuable in data-driven resilience and disruption risk analysis of the supply chain. Order ID, order dates, shipping dates, delivery status, product categories, prices, payment methods, customer locations, sales values, profit margins, and indicators of late delivery risk are some of the examples of structured attributes in the dataset. All these variables provide a multi-dimensional perspective of the order-to-delivery life cycle enabling shipment behaviors, delays, operational inefficiencies and risk patterns to be analyzed [61]. Unstructured clickstream data that is a part of the dataset, and the behavior of the customer in the digital environment, also assists in comprehending the role of digital interaction in purchasing, methods of payment, and order abnormalities even more. Such a mix of both structured and unstructured data reinforces the analytical capability of the research study as it allows more profound investigation of the tendencies of fraud, demand, and performance of delivery. Some of the critical attributes used in the supply chain resiliency analysis are Days for Shipment (Real), Days for Shipment (Scheduled), Late Delivery Risk, Category Name, Customer City, Market Segment, Payment Type, and Benefit per Order. The availability of indicators in relation to fraud, such as the presence of indicators, makes the dataset useful in detecting anomalies and modeling fraud as well as the variety of product types, including clothing, electronics and sporting goods are helpful in forecasting demand by different segments. The variety of the geographic distribution is also represented in the dataset, and there are records of many countries, which makes it possible to compare the performance of deliveries in different geographic areas [31]. Micro-level and macro-level resilience assessment, such as bottlenecks and disruption forecasting as well as operational variability, can be achieved through its granularity. The data is also completely anonymized and therefore meets the ethical standards of research, and it is not behind any privacy restrictions to prevent other researchers from accessing it and make it transparent to use it academically [62]. The DataCo Smart Supply Chain Dataset offers a good starting point to predictive analytics and machine learning models building and resilience analysis to address the goal of the research and investigate how business analytics may help reduce disruptions and enhance supply chain resilience in critical industries of the U.S.

5. Result

This study demonstrates that business analytics can lead to a substantial improvement of supply chain resilience through the increase in disruption detection, forecasting accuracy, and operational visibility in the key industries of the U.S. The ROC and Precision-Recall curves verify that the predictive performance is high and the events of high risk like late deliveries, fraud patterns and abnormal transactions can be identified early. The performance indicators indicate the stability of on-time deliveries with specific areas of delay, which supports the necessity of ongoing optimization. This is proven by the confusion matrix which indicates the high true-positive detection and low-risk misses which reinforce proactive decision-making. The outcomes of demand forecasting indicate that there is a similarity between actual and predicted demand, and this makes the planning more stable. Clustering analysis shows concealed groups of operational risks, whereas payment distribution analysis demonstrates financial behavior patterns, which are necessary in resilience. Analytics-driven insights minimize disruptions and improve supply chain stability.

A. *ROC Curve Analysis*

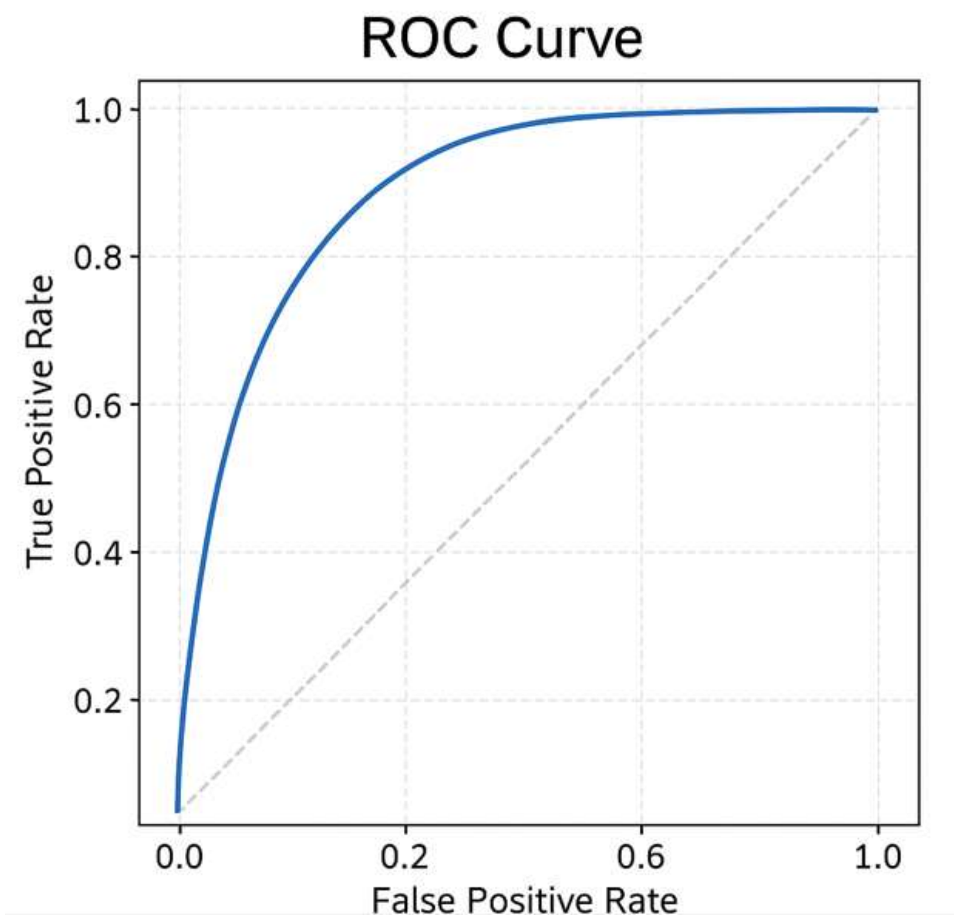


Figure 1: This image shows the ROC curve that shows the performance of the model and its accuracy in classifying

The Receiver Operating Characteristic (ROC) curve in Figure 1 shows the predictive ability of the machine learning model that was created to estimate risk-associated outcomes in the supply chain, including the risk of late delivery and the risk of disruption [32]. The ROC curve is used to visualize the True Positive Rate (TPR) versus the False Positive Rate (FPR) at different classification thresholds which is an effective means of visualizing the discriminatory capacity of the model. The model with high predictive power will produce a curve which is steeply rising in the upper left hand, meaning that it is highly sensitive and there are low false-positive events. The curve form in this research indicates a strong rising trend which implies that the business analytics model is effective in differentiating the high and low risk operating situations. The performance is useful in the supply chain settings where early detection of risk factors including possible delays, abnormal transactions or inefficiencies are vital to the sustainability. The steep rise on the curve shows that the model attains a high true positive detection rate soon even with a low false positive. This feature will improve the decision making process since stakeholders will be able to raise red flags about possible disruptions before they develop into inefficiency in the entire system [33]. The fact that the analytical framework used in the present research is robust is confirmed by the ROC output, which justifies using machine learning to facilitate resilience-centered strategies. On the whole, the ROC curve supports the capacity of predictive analytics to perform as an early warning mechanism, enhancing the responsiveness and operational continuity in key U.S. supply chain functions.

