

Machine Learning for Supply Chain Risk Analysis and Business Resilience under Uncertain Demand

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ABSTRACT

Objective: The study is focused on finding the relationships between demand uncertainty, supply chain-related factors, and total supply chain cost in order to improve the understanding of the risk exposure and the risk resilience-related factors.

Method: In this research, risk patterns and business resilience in a pharmaceutical supply chain that operates under uncertain demand are explored through an exploratory analytical approach with the aid of machine learning. The research is based on a secondary dataset generated from a blockchain-enabled pharmaceutical supply chain (Pharma SC) environment consisting of 5000 generated observations. The distributions, differences, and inter-relationships of variables are explored using descriptive statistics, visualization methods, and correlation-based methods. **Results:** The results indicate that there is a significant range in the total supply chain cost, with a higher share of observations in the medium cost range and a lower share of high-cost scenarios. Comparative analysis shows that the installation of the blockchain and the variables related to the finished product show significant differences in the various cost categories, while the other variables suggest fewer differences. The results of the correlation analysis also reveal that the installation of blockchain and the finished products were found to have a higher correlation with the total supply chain cost when compared to demand uncertainty only. **Novelty:** The results indicated that supply chain risk is not a single source of uncertainty but rather is a result of the interaction of various operational and resource-related uncertainties. The findings underscore the significance of machine learning-driven exploratory data analysis in identifying meaningful patterns in intricate supply chain data.

INTRODUCTION

Supply chains link suppliers, manufacturers, logistics providers, and customers, necessitating the seamless flow of materials, information, and products in order to run a business. For many organizations, continuity and being able to respond to unexpected events is a matter of resilience in the face of disruptions. The COVID-19 pandemic has shown how major disruption can reveal fragilities in the structure of supply chains and enhance the demand for capabilities to withstand disruptions. Naz et al. were aware of the need for supply chain resiliency during the pandemic and view AI as a potential technological solution to enhance resilience [1]. During crisis situations, AI can help organizations handle information from the supply chains, recognize patterns, increase visibility, and assist in making apt decisions. One of the more salient points of relevance is the role of machine learning that can look at the historical and operational data and draw relationships between demand, supply, inventory, cost, and other factors that present risk. These capabilities can contribute to shifting from reactive response to

informed risk assessment and preparedness. Data-driven analysis can be useful in pharmaceutical supply chains that demand uncertainty and supply continuity impact operational performance. By analyzing supply chain factors in a machine learning-centric manner, information can be obtained from the chain to assist in understanding patterns of risk and resilience. In this study, the work will be focused on exploratory analysis of pharmaceutical supply chain data, in the presence of uncertainty of demand, to uncover the relationships that can be used to facilitate risk analysis tasks and/or resilient business decisions.

There are risks associated with supply chain systems that can impact the flow of materials, information, and products, and affect business performance. The disruption can come from demand changes, supply issues, process failure from environmental factors. Chinese supply chain research indicates that there are four major sources of disruption: demand disruption risk, supply disruption risk, process disruption risk, and environmental disruption risk [2]. These risks can result in problems with operations such as shortages, delays, inefficiency, and challenges to operational performance. Research on 315 Chinese companies revealed that supply disruption risks and process disruption risks have a significant impact on the performance of the supply chain [2]. If performance is poor, the business could have to pay higher prices, be less productive, have service issues or have issues adapting to market shifts. The uncertainty of demand adds to the complexity of planning as organizations must negotiate and balance the needs with the resources available. These issues are key in the pharmaceutical supply chain, where availability of the product is linked to supply chain reliability. The real challenge is determining the pattern of supply chain risk, which enables the decision-making process in operations. Analytical approaches based on data can analyze relationships between factors and provide evidence for risk management and resilience planning.

The purpose of this study is to understand the nature of the supply chain risk pattern via machine learning analytical techniques to derive disruption factors, resilience features, and relationships that can inform effective and sustainable business continuity planning decisions.

The following objectives have been accomplished in this research paper given as follows:

- a. To recognize and explore key supply chain risk and disruption patterns and their interconnections through exploratory data analysis and visualization.
- b. To explore the differences of supply chain resilience-related factors under different risk scenarios and look for patterns that could be used to aid business resilience and risk prediction.

What patterns can be detected with machine learning analysis of the supply chain factors in the presence of uncertainty in demand, relevant to supply chain risk and business resilience?

This research makes a valuable contribution to the study of supply chain risk because of the use of machine learning-inspired exploratory analysis in the context of a

pharmaceutical supply chain with uncertain demand. It gives a data-driven view of the relationships between the factors of a supply chain and the costs that could be a sign of operational risk. The study also links analytical results to business resilience, examining how to apply supply chain evidence to enhance preparedness, planning, and decision-making. Another contribution is the explicit communication of relationships among variables in the supply chain using visual analysis. The results can be used as a basis for further studies with supervised machine learning models to predict supply chain risks. The study can practically contribute to the understanding of patterns in uncertainty and resource needs in a supply chain from a supply chain manager's point of view. It can also provide a foundation for more responsive and resilient strategies in the pharmaceutical supply chain.

