Enhancing Supply Chain Resilience Through Supervised Machine Learning: Supplier Performance Analysis And Risk Profiling For A Multi-Class Classification Problem

Parminder Singh Kang, Bhawna Bhawna

Enhancing Supply Chain Resilience through Supervised Machine Learning: Supplier Performance Analysis and Risk Profiling for a Multi-Class Classification Problem

Abstract:

Purpose – This paper explores the application of supervised machine learning classification models to address supplier performance analysis and risk profiling as a multi-class classification problem. The research highlights that current applications of machine learning in supplier selection primarily focus on binary classification problems, underscoring a significant gap in the literature.
Research methodology – This research paper opts for a structured approach to solve supplier selection and risk profiling using supervised machine learning multi-class classification models and prediction probabilities. The study involved a synthetic data set of 1600 historical data points, creating a supplier selection framework that simulates current supply chain performance. The "Supplier Analysis and Selection ML Module" guided supplier selection recommendations based on ML analysis. Real-world variability is introduced through random seeds, impacting actual delivery dates, quantity delivered, and quality performance. Supervised ML models, with hyperparameter tuning, enable multi-class classification of suppliers, considering past delivery performance and risk calculations.
Findings - The study demonstrates the effectiveness of the supervised ML-based approach in ensuring consistent supplier selection across multi-class classification problems. Beyond evaluating past delivery performance, it introduces a new dimension by predicting and assessing supplier risks through ML-generated prediction probabilities. This can enhance overall SC visibility and help organizations optimize strategies associated with risk mitigation, inventory management, and customer service.
Research Implications - The findings underscore the adaptability of ML-based methodologies in dynamic SC environments, providing a proactive means to identify and manage risks. These insights are vital for organizations aiming to bolster SC resilience, particularly amid uncertainties.
Practical and Social Implications - The practical implications of this study are significant for both commercial and humanitarian supply chain management. For commercial applications, the ML-based methodology allows businesses to make more informed supplier selection decisions, reducing risks and improving operational efficiency. In disaster and humanitarian supply chain contexts, the use of ML can improve preparedness and resource allocation, ensuring that critical supplies reach affected areas promptly.
Originality - Unlike conventional methods focused on quality, cost, and delivery performance aspects, the current study introduces supervised ML to identify and assess supplier risks through prediction probabilities for multi-class classification problems (delivery performance as late, on-time, and ahead), offering a refined understanding of supplier selection in dynamic SC environments.

Keywords: Supplier performance, Machine learning, Supplier selection, Supply chain resilience,

Introduction

Today, one of the primary subjects of academic investigation and the business community in relation to macroenvironmental risks, specifically disruption risks, is the selection of suppliers' capacity to manage such risks (Al-Ayed & Al-Tit, 2023; Camur *et al.*, 2023). In supply chain management (SCM), the selection and management of suppliers are pivotal strategic decisions, as they lay the groundwork for establishing long-term, value-driven partnerships (Teller *et al.*, 2016). The integration of agile and lean methodologies has become a cornerstone for organizations striving to navigate the growing complexity and competitive nature of modern SCs. However, these methodologies alone are insufficient in today's volatile and unpredictable environment. Modern supply chains are intricate networks characterized by multi-layered interdependencies, which inherently increase their vulnerability to disruptions (Cerqueira-Streit *et al.*, 2021; Kazancoglu *et al.*, 2023).

The risks facing SCs are diverse and multifaceted, stemming from natural and human-caused sources, including geopolitical tensions, economic fluctuations, and health crises. Such disruptions pose significant threats to supplier operations and performance, which can cascade through the SC, affecting productivity, competitive advantage, and financial stability (Baz & Ruel, 2021; Sedamaki & Kattepur, 2022). The repercussions of SC disruptions extend beyond operational inefficiencies, potentially resulting in longer lead times, product shortages, unmet consumer demands, and inflated costs, all of which can undermine a business's market position (Ivanov & Dolgui, 2021; Jabbarzadeh *et al.*, 2018). In response to this complex risk landscape, businesses must proactively enhance their SCs to be more adaptable and responsive. This necessitates a shift towards data-driven strategies, where the selection of resilient suppliers is not merely an operational decision but a strategic imperative. Supply chain resilience (SCR) has evolved from a discretionary approach to a critical necessity. Resilient SCs possess the capability to withstand disruptions, swiftly recover to their original state, or transform such challenges into opportunities for growth and innovation (Machuca *et al.*, 2020; Abubakar *et al.*, 2017). In the context of SCR and SC risk management, supervised machine learning (ML) can facilitate identifying potential vulnerabilities and optimizing supplier networks to bolster risk resistance. By leveraging ML models, organizations can anticipate risks, allocate resources more effectively, and make informed decisions, reinforcing the robustness and resilience of their SCs. As such, pursuing SCR through data-driven insights mitigates risks and positions organizations to thrive in the face of uncertainty, ultimately driving sustained competitive advantage in the dynamic global marketplace.