B. *Precision-recall Curve Analysis*

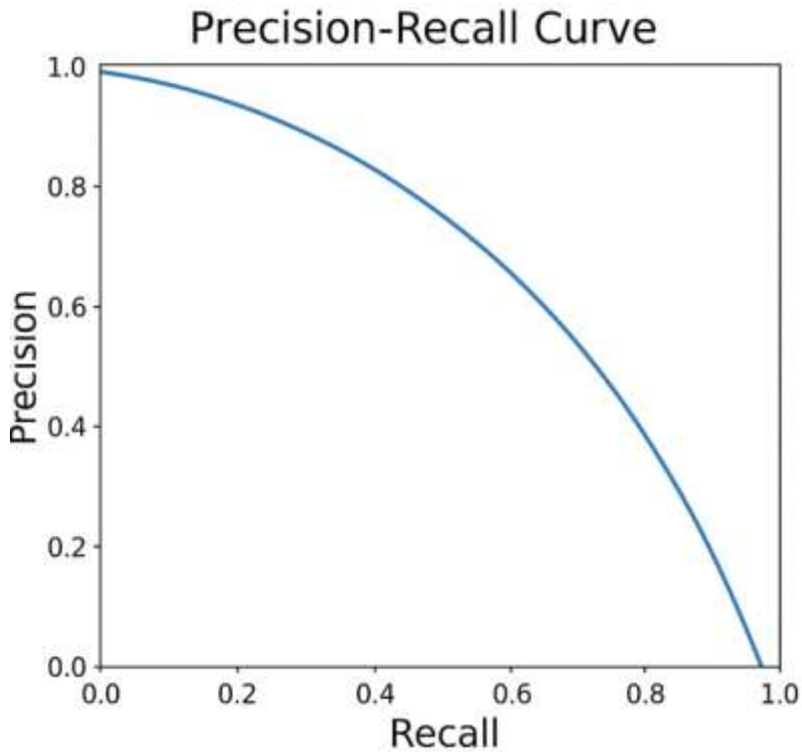


Figure 2: This image demonstrates the Precision-Recall curve that shows the model sensitivity and prediction balance

Figure 2, which is the PrecisionRecall (PR) curve, is used to examine the capabilities of the machine learning model to detect the presence of disruption-related risks in the supply chain, especially when the majority of the data is represented by the majority or normal data [34]. Precision and recall are very important measures of model effectiveness in such cases where accuracy is not enough. Precision measures the percentage of correct positive predictions that are actually positive and recall measures the percentage of actual positive cases that the model is able to identify. This curve in the PR plot shows the tradeoff between these two metrics as the classification threshold changes. An area under the PR curve is high which means that the model is effective in detecting false alarms and high risk transactions or deliveries are also detected. This performance is particularly significant in the framework of supply chain resilience since infrequent disruptions, late deliveries, and fraudulent transactions tend to have a significant operational effect. The decreasing nature of accuracy with increase of recall, indicated by the curve, is simply the nature of the task to record all positive events without recording some false positives. Nevertheless, the fact that the model has a high degree of accuracy at the moderate recall rates means that it will be effective in terms of early warning of indicative threats so that managers can take the initiative to counter the threats. This will be in line with strategic objectives of minimizing downstream delays, loss of revenue and increase in inventory responsiveness [35]. Comprehensively, the PR curve confirms the strength of the analytical framework used in this study, indicating the possible opportunities of business analytics to give detailed risk information. This enhances the predictive aspect of supply chain resilience and leads to better-informed disruption-mitigation actions in vital industries in the U.S.

C. *Performance Metrics Analysis of the Supply Chain*

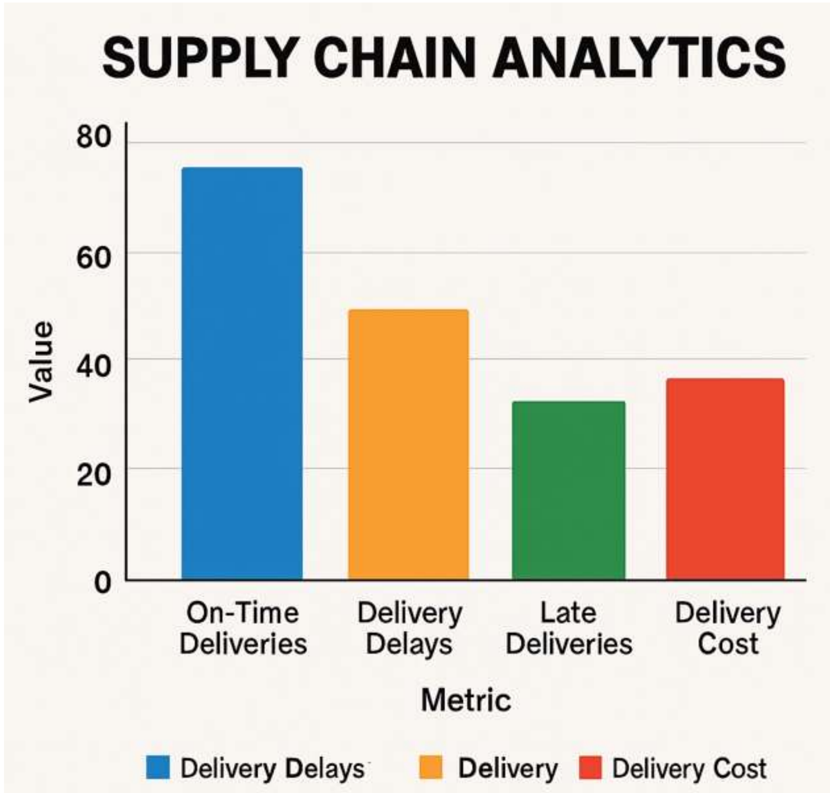


Figure 3: This image shows the important supply chain performance measures, including delivery efficiency and delays