SCRM has shifted from thinking about individual incidents to thinking about the continuity and adaptability of networks, given their interconnectedness. In the context of Gurtu and Johny [6], the associated risks of the supply chain were aligned with economic policies, globalization, outsourcing, and supplier relationships with an intent to identify, rank, and prioritize the disruptive events. This is a key perspective as risks represent not an isolated event, but an event that can occur across a range of different scenarios. They can extend to other firms or activities, and affect the vulnerability of one firm contributor to the overall performance of the network. The review reveals, however, that there are various types of risk categories in different industries and supply chain set-ups, which makes it difficult to implement uniform mitigations. Thus, a resilient approach must focus on the origin, the way risk is passed on, and the impacts of risk, rather than just identifying disruptions. This is a different focus from protecting individual operations to appreciating how a supply chain could operate at an acceptable level of performance if multiple interrelated risks were to occur.

Digital technologies have added extra dependencies and new opportunities for control to this environment. Industry 4.0 supply chains face operational, demand, financial, supply, disruption, system, cybersecurity, safety, social and environmental, and organisational risks, according to Pandey et al. [4]. They view risk as multi-dimensional and employ risk prioritization as a method to help differentiate significant risk sources from less impactful sources. However, the use of expert opinion and structured decision-making methods may be restrictive in a dynamic environment with frequent changes in risk conditions that occur between the scheduled assessments. It is possible to use the study of TOPSIS and DEMATEL to carry a systematic prioritization and cause-and-effect analysis; however, these techniques are not able to continuously predict the disruptions that will occur. The identification of important risks does not imply a time of disruption or the likely evolution of effects throughout the network. It is therefore essential to have mechanisms to convert changing operational information to timely assessments for effective risk management. This is particularly important if disruption triggers are observed gradually throughout activities that are connected within a supply chain.

The COVID-19 pandemic demonstrated the importance of interactions between supply conditions, demand behavior, inventory decisions, and external restrictions for resilience. In their digital twin and DE simulation validation, Burgos and Ivanov [5] show that the intensity of the pandemic, government measures, inventory ordering dynamics, and customer behaviour all played their part in the performance of the food retail supply chain. Their analysis is not just about identifying a source of disruption, but also the impact of conditions on operational outcomes. The results also reveal that in the scenarios investigated, there were significant impacts on both demand and supply, with the impact on supply from interruption to shutdowns being greater than the impact on demand from surge, and that impacts were relatively small on transportation disruption. These findings highlight the importance of basing resilience strategies on real considerations of the level of disruption, rather than blanket assumptions. Xu et al. [3] explore the pandemic risk through both supply and demand perspectives, and categorize resilience into responsiveness before disruption, resilience during disruption, and restoration after disruption. The GREAT 3Rs they have developed expand the response to include government action, supply chain redesign, financial strategies, operational adjustment, and technology adoption. However, a framework-based approach can help identify strategic needs and distinguish which indicators would trigger intervention under different conditions.

Risk management and resilience are linked in the sense of mitigation strategies, learning from disruption and adapting responses. Hohenstein [7] analyzes ten logistics service providers active in different countries and relates the experiences of the pandemic with the changes in the management of supply chain risks and the ability to become more resilient, which are of obvious importance from a practical perspective. The case-based perspective highlights that the ways that organizations transform disruption experience into new ways of doing things influence the extent to which they are resilient, but the results from logistics participants do not necessarily reflect those of other supply chain actors. A consistent challenge in the literature reviewed is the problem of translating from general risk identification to the timely and evidence-based prediction of risk. Xu et al. [3] highlight technology adoption as an important aspect of reform, Pandey et al. [4] illustrate the importance of structured risk prioritization, and Burgos and Ivanov [5] provide a digital simulation approach to exploring changing disruption scenarios. These simple strategies offer complementary bases, but leave room for data-informed techniques that identify patterns in risk indicators and help identify disruptions sooner. This is especially significant for business resilience, as it enables risk prediction to be made proactively based on observed conditions in supply chains to make preparedness, continuity, and recovery decisions.

Demand uncertainty is one of the main problems in the supply chain as it can impact purchasing, production, inventory, and distribution decisions. Abolghasemi et al. [8] demonstrate that the volatility of demand has a significant impact on forecasting accuracy, especially when promotional activity generates abnormal demand behaviour.