Businesses implementing the concept of SC diversity by procuring goods from several international vendors resulted in significantly increased complexity of SCs. The need for resilient suppliers that can survive interruptions, execute orders quickly, and proactively react to changing conditions complicates company partnerships and requires strategic cooperation, careful planning, and communication (Abubakar *et al*., 2017; Kamalahmadi & Parast, 2017). With the increasing complexity of SCs, their potential risks also increase. Amindoust (2018) emphasized that the factors that influence suppliers' decisions in a risk-focused environment are distinct from those in a conventional context. Consequently, there has been a recent emphasis on identifying resilient supplier selection criteria to fortify the SC in the face of disruptions and deficiencies (Cavalcante *et al.*, 2019; Zhaoa *et al.*, 2021). Supplier selection criteria must include resilience components since they affect SC performance (Amindoust, 2018; Chaouni Benabdellah *et al.*, 2021). Literature has identified a wider range of Multi-Criteria Decision-Making (MCDM) methods and tools for rational and forward-looking supplier choices (Es-Satty *et al.*, 2020; Zhaoa *et al.*, 2021). These include Best Worst Method (BWM), Analytic Hierarchy Process (AHP), Pythagorean fuzzy AHP, and Fuzzy/Analytical network Fuzzy axiomatic Design etc. (Ali & Zhang, 2023; Ayyildiz & Taskin Gumus, 2021; Haldar *et al.*, 2014; Liu *et al.*, 2023; Nazim & Raja Yaacob, 2017; Pramanik *et al.*, 2017). The MCDM approach allows for structured, transparent decision-making by assessing supplier costs based on multiple criteria such as cost, quality, and delivery capabilities. However, one of the primary challenges in employing MCMD methods for supplier selection is the complexity of criteria selection. The dynamic nature of global markets and the rapid evolution of risks make it difficult to standardize criteria that remain relevant over time. Additionally, many MCDM methods, such as the AHP and Fuzzy AHP, rely heavily on expert judgment and subjective input, which can introduce bias and reduce the objectivity of the decision-making process. Such subjectivity can skew results, especially if decision-makers have varying levels of expertise or differing priorities. Moreover, accurate and comprehensive data on supplier performance and risk factors are often scarce, making it challenging to apply these methods effectively. Organizations frequently rely on historical data, which may not accurately reflect current conditions or emerging risks. As supply chains become more complex, the scalability and adaptability of MCDM methods are put to the test, with traditional methods often struggling to accommodate large datasets or rapidly changing environments, thereby limiting their effectiveness in dynamic contexts (Alavi *et al.*, 2021; Ali & Zhang, 2023; Islam *et al.*, 2024).

Conventional supplier selection methodologies are restricted in their ability to scale in high-frequency relationship scenarios. Predictive analytics techniques, such as artificial intelligence (AI), artificial neural networks (ANN), decision trees, support vector machines (SVM), and data-driven analysis, can overcome this constraint (Tavana *et al.*, 2016). Similarly, ML can accommodate imprecision, uncertainty, and partial truth to function effectively in human decision-making simulations (Cavalcante *et al.*, 2019; Wilson *et al.*, 2020). This capability is a response to the scope and rate of development that were absent in conventional techniques and to the constraints imposed by the current complex supplier arrangements. Resilient suppliers enhance a critical strategic capacity, resulting in cost savings, faster delivery, and innovative technology (Abdulla *et al*., 2019; Eyika Gaida *et al*., 2022). In this context, organizations can utilize advanced, data-driven, and predictive analytics to evaluate suppliers' reliability, stability, capabilities, and risk factors, thereby optimizing their decision-making processes. To address this gap, this paper investigates the potential of supervised ML as a multi-class supplier classification problem to identify and oversee resilient suppliers and their relationships.

Some of the protective measures firms are using to mitigate disruptions have been through putting in place technologies like predictive analytics, ML, real-time monitoring and AI. These technologies assist SCs in managing how disruptions occur and how to address them efficiently and properly (Abubakar *et al*., 2017). Organizations depend on suppliers for acquiring resources, achieving timely operations, and cost efficiency; thus, supplier selection becomes a crucial operational management issue, where ML complements by making data-driven decisions, such as patterns and anomaly detection, data automation, etc. (Abdulla *et al*., 2019; Eyika Gaida *et al*., 2022; Khan *et al*., 2023; Kıotaran *et al*., 2020). Thus, in case of limited data availability, ML can assist human decision-making processes with lesser inaccuracy and vagueness or lower imprecision (Sepehri, 2020). Additionally, the complex factors contributing to SC performance disruptions caused by SC disruptions remain closely linked with supplier performance risk profiles. Therefore, integrating ML and digital technologies into supplier performance analysis and risk profiling is a crucial frontier in advancing SCR. This integration enables organizations to adapt, respond, and thrive in an increasingly volatile and interconnected business environment. ML's application in SC and operations management has improved in recent years, but the literature lacks the application of ML to develop supplier portfolios and risk profiles using supervised or unsupervised ML models. This knowledge gap limits comprehension of conceptual and technical methodologies for supplier selection and management to promote SC resilience.

SCM delivers value to the SC, including both upstream and downstream SC partnerships, but the downstream SC has received most of the attention, while the upstream SC's focus, relationship value, and proximity comparatively receive less attention (Christopher & Holweg, 2017; Cavalcante *et al.*, 2019). This study explores the pivotal role of ML and digital technologies in leveraging SCR through supplier performance analysis and risk profiling, treating this as a multi-class classification problem (e.g., supplier delivery performance as late, on-time, and ahead). The existing literature addresses supplier selection and analysis problems as binary classification problems (e.g., supplier delivery performance as late and on-time). We also aim to provide a structured methodology through analytics modeling to address supplier selection and risk profiling problems, making it more attuned to the demands of a dynamic SC environment. Through empirical analysis and synthetic data cases, we aim to provide actionable insights for organizations striving to fortify their SCs and ensure their resilience in disruptions. As we navigate this digital frontier, we unveil the promises and possibilities that await those who dare to embrace the transformative power of ML and digital technologies in SCR.