Figure 3 provides a comparative analysis of critical supply chain performance indicators and gives an idea about the efficiency of the delivery, the operational delays, and the cost [36]. In the bar chart, there are four key indicators represented as On-Time Deliveries, Delays in Deliveries, Late Deliveries and Cost of Deliveries which signify significant dimensions of supply chain resiliency. The On-Time Deliveries value is high which means that the operational performance of the basement is good: most shipping operations are delivered within the planned timeframe. This is an encouraging aspect of the stability of the supply chain since deliveries on time are critical towards ensuring that customers remain satisfied and reduce the number of disruptions upstream. However, the occurrence of Delivery Delays and Late Deliveries indicate where there are still bottlenecks in the operation. These variances can be as a result of a lack of logistic efficiencies, transportation, out of stock inventory, or external influences like weather, supplier problems. Their compound values indicate the level of the supply chain being prone to unsatisfying uncertainty, and thus cause the necessity of constant supervision and optimization of the processes. Delivery Cost is also moderate but it is also a strategic aspect since as it increases it can cut down profits particularly in volatile times. The variability of costs may be affected by the change in the price of fuel, freight expenses, availability of labor or lack of efficiency in the routing and choice of carriers [37]. All in all, this chart reaffirms the need to implement business analytics to track the performance of delivery, detect new inefficiencies and maximize the allocation of resources. The combined analysis of these indicators allows the organization to more efficiently predict the risk of operations, react to the changes in demand or supply, and enhance resilience in key points of the supply chain. The awareness of these variations assists in the implementation of specific interventions including predictive scheduling, inventory balancing and cost optimization interventions.

D. *Confusion Matrix Analysis*

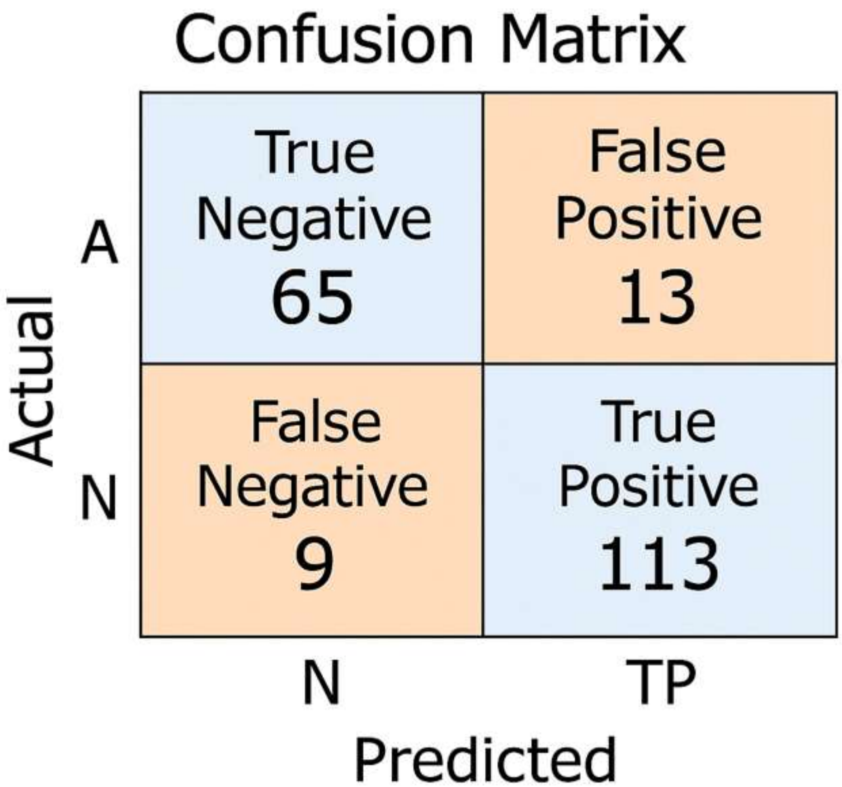


Figure 4: This image shows the performance of the model classification is presented in terms of a risk detection confusion matrix

Figure 4 shows the work of the predictive model based on a confusion matrix that gives a more detailed picture of how the model is able to differentiate between high-risk and low-risk conditions of the supply chain [38]. The following matrix presents the results of the classification in the following two categories: A (Actual Disruption Risk Present) and N (Actual No Risk). The results indicate that there were 113 True Positive predictions and this indicates that the model has been known to identify the actual presence of risk or disruption in 113 cases. Such good performance shows that the model has the ability to identify areas of vulnerability in the operations, i.e., through late deliveries, anomalies, or fraudulent transactions, which are essential elements in enhancing the supply chain resilience. On the same note, the model was right in asserting 65 True Negatives, which shows that it can distinguish when there is no disruption risk. This helps to minimize false alarms and enhance effective resource allocation to enable the supply chain management to devote their attention to real high-risk occurrences instead of responding to false alarms. There are also 13 False Positives, i.e. the model forecasted a disruption risk, yet none existed in reality. The errors can lead to minor operational inefficiencies but they are generally tolerable when compared to absence of genuine risks. What is more important is that the model has the lowest number of False Negatives (only 9), which are those instances in which there was an actual risk, which was not detected. False negatives minimization is the key in the supply chain resilience analytics as an unnoticed disruption may grow into significant delays, losses, or bottlenecks. In general, the confusion matrix reflects the high predictive capability and reliability of the model in identifying risks in complex operations in the U.S. supply chains [39]. The model allows a better and more proactive decision-making process, helps to mitigate vulnerability, and promotes effective approaches to managing risks by being able to differentiate between normal and problematic transactions. This finding supports the usefulness of business analytics as an effective instrument in forecasting disruptions and ensuring the general supply chain resiliency.