They have analyzed 843 demand series and found that volatility is not a homogeneous forecasting condition and that different levels of volatility demand different models that can capture different types of demand behaviour. This is crucial for the pharmaceutical supply chain where demand variation may occur due to disease incidence, prescribing habits, seasonal factors and public health measures. One of the major implications is that errors in forecasts are not just a statistical issue, and poor estimates can have operational consequences throughout the supply chain. Gonçalves et al. [9] also show that it is more challenging to forecast demand when the demand for components relies on a random end customer demand and when several different periods in the future need to be forecasted at the same time. They offer a multivariate view, suggesting that information from variables related to the demand of interest can lead to better forecasting than can be obtained by univariate methods alone. But increased reliance on multiple information sources also means increased reliance on the availability and quality of the information, as poor-quality input can lead to uncertainty cascading through to subsequent planning decisions.

When forecast decisions are turned into replenishment quantities and service levels, so do the inventory implications of uncertain demand. Seyedan et al. [10] directly link demand forecasting with inventory optimization, where they forecast the future demand using ensemble deep learning and calculate safety stock, order quantities, and replenishment levels. Their method is analytically significant as it considers forecasting and inventory control as two interrelated decisions, not activities. The fact that they use different types of models suggests that they are trying to represent the models in the data set in a different way in order to capture different temporal characteristics. However, this approach also uncovers a drawback when used in the field of pharmaceuticals, as it is an empirical setting and it is assumed that unpredictable events will not occur. For pharmaceutical systems, such an assumption can be limiting, especially in the event of outbreaks, treatment changes, and emergency procurement that can create demand patterns that historical observations are unable to capture. The importance of complex forecasting is not only in its prediction accuracy, but in its ability to represent uncertainty relevant to the operational environment is also important.

The uncertainty of lead time also complicates matters, as even an accurate demand estimate might not avert shortages if lead time is not predictable. Mohammed and Mandal [11] study lead time variability using simulations and real-life examples, and relate lead time variability to stockouts, excess inventory, production scheduling problems, and changes in supply chain responsiveness. In fact, what they found is that inventory exposure is dependent on the interplay between demand uncertainty and replenishment uncertainty, and not just demand variability. This is especially relevant for pharmaceutical supply chains as products will have a service requirement that relates to continuity of treatment, while procurement procedures and distribution constraints can hamper rapid replenishment. The operational risk can thus be underestimated if the forecasting system is purely demand-centred and does not take account of uncertainty in

the supply timing. The evidence indicates that there is a trade-off between having too much inventory and too little available when there is uncertainty in demand and lead times in determining pharmaceutical inventory decisions. In such a context, forecasting models should give information that will help with the maintenance of inventory buffers and replenishment decisions, while also being responsive to changes in the demand behavior and supply conditions. This establishes a foundation for discussion of how machine learning might be used to establish a link between demand signals, supply chain risk, and decision-making.

The amount of data produced and the diversity of data types and structures in supply chains make it increasingly relevant to apply machine learning to this domain of business. The systematic review and bibliometric analysis of Akbari and Do [12] reveal that machine learning is becoming an increasingly popular field in logistics and supply chain and also identify gaps in research design, industry engagement, and application. This view is significant because if the algorithms are advanced, it does not necessarily lead to valuable intelligence in the supply chain. The importance of machine learning relies on the usefulness of the data, the choice of variables, learning process quality, and the ability to include the result in operational decisions. Tirkolaee et al. [13] give a wider application scope including supplier selection, risk forecasting, demand forecasting, production, inventory, transportation, and distribution. Their review suggests that several decision areas could be covered by the use of machine learning; however, limitations were raised, such as the need for human evaluation of outputs produced by machine learning, and validity and fairness. This implies that machine learning tools should be considered as a complement rather than a replacement for managerial judgment in the field of supply chain management.

The use of predictive analytics becomes even more important when predictions must be made about the potential impact of the risks in supply chain decisions. Aljohani [14] suggests an approach in which machine learning and predictive analytics organize past and present data and information to detect deviations, trends, and signals of future disruptions. The study explores various methods such as time series analysis, anomaly detection, and natural language processing, and demonstrates the potential of combining different types of data for timely risk monitoring. One of the important analytical points is moving from the analysis of events to prior identification of risk; this offers more opportunity to be able to make adjustments to operations, reallocate resources, or identify alternative supply options. But the delivery of the value of such systems relies on the quality and timeliness of data in the supply chain that is constantly being updated, and predictions made in the face of disruption conditions that are far removed from those seen in the past may not be as accurate. Another case of supervised learning is when you have known outcomes to use for classification or prediction of future outcomes if there is valid labelled data. However, the value of prediction should be assessed from a decision-making perspective, not in terms of accuracy. False alerts, missed risks or incorrect cost estimates can add extra work to operations.