Literature Review

Supplier selection is the process of choosing a reliable supplier from a pre-qualified candidates list based on predefined goals and standards (Sepehri, 2020; Yazdi *et al.*, 2022). Different methods such as optimization, multiple criteria decision-making, and, recently, ML methodologies have been applied to achieve different objectives such as green and sustainable supplier selection and supplier development (Garg, 2021). The supplier selection process is critical for any company's growth, often seen through a cost-based or single-criterion lens, and entails several misconceptions (Eyika Gaida *et al.*, 2022; Hashemzahi *et al.*, 2020). Selecting the right supplier is crucial in meeting customers' requirements by delivering high-quality products on time and is the initial step in designing an effective and integrated SC network to build the resilience capabilities in SCs (Khan *et al.*, 2023; Kusi-Sarpong *et al.*, 2023). However, some risks, such as natural disasters, pandemics, economic instability, etc., are external forces to suppliers, impacting the entire SC's efficiency (Al-Ayed & Al-Tit, 2023; Jabbarzadeh *et al.*, 2018). Thus, it is essential to prioritize the selection of resilient suppliers to maintain stable SC operations, control expenses, and reduce the impact of risks and unexpected incidents. This approach is beneficial because it enables one to offer timely response to such disruptions, thus affording a competitive edge. However, the issue of optimizing the costs and the ability to recover from problems proves to be rather complex as it implies the constant weighing of resources, which is quite difficult. Moreover, it becomes challenging to establish supplier performance measures and apply supplier competence to eliminate the existing disruptions (Alavi *et al.*, 2021; Rezaei *et al.*, 2020).

ML approaches can work with datasets of different sizes and scales and accommodate qualitative qualities for different model construction without ambiguity and imprecision (Steinberg *et al*., 2023; Wang *et al*., 2022; Lin *et al*., 2009). With the increased SC operations and availability of many external and internal datasets, the application of ML in supplier selection and decision-making has gained momentum. Literature has mainly used ANN, SVM, and decision trees for supplier selection techniques (Hosseini & Barker, 2016; Kamalahmadi & Parast, 2017; Tavana *et al*., 2016). Literature highlights that suppliers are assessed according to price, quality, delivery terms, and service (Ali & Zhang, 2023; Zimmer *et al*., 2016). The literature demonstrates the application of ML models as part of binary classification problems to selected suppliers based on historical performance, supplier performance pattern recognition from a dataset of shipping records, and clustering of suppliers using unsupervised ML models for the supplier selection process for the improvement of the distortions of the traditional supplier selection techniques (Lin *et al*., 2009). Kuo *et al*. (2010) applied particle swarm optimization to increase the performance of fuzzy neural networks to deal with the quantity and quality variables, including long-term connections, technical skills, management capabilities, and rapid reaction capabilities. Golmohammadi's (2011) study considered four parameters, namely quality, delivery, technology, and pricing. The actual value of these parameters was defined by fuzzy linguistics using ANN to predict supplier performance. There are other examples of supplier selection criteria being used that include factors specific to the desired outcomes of supplier selection, such as the selection of green suppliers and those with a focus on strong environmental and social responsibility practices. Kuo *et al.* (2010) used an ANN to forecast the conventional and green criteria-based suppliers, ultimately establishing the green efficiency score. Azadi *et al.* (2015) developed a model incorporating data envelopment analysis in the fuzzy environment for rating the suppliers and identifying the right strategies to implement for smooth SC operations.

Earlier research involves the use of particle swarm optimization and fuzzy neural networks to formulate a decision framework of suppliers applying Porter's AHP and DEA to single out the effectiveness of the suppliers' evaluation (Gökler & Boran, 2023; Nasri *et al.*, 2023). Authors have investigated the approach that combines the AHP and Ranking Neural Networks (RankNet) to rank sustainable supplier performance (Abdulla *et al.*, 2019; Ali & Zhang, 2023; Nazim & Raja Yaacob, 2017). There are numerous other examples highlighting the usage of AI, ML and advanced analytics for supplier selection and performance analysis (Cavalcante *et al.*, 2019; Kıotaran *et al.*, 2020). Multi-agent systems (MASs) are also used to improve supplier-manufacturer communication and transparency (Ghadimi *et al.*, 2019).

However, the criteria used in the literature are primarily subjective and do not address the identification of potential suppliers for supplier relationship and development management. In contrast, ML methods offer insights into the current performance and the capabilities of potential suppliers. As AI continues to gain prominence, ML has been implemented in numerous SCM subfields, such as supplier selection, supplier evaluation, and the development of sustainable and resilient suppliers. For instance, Sepehri (2020) combined the contract history, interpersonal value, and attributes of the supply network to predict the future value of supplies; however, the performance and feasibility of such an integration need to be questioned while considering the real-life SC environment. In addition, researchers have assessed the Relational Regressor Chain (RRC) method to improve the forecast accuracy and determine the appropriate suppliers and order quantities (Islam *et al.*, 2021), proposed the hybrid BWM and Pythagorean fuzzy AHP approach to determine the weights of the metrics (Ayyildiz & Taskin Gumus, 2021; Gökler & Boran, 2023), MCDM integrated with in addition, the AHP algorithm and a fuzzy system have also been utilized in ML models to optimize supplier risk indices in order allocation factors such as quantity, cost, and delivery time (Sedamaki & Kattepur, 2022). This approach helps rank depending on green and resilience aspects and ensures that suppliers are timely and do not slow down the processes (Mohammed *et al.*, 2018). Khan *et al.* (2023) proposed a two-phase SCA model with the help of SCOR 4. 0 with BWM weights and ML to rank resilient suppliers. Similarly, Ali & Zhang, (2023) highlighted the quality, on-time delivery, and material price using Random Forest ML while pointing toward the overlooked aspect of transportation cost.