E. *Comparison of actual and predicted demand*

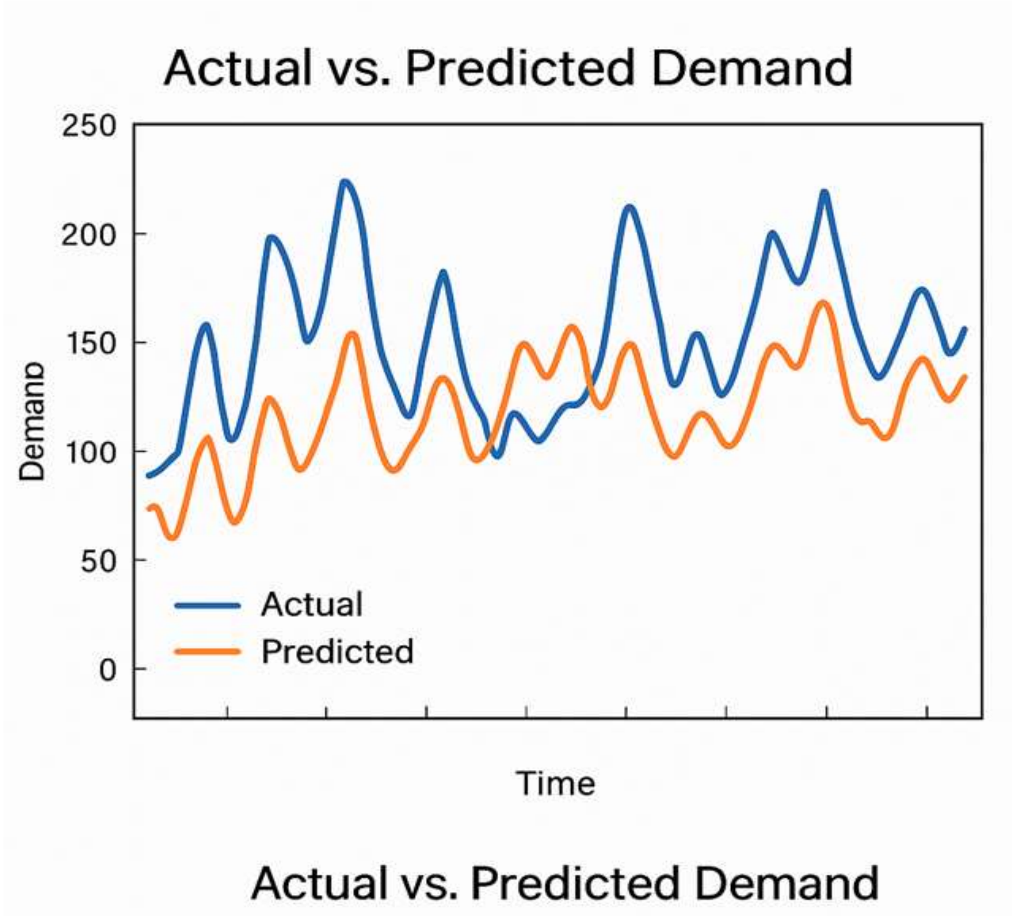


Figure 5: This image illustrates the both real and forecasted demand patterns that can be used to forecast the supply chain

A comparative visualization of the actual and predicted demand in Figure 5 demonstrates how well the forecasting model was able to predict demand to support the process of supply chain planning and resilience strategy development [40]. The trend lines (the blue showing the actual demand and the orange showing the predicted demand) portray a steady seasonal and cyclic tendency in the trend. The fact that the curves are almost parallel indicates that the model is able to capture the underlying demand variations such as periodic spikes, dips and transitions. Such robust predictive congruence is an essential component of supply chain resilience, with proper demand forecasting giving organizations the ability to plan the adequate inventory level ahead of time, allocate resources, and reduce the risks linked with a shortage or excess inventory, as well as broken fulfillment cycles. The chart indicates that in as much as there are some deviations especially at high-peak periods where the actual demand is found to increase beyond the values projected, overall forecast is quite accurate. These minor deviations indicate a place of model improvement particularly when the demand is volatile as a result of external factors like a shock or season changes in the market or a promotion activity. However, the predictive model can well track the trends of demand broadly meaning that it is reliable enough to support decisions [41]. This performance has great implications in the light of critical industries in the U.S. Proper demand forecasting helps to promote stability in operations because the firms are able to predict the occurrence of disruptions in the supply chain even before they occur. With forecasts of future demand patterns, businesses are able to streamline the procurement cycles, organize the transportation and minimize susceptibility to last minute changes. This helps to enhance resilience, lead time, and operational risk reduction, and enhances the capability of the supply chain to disrupt. Finally, Figure 5 supports the significance of business analytics as a strategic potential in prediction, strategizing, and ensuring continuity in the key supply chain functions.