Machine learning also has a significant impact on the decision value, since the prediction results can be used in the broader process of planning and coordination, as well as for resource allocation. Singh [15] calls AI and machine learning catalysts for value creation in the transformation of the supply chain, highlighting applications that can enhance forecasting, automation, visibility, and decision support. This view takes machine learning beyond prediction - and makes the analytical results the input for coordinated managerial actions. However, this is not easy to make happen without proper digital infrastructure, data integration and organisational capacity. Tirkolaee et al. [13] also note that machine learning applications are used in various areas of a supply chain, including demand, inventory, transportation, and risk decisions, offering possibilities for linking the predictions across multiple functions within the supply chain. This holistic view is particularly relevant for pharmaceutical supply chains as it is important to know what the risk of a drug running out of stock is, while also predicting the cost of replenishment and allocation. For a useful decision support framework to be built, models that are able to convert risk signals into understandable operational information and at the same time capture uncertainty are required. There is additional evidence in the literature for the need to maintain ongoing human monitoring, as the output of the model can reflect limitations in historical data and may not accurately represent rare or emerging disruptions. All these challenges underscore the need for predictive analytics to be associated with adaptive decision-making for optimizing supply chain responsiveness and adaptation.

The prior literature focus on the issues of demand uncertainty, inventory optimization, and machine learning-based prediction of supply chain risks; none of these areas is sufficiently explored in the pharmaceutical supply chain. There is little focus on exploratory identification of cost-related risk patterns, demand uncertainty, and potential early indicators that can assist businesses in being resilient and informed.

RESEARCH METHOD

A. Research Design

This research uses a quantitative exploratory research design to analyze the patterns in the available data of the pharmaceutical supply chain when dealing with uncertainty in demand. This research is not based on a new machine learning model; it is rather extending the existing models. Instead, it uses exploratory data analysis to search for relationships between the supply chain factors and the cost outcomes that can help to gain insights into supply chain risk and business resilience. The quantitative approach allows for the analysis of numerical and categorical variables in the chosen data set. Exploratory analysis is suitable as the study aims to learn about the distribution, variation, and relationships between the variables available, without the intention of predictive modelling in the future. Analysis is concentrated on finding meaningful patterns that can help explain the uncertainty of the supply chain and operational risks. The dataset is analyzed and presented to be easily understood using statistical summaries

and graphical techniques. This research design thus offers a framework for understanding and researching supply chain factors and their possible implications for risk management and resilient business decision-making.

B. Dataset Description

Cost Prediction of Pharmaceutical Supply Chain enabled Blockchain Technology under Uncertain Demand is a secondary dataset obtained from Mendeley Data. The dataset was released in the year of 2023 and includes 5,000 simulated data series for a supply chain in the pharmaceutical industry with uncertain demand [16]. The dataset was created under a machine learning setting and concentrates on the prediction of costs in a blockchain-enabled pharmaceutical supply chain. It offers quantitative data for each element and the connections with the total cost of the supply chain. The dataset is also applicable to this research because of the uncertainty of demand that can also pose operational issues and impact supply chain cost and risk. There are also several variables related to the supply chain available to make exploratory investigation of relationships and patterns. This study uses the dataset as the main source in conducting quantitative analysis. Its structure offers a suitable framework for analysing supply chain conditions and for finding patterns in the analysis, which can assist in risk assessment and business resilience.

C. Data Variables and Analytical Framework

The analytical framework is directed to analyze the connection between input factors along the supply chain and the output result (the cost). These predictor variables are different facets of the pharmaceutical supply chain and contain information that can be analyzed with reference to uncertain demand and supply chain performance. To understand the effect of changes in the demand condition on the outcomes of the supply chain, demand-related variables are considered. The variables of the supply chain are analyzed for any relation to cost and possible operational risk. The cost-related variable becomes an important outcome, as increases and decreases in the cost of the supply chain may be due to different operational conditions or requirements for resources. Numerical variables are analyzed descriptively and for relationships, and categorical variables, where there are some, are analyzed. The framework aims to recognize patterns, not to draw causal conclusions. These observed relationships are then interpreted in the context of supply chain risk and business resilience. The following method also provides identification of variables that could be more relevant for future predictive analysis using machine learning.

D. Data Preprocessing and Exploratory Analysis

Data quality is initially assessed, and the data set is examined to determine its structure, variable types, observations and data quality. Data pre-processing is the process of cleaning the data and determining whether the variables have the correct numerical or categorical format. Descriptive statistics are computed to analyse the central tendency, variation, minimum and maximum values of available variables, and other characteristics. Important variables are then distributed to see if there are any common

patterns and unusual observations. If appropriate, the presence of potential outliers is investigated to see if they are significant observations or outliers that may affect interpretation. No observations are eliminated without sound analytical reason. The purpose of the preprocessing stage is to make the exploratory analysis more reliable and consistent while retaining the information in the dataset. These procedures offer a starting point for choosing the right visualization methods and exploring interactions between demand factors, the supply chain, and cost outcomes.