These areas, such as demand forecasting, inventory management, and selecting suppliers, are critical aspects of ML. New and updated SC data creates awareness of the model and helps update it to serve current supplier needs and changing conditions (Ng *et al.*, 2023). This paper identifies that the ML models mimic different supplier conditions well and assist in planning robust supplier choices. The assembled models update themselves with the new supplier performance data and continue to fit the bill as the new metrics come in (Li *et al.*, 2023).

Combining ML methodology and optimization models for supplier selection and order allocation improves the effectiveness of the decision-making processes and, in turn, strengthens the robustness of the SC. The key component of ML models is historical and real-time SC data fed into the system and updated according to supplier conditions and changing market requirements (Chopra *et al*., 2023). ML can contribute by enhancing accuracy and robustness by continuously learning from new data of supplier evaluation to assess and identify the best resilient suppliers (Liu *et al*., 2023). Complex ML-based models, such as ANN the random forest, can lead to improved supplier classification, enhance supplier selection procedures, and be updated from time to time to remain effective (Sepehri, 2020; Steinberg *et al*., 2023; Wilson *et al.*, 2020). Similarly, Hu *et al.* (2023) used average approximation for supplier selection using ML, indicating that leveraging ML methodology improves supplier selection under uncertainty. By picking the best suppliers and upgrading ML models based on their performance, adaptive learning may be improved to ensure high accuracy and flexibility while boosting the supplier's capacity to survive interruptions (Ali & Zhang, 2023).

The supplier performance classification and risk profiling literature has mainly focused on conventional approaches, although the assessment issues are cumbersome and contain risks that are immanent to human decision processes (Baryannis *et al.*, 2019; Ghadimi *et al.*, 2019). Nonetheless, while RF, SVM, ANN, PCA, k-means, and so on algorithms have been actively discussed in prior research (Kusi-Sarpong *et al.*, 2023; Steinberg *et al.*, 2023; Wang *et al.*, 2022), the research involving ML for this area is somewhat scarce and mostly confined to the tentative application of binary classification models. Noting that ML is valuable in solving the supplier selection issue (Camur *et al.*, 2023; Cavalcante *et al.*, 2019; Islam *et al.*, 2022, 2024), it is necessary to mention that ML provides stable results and always highlights tendencies as well as options among those derived in a particular situation (Duan & Ventura, 2019; Zangaro *et al.*, 2021).

However, addressing the challenge of developing a precise "risk index" for various SC nodes, including forecast accuracy, demand shifts, lead time delays, and supplier capabilities, remains underexplored. ML techniques must effectively capture variations across these variables to establish accurate risk indices for suppliers or products. Additionally, the contribution of ML to the conceptual and technological methodologies of resilient supplier selection remains unclear.

Thus, the current study uses supervised ML to develop a proactive, data-driven decision-making methodology for SC supplier selection and disruption risk management as a multi-class classification problem instead of binary classification.

Research Methodology

The research methodology uses a structured approach that primarily focuses on quantitative methods involving data collection, data pre-processing, and application of supervised ML models for a multi-class classification problem to predict supplier performance and risk profile.

Step 1: Literature Review and Gap**:** Section 2 provides a comprehensive literature review on supplier risk management and data-driven decision support systems based on ML-based methods. It underscores the need for ML approaches to promote data-driven decision-making. Notably, there is a prevalent emphasis on descriptive analytics in SCM research, with a lack of predictive analytics (particularly decision-making based on prediction probabilities), except for demand forecasting. From the supplier analysis problem perspective, the existing literature has only quantified the effects of on-time and late delivery as binary classification problems (Steinberg *et al.*, 2023). Similarly, no research has looked at the effects of ahead-time deliveries, even though some seem to affect today's supply environment, highlighting a significant research gap.

Conventional supplier selection approaches like mathematical modelling, evolutionary algorithm and relative importance ratio, multi-attribute rating, and AHP involve labor intensive calculations and limited scalability and may yield different results with large and complex datasets. The literature suggests the use of ML to enhance the speed of the supplier selection process while at the same time improving the levels of accuracy (Khan *et al.*, 2023; Nazari-Shirkouhi *et al.*, 2023; Wilson *et al.*, 2020; Zheng *et al.*, 2023). Specifically, in terms of the ML approach, it is also highlighted that there is a need for more research on supplier classification and reliability and to establish the supply performance profiles ((Islam *et al.*, 2024; Kusi-Sarpong *et al.*, 2023; Yazdi *et al.*, 2022). Therefore, this paper addresses this research gap by considering supplier classification as a multi-class classification problem (on-time, late, and ahead) and developing a supplier risk profile based on prediction probabilities obtained from the supervised ML models.