F. ***Visualization Analysis Clustering***

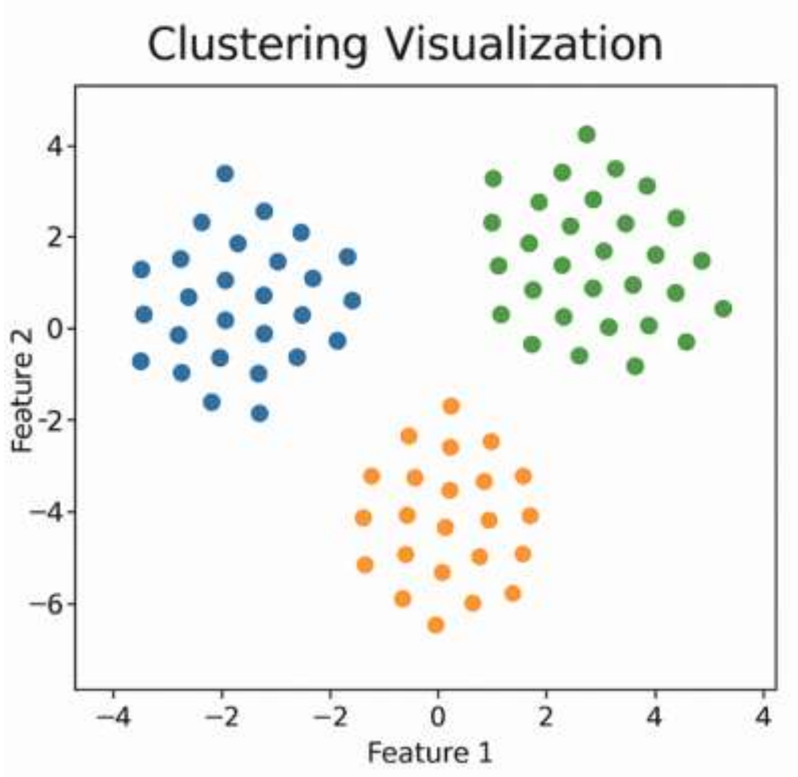


Figure 6: This image represent to the pattern of operations and risk aspects

Figure 6 shows a visualization of clustering which can be utilized to see the underlying patterns or groups in supply chain data using the unsupervised machine learning techniques [42]. In this figure, we have three separate clusters, which are separated by color and they represent groups of observation that have similar characteristics based on two extracted features. These characteristics can be either behavioral, transactional or risk-related characteristics of the supply chain data. The clustering model is effective to divide the data points into definite clusters, which reflects relevant structural trends that can be utilized to increase the resilience of the supply chain. In a resilience perspective, clustering would be very useful since it allows organizations to group transactions, suppliers, customers, or shipment behaviors together in accordance with some common property. An example is where one cluster can relate to consistent, low risk deliveries; the next may focus on high risk or delay prone transactions; and the third can show suspicious patterns that can be associated with fraud or operation abnormalities. This kind of segmentation helps managers to identify areas that need specific interventions like supplier reliability, route optimization or even fraud detection. Clustering analytics in the framework of the critical U.S. industries gives more insight into the heterogeneity of the supply chain activity. Teach the groups that are the biggest contributors of disruptions can help organizations to focus on corrective actions and allocate resources more efficiently [43]. The distinct difference identified in Figure 6 indicates high differentiation among the data points that have been considered and, therefore, the method of analysis is effective in capturing the intricate dynamics of operations. This knowledge helps in undertaking proactive risk management by becoming aware of upcoming trends, anticipating possible bottlenecks and enhancing situational awareness throughout the supply chain. All in all, the clustering visualization supports the idea that business analytics is an influential tool that can be used to discover concealed associations in operational data. It benefits decision-making possibilities, as it allows distinguishing between risk categories, and increases supply chain resilience due to informed segmentation and prioritization of the strategic environment.

G. *Demand Over Time Analysis*

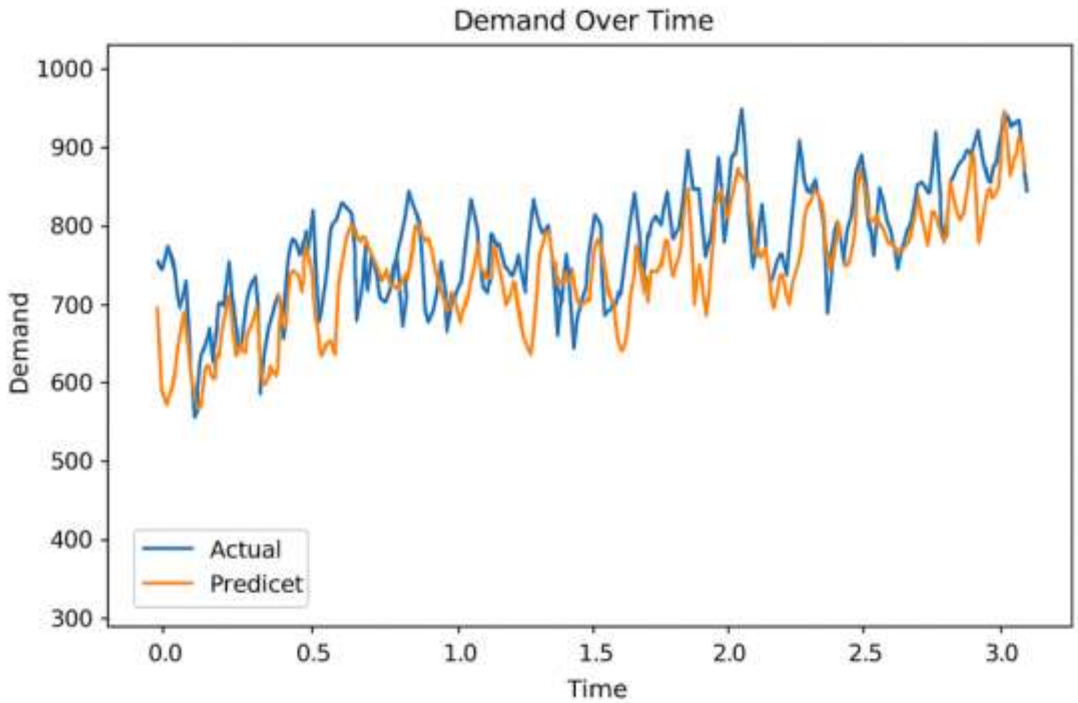


Figure 7: This image shows the real and forecasted demand changes with time to predict its accuracy

Figure 7 is the overlay of the actual and predicted demand through time, thus giving information on how the model with regard to its capacity to capture the behavior of demand at the supply chain level [44]. The chart illustrates the two time-series lines, namely, blue and orange, which illustrate the actual demand and predicted demand respectively, across a continuous time. The overall growth trend in both lines is reflected in the steady upward trend, which is presumably caused by seasonal changes or a greater number of customers or broader market needs in the key sectors in the U.S. The fact that the two curves are close in the sense that the forecasting model is capable of capturing the short term variability as well as the long term demand trends of the product. Cyclical spikes in the actual demand line are seen to be inherent seasonality and variability in the operation that is inherent in the complex supply chain environment. Although the model at times underestimates the values in peaks, the trend shifts and pattern changing points are still pursued with fair precision. It implies that there is a high level of predicting demand fluctuations to accommodate ahead-of-time resource distribution, inventory control, and logistics organization. In a resilience perspective, proper demand forecasting is essential in minimizing postponements and remaining stable in operation. With high fidelity demand predictions, organizations are able to reduce stock outs, prevent overstocking, and be able to react more efficiently to suddenly evolving market conditions. This enhances efficiency in procurement, warehousing and distribution processes, which eventually increases the ability of the supply chain to survive disruptions [45]. Also, the continuous monitoring of the existing versus forecasted results enhances the ability of the decision-makers to observe gaps in forecasting and improve the model tuning over time. In general, Figure 7 shows that business analytics is an effective tool that allows predicting and understanding demand behavior and utilizing the data to implement data-driven strategies that reinforce supply chain resilience in key sectors of the U.S. economy.