E. Exploratory Visualization and Relationship Analysis

The main analytical method employed is exploratory visualization to look for and share patterns in the data. Distribution plots are employed to analyze important supply chain variables and cost outcomes in terms of spread and concentration. Comparative plots are used to compare the various conditions of the supply chain within the category and level of cost. Correlation analysis is a technique that measures the strength and direction of the relationship between two numerical variables and to see if there are any variables that show greater correlation with the cost outcome. Heatmaps are provided to clearly visualize the correlation patterns and can be used for comparing multiple variables. Relationship plots also look at the possible connections between demand-related variables, supply chain variables, and cost. The selected visualizations aim to offer useful evidence to interpret supply chain risk patterns and resilience-related conditions. The results of these visual analyses are interpreted in light of the research question and objectives.

F. Limitations

There are some limitations to this study that should be taken into consideration when interpreting the results. Analysis is based on a secondary data set and thus relies on the variables, structure, and assumptions used by the creators of the original data set. The data includes simulated data series that might not accurately capture the complexity and variability of real-world pharmaceutical supply chain practices. Therefore, the results may be less generalizable to real-world organizations, markets, or supply networks for pharmaceuticals. This study also follows an exploratory analytical approach instead of creating a new machine learning model for prediction and then testing it in the experimental phase. Thus, the identified relationships cannot be considered as "confirmed" predictive relationships. In addition, the analysis applies to the variables and conditions included in a specific set of data. Other factors along the supply chain that could affect risk and resilience might not be accounted for. These restrictions suggest the need for future research involving real-world supply chain data as well as validated predictive machine learning models.

G. Ethical Considerations

The study is based on secondary data which is publicly available and does not include direct contact with human participants. The selected dataset does not require collecting or disclosing personal information for this research. The analysis is carried out responsibly, including the maintenance of the integrity of available data, and the non-

necessary modification of observations. The results are drawn from the evidence in the data and are not given as generalizations about the operations of the pharmaceutical supply chain. Special attention is given to the difference between observed and causal/predictive statements. The results are not specifically related to any pharmaceutical company or organization, as the data set is based on a simulated pharmaceutical supply chain environment. The study also refrains from making unsupported statements on the real performance of companies or their business operations. All analytical findings are, therefore, discussed within the context of the data and the research design. This method facilitates the responsible use of secondary data and accurate interpretation of the research for the supply chain, which is machine learning-oriented.