Step 2: Supplier Data Collection and Analysis: Before applying ML for supplier classification risk profiling, the relevant previous data of suppliers has to be gathered as a standard procedure. This study addresses this by creating a synthetic dataset of 1600 historical data points, forming the basis for supplier selection and supplier risk profiling problems to mirror the SC performance. A simulated SC structure, detailed in Figure I, represents a manufacturing firm dealing with four suppliers with similar capabilities regarding the type of product they are supplying, product quality and available capacity at a given point. Python library "random" was used to create the synthetic dataset representing the supplier performance. Guided by the "Supplier Analysis and Selection ML Module," the manufacturing firm selects a supplier, providing order quantity and delivery date. To mimic real-world scenarios, actual delivery, quantity, and quality performance variations are introduced based on random seeds in the supplier performance datasets. Table I provides a brief description of the supplier performance dataset.

Table I Supplier Performance Dataset (Source: Author's own work)

Variable	**[Range]; Description**
Order ID	[1, 1600]; Continuous variable to track the order number. The dataset contains 1600 orders placed by the manufacturing firm.
Supplier ID	[1, 4]; Nominal categorical variable to distinguish between different suppliers. Supplier IDs do not imply any order or rank among the suppliers. To simulate the supplier performance, the supplier is selected based on a random seed provided at a given instance.

*Number of Orders	[0, 25]; Continuous variable to track the number of orders placed with a selected supplier at a given point. Based on a random seed at a given point, selected suppliers can have from 0 to 25 orders open.
*Order Quantity	[45, 38236]; Continuous variable to provide order quantity at a given point for selected supplier.
*Lead Time	[20, 88]; Continuous variable to capture lead time associated with each order for a selected supplier.
On-Time Delivery	[On Time, Late, Ahead]; three states of delivery at a given point to create a multi-class classification problem scenario.
Delivery Performance	[0.5804, 0.9802]; Continuous variable to capture the delivery performance as a percentage.
Disruptive Event	[0, 1]; Categorical variable to capture the supply chain disruptions.

*To incorporate the stochastic aspects into the model, different random seeds were used for the Number of Orders, Order Quantity, and Lead Time. Simulating a SC scenario is a commonly used approach for planning and improvement initiatives to predict supplier performance based on delivery, quality, or price (Cavalcante *et al.*, 2019; Ali *et al.*, 2023). However, the existing research only focuses on binary classification problems, where supplier delivery performance is predicted as on time or late only. This research extends the application of supervised ML from binary (on time and late) to a multiclass classification (ahead, on time, and late). It develops a supplier risk profile based on the predictive probabilities related to delivery performance. The supervised ML module provides prediction probabilities related to three classes to improve the overall decision-making process.

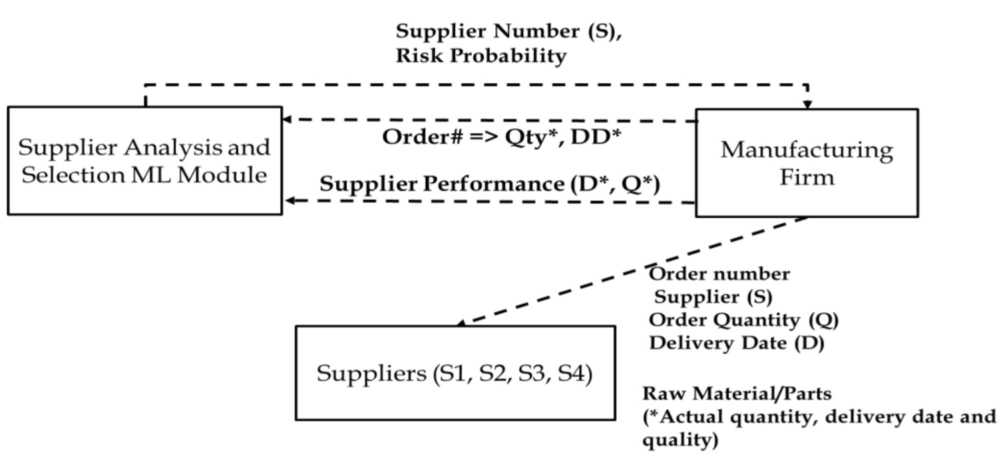


Figure I Simulation and Machine Learning Modules (Source: Author’s own work)

Step 3: Data Preprocessing and Visualization: In this step, demand data was analyzed to understand the demand patterns and identify outliers. The demand generated through the simulation process is nearly normally distributed (Figure II). Examining delivery performance (Figure III) highlights variations tied to the number of orders and order quantity. As the number of orders and order quantity reach capacity, delivery performance is adversely impacted, leading to lateness due to supplier-end capacity constraints. Also, it is important to note that the dataset predominantly comprises on-time deliveries (OT - 91.38%), with late (L - 5.81%) and ahead (AH - 2.81%) deliveries forming the minority classes. Figure IV highlights outliers in late deliveries, where small order sizes coincide with delayed deliveries. These outlier data points simulate disruptive events with very low probability and high impact. Based on the random seeds in this dataset, the probability of disruptive events is 0.006, resulting in a 46% increase in the average lateness (impact).