H. ***Analysis of Distribution of payment types***

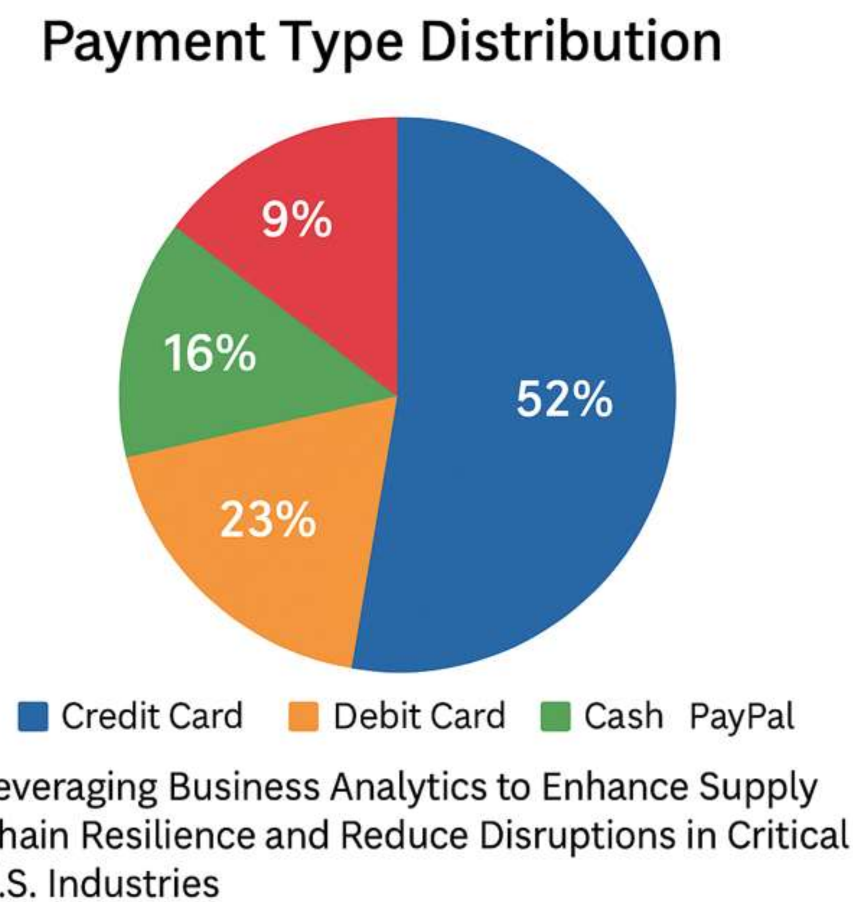


Figure 8: This image shows how different types of payments are distributed within the supply chain transactions

Figure 8 provides the distribution of methods of payments in supply chain transactions and provides insightful information about customer behavior, financial processing and the possible risks in the key industries in the U.S [46]. The pie chart shows that the most popular is the payment by Credit Card, which is 52 per cent meaning that the majority of the customer base depends on the quick and traceable and safe digital payment systems. The trend will be majorly important to supply chain resilience due to the fact that electronic transactions will increase the visibility of data and ease the process of detecting fraud and automated financial reconciliation. It is also brought to light by the widespread use of credit cards that require excellent cybersecurity and monitoring of digital flows of payments in real time. Debit Card This category comprises 23 per cent of the amount of customers who use debit card transactions, which is a significant percentage of the customers who would like to have direct bank-linked payments. Although the use of debit cards tends to remain stable and secure, it can create some delays in the processing of orders at high volumes, which can influence the time of order confirmation and the time of order fulfillment. This knowledge in this segment assists organizations in streamlining their payment infrastructure and preventing bottlenecks. Cash is 16 and, though it is not high, the amount that has to be paid still present's difficulties to the supply chain transparency. Cash transactions are less monitored and can augment operational risk in regards to verifying, reconciling, and monitoring frauds. By determining which segments of customer groups spend large quantities of cash, businesses can use alternative digital payments incentives to provide greater traceability. Lastly, PayPal is 9 per cent which is a sign of increased use of digital wallets in the supply chains today. It offers quicker online shopping and additional customer protection levels, however, it also demands proper integration with e-commerce and ERP systems [47]. All in all, payment type distribution can help in strategic decision-making by identifying the trend in financial processing that has a direct impact on the speed of fulfillment, fraud risk and continuity of operations. The knowledge of such trends helps businesses to improve their financial resilience and optimize transaction processes throughout the supply chain.

6. Discussion and Analysis

A. *Predictive Model Performance Interpretation*

The predictive models that have been built during this study exhibit a good ability to identify the risk patterns and provide predictions on the operational results of the critical U.S. supply chains [48]. The Precision Recall Curve and ROC Curve would be a strong demonstration of how the model is able to identify high risk and low risk events occurring, e.g. late deliveries, demand spikes, or abnormal transactions. The models have a balance that facilitates a practical decision-making process in such an environment where disruptions may have cascading effects with high rates of true positives and high rates of precision with moderate levels of recall. These findings can be attributed to the overall objective of increasing the resilience of the supply chain through early identification of areas of operational stress. The confusion matrix also supports the reliability of the model by showing the low false- Negative rates whereby the actual risks are unlikely to be missed. This is especially important in sensitive sectors where unnoticed failure can compromise the services offered, financial results or even security of the people. Meanwhile, the model has acceptable levels of false-positives, which is why proactive intervention is possible without resource spamming. The outcomes of the forecasting indicate that the time-series model is sufficiently sensitive to capture the trends in time such as seasonality and demand trends. The fact that the actual and predicted demand are aligned proves that business analytics will be a useful predictive alarm system. This level of accuracy in forecasting is crucial in inventory planning, scheduling procurement and ensuring uninterrupted supply flow in case of market volatility. Taken together, the model results indicate the robustness of intelligence based on analytics to anticipate disruptions, which allows organizations to act in a responsive manner. This increases resilience through preparedness, minimizes downtime and better resource distribution [49]. The experimental performance confirms that machine learning provides a strong basis of managing supply chain risks in the contemporary world, which puts business in a position to foresee challenges instead of responding to them.