H. Conceptual Framework

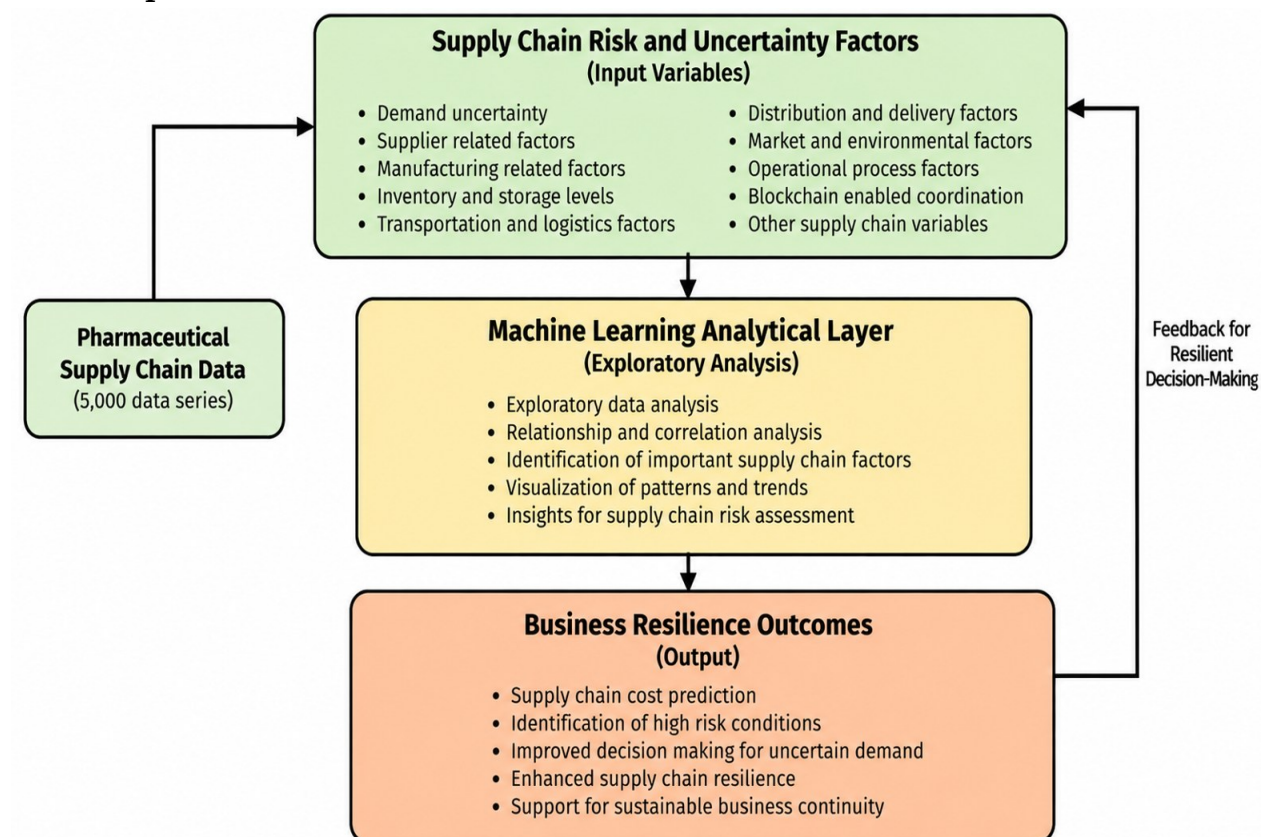


Figure 1. Conceptual Framework Diagram
(Source: Created by learner)

RESULTS AND DISCUSSION

Result

A. Distribution of Pharmaceutical Supply Chain Cost under Uncertain Demand

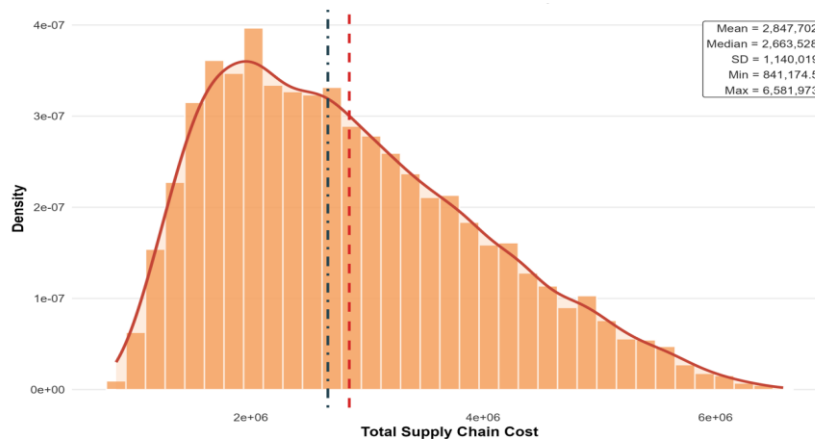


Figure 2. Cost Variation Under Certain Demand Across 5000 Generated Data Series
(Source: Created by learner)

Figure 2 depicts the distribution of the total cost of the supply chain by generating 5,000 observations with uncertain demand. The histogram is positively skewed, with the majority of observations clustered at moderate cost levels and a few observations reaching significantly higher costs. The mean is higher than the median, which indicates that the high-cost operational scenarios are having an impact. This trend suggests that while usual supply chain dynamics are still manageable, sometimes uncertainty can lead to high-cost escalation. This variation is evidence of operational risk exposure and signals how critical it is to understand conditions that lead to costly outcomes.

B. Supply Chain Factor Patterns across Different Cost Levels

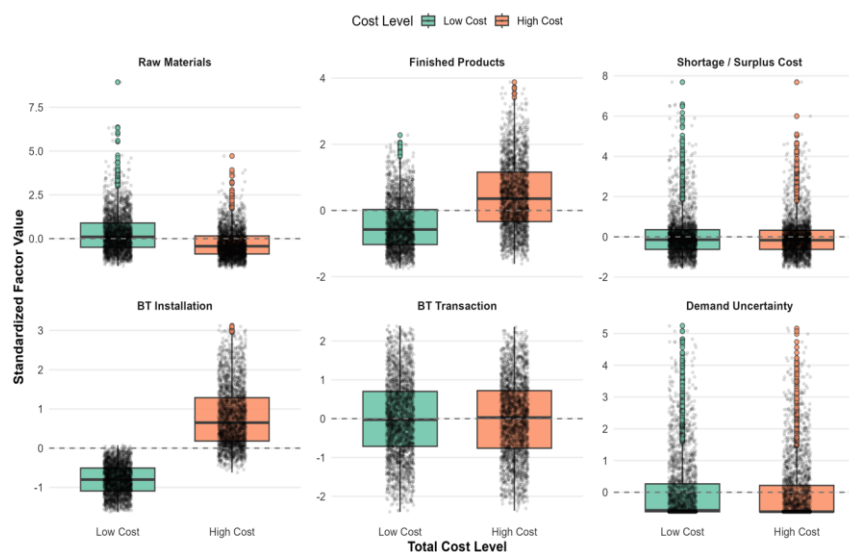


Figure 3. Comparison of Standardized Factor Values Between Low and High Total Cost Observations
(Source: Created by learner)

Figure 3 shows that the standardized supply chain factors were compared for low-cost and high-cost observations. The visualization shows that there are distinct clusters for some variables, especially blockchain installation and finished products, where higher values are correlated with high-cost conditions. The difference between expensive and inexpensive observations is relatively small for raw materials, and similarly small for blockchain transactions. The uncertainty of demand and shortage or surplus costs have significant variations across both types, indicating that they affect a variety of operating conditions. The differences illustrate the link between the nature of the supply chain and various cost settings and give some indication as to which operational configurations are likely to have a higher risk exposure and resilience needs.