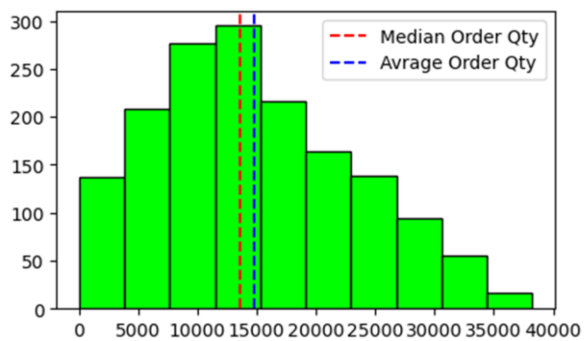


Figure II Demand Data (Source: Author's own work)

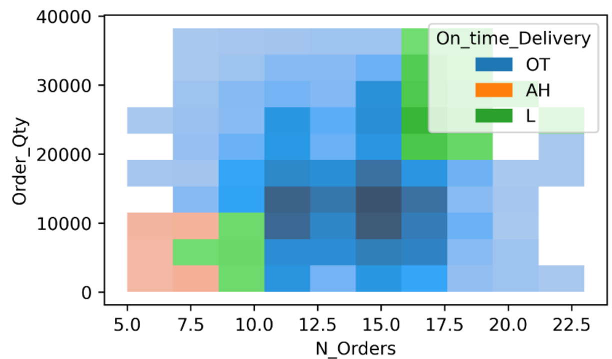


Figure III Delivery Performance (Source: Author's own work)

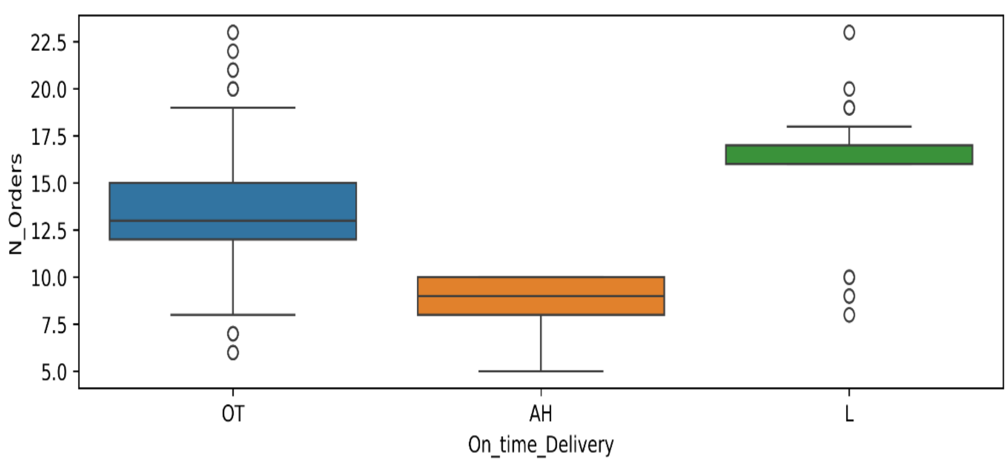


Figure IV Delivery Performance Distribution (Source: Author's own work)

Step 4: Data-driven Approach for Supplier Selection: In this step, supervised ML-based models, coupled with hyperparameter tuning, were used to classify suppliers based on past delivery performance (multi-class classification) and risk calculations.

1. The process started with data preprocessing, focusing on normalization (Figures VI and VII). This ensured that variables were standardized to a common range, preventing larger magnitudes from dominating the analysis. For instance, the number of orders (N_Orders) is relatively much smaller than the order quantity (Order_Qty). The same is applied to other variables such as disruptive events (0 - absent; 1 - present), delivery performance, lead time, etc.
2. After normalization, feature selection was performed to eliminate irrelevant features and reduce noise from the dataset, including Supplier ID and Order ID, to create the test and training datasets. In complex datasets, feature selection reduces dimensionality, improving model performance and speeding up training and inference.
3. Further, the supplier classification module used supervised ML, using input vectors (number of orders, order quantity, lead time, disruptive event, and delivery performance) and output vectors (delivery class - AH, OT, and Late) derived from the normalized dataset. Post-normalization, test and target datasets were split 60% for training and 40% for testing. To address the class imbalance problem, the synthetic minority over-sampling technique (SMOTE) was applied to ensure the supervised ML models are trained properly on the training dataset - the on-time (OT) delivery is the majority class (Figure III). Table I shows different supervised ML models used for supplier classification. To ensure the selected models generalize well to unseen data and avoid overfitting or underfitting, hyperparameter tuning was performed to optimize the performance of ML models. This also helps in improving model performance, accuracy, stability, and efficiency. Table AI in the appendix includes information related to hyperparameter tuning.
4. Supplier Classification and Risk Calculation – This step entailed the application of different supervised ML models, including KNN, Logistic Regression, DTC, Random Forest (RF), Bagging-DTC, and Neural Networks, to the supplier classification and supplier risk calculation problems. Grid search criteria were used for the hyperparameter tuning of decision trees and random forest classifiers. F1-Score, ROC curve, and confusion matrix were used to evaluate the model's performance. For supplier classification, suppliers were classified into three classes: AH, OT, and L. For supplier risk profiling, prediction probabilities are used to determine the supplier risks. Table AI in the appendix includes information related to hyperparameter tuning.
5. In the proposed methodology (Figure V – extension of work proposed by Cavalcante *et al.*, 2019), the "Supplier Analysis and Selection ML Module" uses historical data from various suppliers on quantities delivered, actual orders (demand), delivery performance (AH, OT, and L), and quality to predict product quality and on-time delivery performance. The selected supplier received information on the order number, order quantity, and delivery date. The chosen supplier is provided with order information, including order number, quantity, and delivery date, accounting for capacity constraints. Delivery time is generated using a random seed, considering factors like the number of orders, disruptive events, and

quantity. The supervised ML module then classifies deliveries from a specific supplier as early, on time, or late.