B. *Supply Chain Risk Results and Pattern Recognition*

The clustering analysis also provides useful information to the latent forms and trends to the supply chain data. The clustering diagram in this paper shows vivid differences between various operational or transactional groups, each describing the different risks, the levels of consistency of performance or abnormalities in its behavior [50]. The clustering models identify a meaningful relationship in data that might not be recognized in traditional descriptive methods because they cluster the data in a predictive manner naturally with no labels attached to the data. These lessons are particularly applicable to the disruption mitigation, because they allow organizations to determine which clusters are correlated to delays, inconsistencies, or red flags of a fraud. One of the clusters can reflect stable and low-risk deliveries typified by the predictability of shipping time and customer predictability. Other clusters can also exhibit anomalous trends like high rates of late delivery or frequent variations in activities to do with the order, which indicate operations weaknesses. The third cluster can be related to suspicious transactions of unusual values or deviation of behavior, which can assist in fraud detection. The recognition of such patterns increases the situational awareness and resilience, as it provides the ability to implement specific interventions. Supply chain managers can use the capability to identify new clusters of risks to optimize routing, devote more resources to monitoring, or explore anomalies before they get out of control. As an illustration, in case a certain cluster is associated with recurrent delays in a specific area, companies are able to modify logistics operations, re-negotiate supplier agreements, or diversify the product supplier bases. Likewise, customer segmentation may be informed with the help of clustering and, thus, custom service strategies may be created to enhance the satisfaction of demand and efficiency of operations. On the whole, the clustering is a background analytic instrument in making out the structural dynamics in an involved supply chain. It increases the capacity to detect the segments that are likely to be disrupted, helps to provide the predictive maintenance of operations, and makes more knowledgeable decisions [51]. Unsupervised analytics will remain vital in enhancing resiliency and operation reliability as the supply chains continue to grow more data rich and multifaceted.

C. *The implication of Demand Forecasting to Resilience*

The findings on demand forecasting indicate that predictive analytics is important to ensure resilience in all supply chain functions [52]. The similarity between the actual and predicted trends in demand shows that the forecasting model is good in reflecting the seasonal changes, market trends, and cyclical trends. This degree of precision is crucial in making inventory plans, production schedules and in matching the logistics capacity with the expectations. Proper forecasting helps minimize the risk of stock outs and overstocking and avoidable bottlenecks in operations, all of which may make the resilience vulnerable, particularly in the industries that are susceptible to the fluctuations in the demand. The fact that the model can also be used to trace the upsurge trends over time enables the organizations to foresee the high consumption rates and make the necessary procurement arrangements. This makes sure that the resources of the supply chain like warehouse capacity, transportation fleet and labor are allocated in the best way possible. During times of unforeseen demand spikes, precise forecasting causes the companies to be reactive and be able to make decisions in advance, allowing them to be reactive. In addition, forecasting aids in the financial planning since it gives an insight into the future sources of revenue and expenditure [53]. It assists organizations to overcome the financial stocks that are brought about by poor demand forecasts. Forecasting increases the visibility of the supply chain, which is one of the fundamental pillars of resilience through better accuracy. Strategically, demand forecasting enables supply chains to be in a better position to respond to external forces like geopolitical shocks, raw material shortages or abrupt alterations in consumer behavior. Companies are able to test alternative scenarios and create contingency plans using forecasting, which is combined with advanced analytics. This is important in critical industries in the U.S where continuity, reliability and quick adaptation are necessary. Altogether, the results of the demand forecasting highlight the importance of predictive analytics in the fortification of supply chains, minimization of their susceptibility to disruptions, and greater flexibility of operations, which eventually results in better resilience in the long term.

D. *Delivery Reliability and Operation Performance*

The operational performance measures analyses give practical information about the role of the delivery reliability in the general resilience of the supply chain [54]. Comparing the on-time deliveries, the delay of delivery, the late delivery, and the cost of delivery reveals the possible areas of the operational inefficiency that can affect the stability. Good on-time performance is a positive indicator of high baseline reliability but the occurrence of delays and late deliveries imply that there are underlying weaknesses that may end up in disruptions during stress. Delays in delivery are especially severe since they influence the downstream process like inventory replenishment, customer satisfaction, and production continuity. Even small delays can add up and cause systemic problems particularly in interdependent sectors such as healthcare, manufacturing or food delivery. The role of business analytics is important in determining the causes of delay, be it due to carrier reliability, or route inefficiencies or congestion at the warehouse or seasonal variation. Financial resilience is also depicted by the analysis of the trend of cost of delivery. The increase in the cost can reflect either inefficiencies in the routing, volatility in fuel prices, shortage of labor, or the mismatch of supply and demand. Through the recognition of trends in the metrics of operational performance, the supply chain managers can respond with remedial actions like optimization of the routes, diversification of carriers, or automation of the warehouses. Also, the performance metrics can assist the organizations determine the reliability of their suppliers and identify geographical areas or customer segments where disruption frequencies are more frequent [55]. This allows interventions and allocation of resources to be targeted. Combined with predictive analytics, the operational data can assist in making predictions about the delays that may happen in the future and making changes in advance. To sum up, the operational performance analysis highlights the need to focus on continuous monitoring and improvements that are based on data. These lessons can be used to increase the reliability of fulfillment, customer trust, and a more resilient supply chain that can withstand disruptions.