C. Relationships among Demand, Supply Chain Factors, and Cost

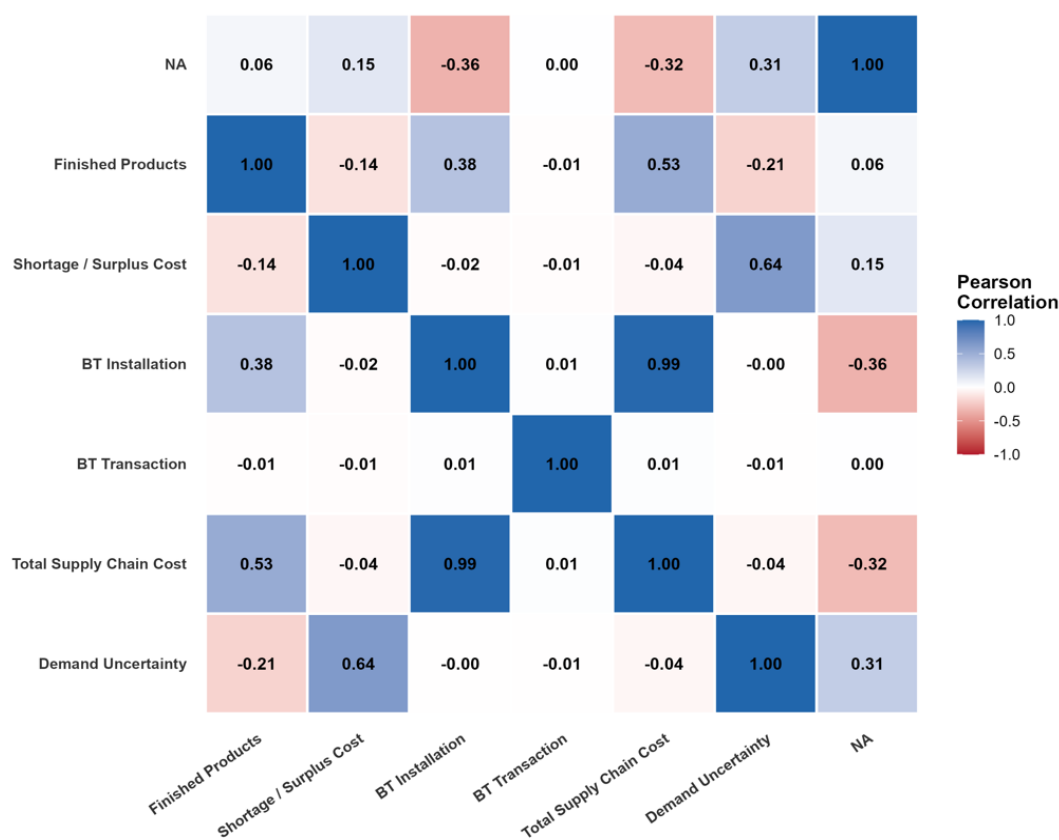


Figure 4. Pearson Correlation Analysis Under Uncertain Demand
(Source: Created by learner)

The correlation matrix of supply chain variables is shown in Figure 4, which uses Pearson correlation coefficients. The correlation between blockchain installation and the total supply chain cost is the strongest positive correlation, and the finished products are also moderately positively correlated with the total cost of the supply chain. Demand uncertainty is only poorly correlated with total cost (with a slightly negative correlation), suggesting that cost results are also driven by the cost of operations and infrastructure rather than by demand uncertainty. The heatmap reveals interdependencies between variables and helps to understand what risk drivers are and the importance of individual supply chain elements.

D. Machine Learning-Oriented Risk and Resilience Patterns in the Pharmaceutical Supply Chain



Figure 5. Evaluation of Supply Chain Parameters Using Machine Learning

Figure 5 combines scatterplots and correlation analysis in order to assess the risk-related relations in the pharmaceutical supply chain. The plots show that a rise in demand uncertainty and cost of shortage/ surplus has no independent ability to create sharp cost escalation, as there is a lot of variation in the data but the trend lines do not change much. The correlation panel also shows the blockchain installation and finished products as the top drivers of total cost variation. These findings collectively argue for a multi-faceted approach to risk assessment rather than depending on demand uncertainty indicators, for informed resource allocation and preparedness planning, and for decisions that take resilience into account as they consider the various interacting operational factors.