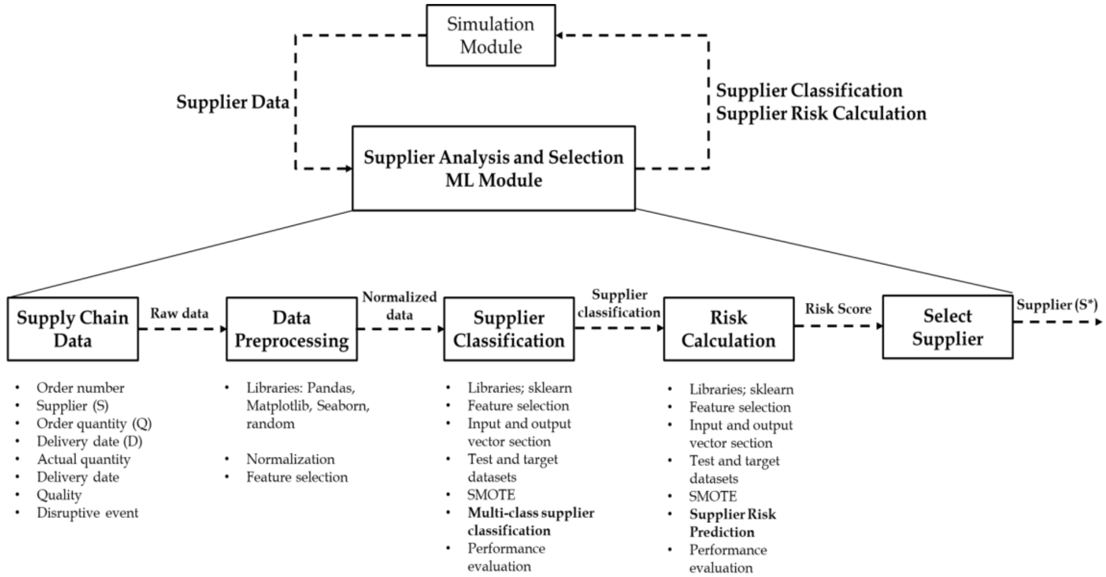


Figure V Proposed Supplier Selection Approach (Source: extension of work proposed by Cavalcante et al., 2019)

	Supplier_ID	N_Orders	Order_Qty	Lead_Time	Disruptive_Event	Delivery_Performance
0	3	13	193	51	0	0.950
1	1	7	504	27	0	0.960
2	1	13	916	51	0	0.970
3	2	13	797	53	0	0.965
4	1	9	230	38	0	0.960

Figure VI Before Normalization (Source: Author's own work)

	N_Orders	Order_Qty	Lead_Time	Disruptive_Event	Delivery_Performance
0	-0.237539	-1.146445	-0.185993	-0.055989	0.052352
1	0.127029	1.134711	0.104811	-0.055989	0.227793
2	-0.602107	-0.450885	-0.670666	-0.055989	0.416713
3	-0.602107	-0.846840	-0.670666	-0.055989	0.416769
4	-2.060378	-1.479156	-1.930816	-0.055989	-0.352237

Figure VII After Normalization (Source: Author's own work)

Step 5: Verification and Validation:

A comprehensive verification and validation process addresses the robustness and accuracy of supervised ML models, which is essential to ensure that the models are implemented correctly. The following steps are used to incorporate the verification and validation process:

1. The verification phase ensures the models are correctly implemented and optimized. The proposed methodology addressed these through data preprocessing and normalization to ensure data consistency and accuracy, feature selection to eliminate irrelevant features and reduce noise, and extensive hyperparameter tuning to optimize model performance (Table AI**)**. This tuning process involved grid search and cross-validation techniques to identify the best parameters for each model, detailed in Table AI in the appendix. Further, to validate the proper functioning of the models and achieve high classification accuracy, models were assessed using methods involving - confusion matrices, F1 scores, and ROC curves.
2. The validation phase ensures whether the models developed reflect a real-world scenario and reach the set objectives or not. Therefore, the synthetic dataset is the input source for building an SC structure in this paper, where manufacturers concurrently interact with several suppliers. The cases were, therefore, introduced with variations in actual delivery performance, which were incorporated randomly with different seeds. The result and discussion section involves empirical analysis of various supervised ML models' training and test accuracy scores, ensuring that the models generalize well to unseen data and do not suffer from overfitting or underfitting. Also, based on these results, the implications of misclassification of suppliers in the supplier classification model are described to further analyze what measures should be taken to avoid misclassification of suppliers in the future and how to improve the models to ensure their further practical use and robustness. In addition, prediction probabilities are obtained for deriving supplier risks to draw better recommendations for managing the suppliers. This included assessing suppliers' delivery performance probability to optimize supplier selection decision-making and risk mitigation strategies.

Results and Discussion

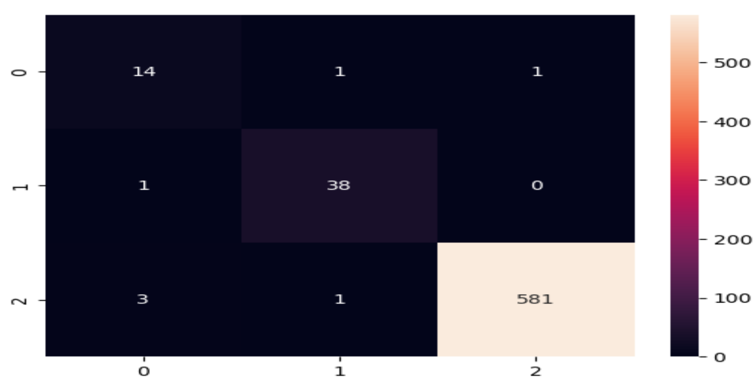
This section provides a detailed discussion of results for both supplier classification and supplier risk profiling problems.