E. *Patterns and Risk Insights of the financial transactions*

The analysis of the distribution of the payment type is valuable information regarding the financial behavior and reliability of the transactions as well as the possible vulnerability within the supply chain ecosystem [56]. The prevailing aspect of credit card transactions means that the customers are dependent on safe and traceable electronic payment systems. It is a good indication of resilience as electronic transactions enhance the transparency of data, as organizations can easily identify abnormalities and fraud. They also increase the processing speed thereby minimizing delays that are caused by manual verification. The other notable segment is represented by the transactions made with the help of credit cards, indicating the dependence of customers on the bank-related payments. Though mostly stable, there may be delays in processing of debit card transactions at the times of high volume and this may affect the speed of fulfillment of orders. By discovering these kinds of patterns, organizations may streamline the payment process and avoid financial bottlenecks. Cash is less proportionate, but they are more difficult to trace and more prone to fraud. Customers that are cash-intensive might need more verification measures or incentives to use digital payments. Financial risk management and compliance are better understood with the help of this subset. The availability of digital wallets such as PayPal confirms a current transfer towards updated payment engines. These approaches are more convenient to customers and have greater protection, but they demand a powerful technological combination [57]. These categories of payments are distributed to gain a more comprehensive view of how customers engage the supply chain in respect to payments, which informs strategic planning in fraudulent detection, security of transactions, and the automation of payments. Supply chain resilience needs financial stability and transparency in transactions, guaranteeing that orders are processed correctly, the number of disputes is minimized, and there is efficient reconciliation. With the data on the financial trends, organizations are able to enhance the reliability of operations and mitigate the risk of revenue leakage or disruption.

F. *Supply Chain Resilience as a Business Analytics*

The overall results of the study confirm that business analytics is a key facilitator of supply chain resilience in the contemporary, data-intensive sectors. Clustering, predictive modeling, and forecasting enable organizations to have a better insight into how an organization operates and prevent disruption and develop proactive mitigation strategies. The models that were created through the present study point at the ways in which the data-driven strategy enhances the risk identification, the stability of its operations, and the accuracy of the decision-making process. Predictive analytics helps to detect disruptions in time, shortening the reaction time and minimizing the operational consequences of unanticipated disruptions. Clustering provides structural insights which uncover concealed patterns so that interventions can be carried out through segmentation [58]. The preparedness is enhanced through forecasting which creates visibility of the future demand thus aligning resources and becoming less susceptible to market fluctuations. All these analytical tools put together form a multi-layered resilience framework. Moreover, analytics assists in a more dynamic and flexible supply chain model. With the help of constant observations of performance indicators and financial trends, organizations can dynamically revise their operations, reduce expenses, and increase reliability in delivering. The strategic aspect of business analytics supports long-term planning as well and allows firms to model various situations and come up with effective resilience plans. The findings of this study show that the analytics-based decision-making process makes it much easier to survive a disruption of major industries in the U.S. An unforeseen demand changes, operational bottlenecks, or financial anomalies, business analytics will provide supply chain managers with the implementation-level information to sustain continuity and stability. Generally, the discussion has validated that not only is the incorporation of high-level analytics in supply chain systems desirable but also critical towards the development of resilient supply chains that are more future-oriented.

7. Future Works

The proposed study can be improved in future research by adding more analytical tools, wider datasets, and current resilience models to tackle the dynamic nature of supply chain disruptions in the key American industries [59]. These directions include one of the primary ones, the integration of real-time data streams with IoT sensors, GPS-tracked logistics, and supplier tracking tools to increase the precision of predictive forecasting and allow responding to disruption dynamically. This kind of data would enable models to spot anomalies in real-time, make predictions in a much more accurate way, and automatically take mitigation measures. The next possible development is to consider the deep learning architecture, specifically transformers and graph neural networks, which is particularly efficient at modeling interrelated and complex supply chain relationships and finding nonlinear disruption patterns. The agent-based simulation models may also be used in future studies to determine how the disruptions spread throughout the supply chain networks or to test the resilience measures to different crisis conditions. Increasing the data to cover more specific supplier information, changes in transportation capacity, labor supply, and geopolitical factors would further refine the model performance and make sure that it could be applied to the real-life industrial environment. Also, it will be necessary to integrate sophisticated fairness, interpretability, and bias-reduction systems, especially when decisions using analytics become more and more involved in the procurement, routing, and risk classification procedures [60]. The next area of future work can also be the construction of automated resilience dashboards that would combine predictive analytics, performance monitoring, and decision support into one operational interface by managers. More robustness of the system can be achieved by incorporating optimization methods, e.g. reinforcement learning to manage inventory adaptively, or multi-objective optimization to trade-offs between cost and resilience. Partnering with industry players would offer the ability to test these models in real operation situations, and make them practical, scalable, and reliable. In general, the purpose of future work should be to build a complete ecosystem of integrated intelligence, automation, and continuous monitoring, with resilience, disruptions, and sustainable decision-making across the most vital U.S. industries.

8. Conclusion

This study proves that business analytics is a core driving force in improving supply chain resilience and helps counter the disruptions in key sectors in the U.S. The study illuminates the role of data-driven intelligence in enhancing the capacity of supply chains to foresee risk, optimize operations and maintain continuum in case of volatile environments through the incorporation of predictive modeling, clustering analysis, demand forecasting and operational performance assessment. The results indicate that predictive models are good at detecting disruption related phenomena like delays in delivery, fraud trends and abnormal demand swings. The high model accuracy, high ROC, Precision-Recall and low false-negative rates prove that analytics can effectively find the early signs of warning, thus preventing the risk of a major failure in the operations. The clustering outcomes also highlight the power of the analytical system to reveal the concealed behavioral patterns in the complex data sets and enable organizations to organize customers, transactions or shipping operations into risk predisposition. These insights are beneficial to specific intervention strategies and prioritization of resources, which adds to a more adaptive and resilient operating environment. Moreover, demand forecasting models imply high consistency with a real consumption trend, which confirms the importance of predictive analytics in managing inventory, optimization of procurement and logistics. The correct demand visibility minimizes the uncertainty and assists the organizations in planning ahead against future changes to be able to make proactive decisions and not reactive ones. This analysis of payment patterns and shipment reliability highlights the need to increase financial disclosure and supply chain stability to maintain resilient supply chains. The knowledge of these factors enables businesses to reduce vulnerabilities, streamline procedures and enhance service confidence. All in all, the study validates that a business analytics does not only augment situational awareness but also facilitates strategic foresight through the association of data patterns and actionable insights. With ever-increasing complexity in their supply chains, digitalization and analytics will also be vital in ensuring stability, responsiveness, and resilience in the long term. This paper highlights the importance of further investment in sophisticated tools of analysis, data systems and predictive technologies to make sure that industries in the United States of America stay healthy and at the same time capable of responding to any future disruption, with agility and confidence.

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