Discussion

The results address the research question about identifying supply chain risk patterns under uncertain demands via machine learning-related exploratory analysis in a comprehensive way. The visualization of the cost distribution shows that the total cost of the supply chain does not have a uniform distribution across observations, but is rather a skewed distribution with a larger number of cases in the moderate cost range and a smaller number of cases in substantially higher cost ranges. The pattern indicates that there is no systematic impact on operations when the uncertainty is present, but some combinations of supply chain conditions are greater contributors to costlier outcomes. The presence of these high-cost observations shows that risk levels in the supply chain can be quite different in different environments and can, in turn, indicate that operational risk situations can lead to cost increases and negatively impact performance if not detected.

The comparison of low-cost and high-cost observations further elucidates the behavior of the various factors in the supply chain under various operating conditions. The visualization shows significant differences in variables like blockchain installation, finished products, and others, where the values are higher for expensive observations. Other factors such as blockchain transactions, on the other hand, show relatively small differences between the two groups. These patterns suggest that factors other than just a single factor affecting inventory also influence supply chain costs, including those related to inventory and those related to operations and technology. Therefore, the results have shown that risk is multidimensional and a result of interactions between various elements of the supply chain. This evidence confirms the value of exploratory machine learning methods for identifying conditions that could lead to higher resource consumption and cost of the disruption.

The correlation analysis and visualization of risk assessment for machine learning help with further insight. The correlation heatmap highlights that the installation of blockchain shows a positive and strong association with the overall cost of the supply chain; the association of finished products is also meaningful. There is only a weak direct relationship between demand uncertainty and total cost, suggesting uncertainty is not enough to account for cost outcomes. The analysis of the scatter plot further confirms this, as it indicates that there is a lot of variation among observations, but not a lot of variation among the trend components. Thus, it seems that supply chain risk is a result of the synergy of operational infrastructure, stock status and cost-related issues. The findings demonstrate that analytical methods inspired by machine learning can reveal significant interactions between variables which can be used to help interpret the risks to and resilience of pharmaceutical supply chains under uncertainty in demand.

Future Work

This study can be further expanded in the future by introducing supervised machine learning algorithms to forecast the consequences of supply chain risk and cost by leveraging the variables analyzed in this study. The current study concentrates on the

identification of patterns by exploratory methods, whereas future research can test the prediction power of the models of Random Forest, Gradient Boosting, Support Vector Machines, or Neural Networks. These models would be able to measure the impact of important factors and can lead to warnings that supply chain disruption may occur. Furthermore, the validation of the models developed based on training and testing datasets would enhance the practical application of machine learning in pharmaceutical RMR.

Another direction of significance is the adoption of real-world data from the pharmaceutical supply chain instead of simulated data. The inclusion of real procurement, inventory, logistics, and demand information would increase external validity and provide a realistic perspective of operational risk. Other risk-related factors that can be incorporated in future studies include supplier reliability, transportation delays, regulatory changes, environmental disruptions, and healthcare demand shocks. Investigative studies among other industries or geographic areas can identify if relationships found are consistent in different supply chain settings. In addition, the application of predictive analytics and decision support systems, coupled with resilience planning, could facilitate the conversion of analytical insights into more actionable steps in business continuity management, resource planning, and the sustainability of value chains.

CONCLUSION

Fundamental Finding: The findings showed that the costs of the supply chain are variable, with a small portion of the observations costing significantly more than the typical supply chain. Through comparative and correlation analysis, it was found that the factors other than demand uncertainty, such as the installation of blockchain and finished product levels, have stronger relationships with total cost. The results also showed that supply chain risk is not a result of just one disruption source, but a result of a number of operational factors. 18092_File_Admin

Implication: The research highlights how machine learning-based analytical methods can help to understand the complexities of the healthcare supply chain and guide evidence-based risk assessments, preparedness, and business continuity decision-making in the pharmaceutical supply chain. 18092_File_Admin

Limitation: Analysis is based on a secondary data set and thus relies on the variables, structure, and assumptions used by the creators of the original data set. The data includes simulated data series that might not accurately capture the complexity and variability of real-world pharmaceutical supply chain practices. Therefore, the results may be less generalizable to real-world organizations, markets, or supply networks for pharmaceuticals. Thus, the identified relationships cannot be considered as "confirmed" predictive relationships. 18092_File_Admin

Future Research: This study can be further expanded in the future by introducing supervised machine learning algorithms to forecast the consequences of supply chain risk

and cost by leveraging the variables analyzed in this study. The current study concentrates on the identification of patterns by exploratory methods, whereas future research can test the prediction power of the models of Random Forest, Gradient Boosting, Support Vector Machines, or Neural Networks. Another direction of significance is the adoption of real-world data from the pharmaceutical supply chain instead of simulated data. 18092_File_Admin

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