Supplier Classification – Delivery Performance Analysis*:* The process starts by classifying suppliers based on their delivery performance (late, on-time, ahead). Different supervised ML algorithms were used in the classification process, and the model accuracy scores are presented in Table II.

Table II Supervised ML Model scores (Source: Author's own work)

Supervised ML Model	Training Accuracy Score	Test Accuracy Score

KNN (K = 7)	0.9844	0.9652
LogisticRegression (penalty="l2", C = 1e42, solver="liblinear")	0.9529	0.9436
DecisionTreeClassifier (max_depth=4, min_impurity_decrease=0.005, min_samples_split =5)	0.9413	0.9385
RandomForestClassifier (max_depth=10, min_impurity_decrease=0.00025, min_samples_split=41, n_estimators=200)	0.9859	0.9368
BaggingClassifier (estimator=DecisionTreeClassifier (max_depth=5, min_impurity_decrease=0.0015, min_samples_split=40), n_estimators=500, random_state=26)	0.9763	0.9485
MLPClassifier(activation= 'relu', alpha= 0.0001, hidden_layer_sizes= (50, 50), learning_rate = 'constant', max_iter= 500, solver= 'adam')	0.9958	0.9891




```
              precision    recall  f1-score   support

          AH       0.72      0.81      0.76        16
           L       0.95      0.95      0.95        39
          OT       0.99      0.99      0.99       585

    accuracy                           0.98       640
   macro avg       0.89      0.92      0.90       640
weighted avg       0.99      0.98      0.98       640
```

Figure VIII KNN Confusion Matrix and Model Performance (Source: Author's own work)

The confusion matrix (Figure VIII) shows the proportion of correct predictions made by different models, offering an initial performance assessment. In the context of a supplier multi-class classification using MLPClassifier (Multi-Layer Perceptron Classifier), the model achieved training and test accuracy scores of 99.58% and 98.91%, respectively. For the test dataset, out of

640 instances analyzed, the MLPClassifier accurately predicted 630 instances, which included 581 instances of OT deliveries when the suppliers were indeed on time, 38 instances of L deliveries that matched actual late deliveries, and 14 instances where the model correctly predicted AH deliveries, corresponding to the actual scenario. On the other hand, precision evaluates the model's ability to predict positive values when it makes such predictions correctly. For example, in the case of AH, the MLPClassifier made 14 correct predictions out of 18, resulting in a precision rate of 0.76. Recall, also known as sensitivity or true positive rate, gauges the classifier's effectiveness in identifying all positive instances. In the presented results, focusing on the "AH" category, the recall rate was 0.81, indicating that the model successfully identified 81% of the actual AH instances. The F1 score, a metric that balances precision and recall, provides a comprehensive measure of model performance. It ranges from 0.0 (worst) to 1.0 (best) and is particularly valuable when considering false positives and negatives. In this study, the model generated F1 scores of 0.76, 0.95, and 0.99 for the AH, L, and OT categories, respectively, demonstrating its effectiveness in capturing the trade-off between precision and recall (Figure VIII). Generally, F1 scores tend to be lower than accuracy measures because they take both precision and recall into account. Finally, support refers to the number of occurrences of a class in the dataset under consideration. In the analyzed model, the support values were AH-16, L-39, and OT-585, signifying the frequency of these categories within the dataset. This first step is useful for classifying suppliers based on selected KPIs (delivery performance). By calculating the probabilities of supplier delivery performance, valuable insights can be obtained for enhanced supplier management. This becomes particularly crucial when alternative suppliers with comparable capabilities are available. Refer to Table III for delivery performance probabilities, where the MLPClassifier was chosen for its superior classification performance compared to other approaches.

Table III Test and Training Dataset - predicted probabilities (Source: Author’s own work)

Training Set			
Supplier	P (AH)	P (L)	P (OT)
1	0.0129	0.0570	0.9301
2	0.0444	0.0126	0.9430
3	0.0207	0.0532	0.9261
4	0.0284	0.0953	0.8763
Test Set			
Supplier	P (AH)	P (L)	P (OT)
1	0.0262	0.0443	0.9294
2	0.0208	0.0200	0.9592
3	0.0143	0.0854	0.9003

4	0.0294	0.0919	0.8788

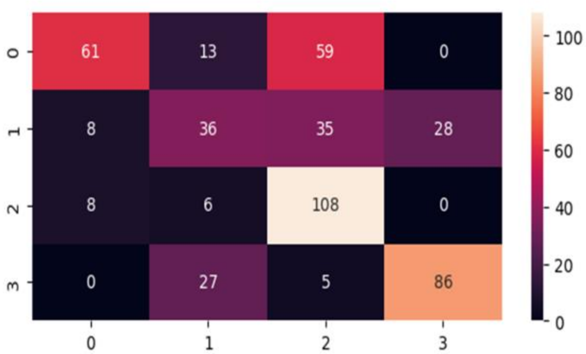
Supplier selection in SCM focuses on cost efficiency and dependable delivery. The primary consideration here is reliable, on-time delivery, which is essential for cost control and smooth operations. Among the available suppliers, supplier 1 emerges as the top choice. It consistently maintains high probabilities of on-time deliveries in both the training and test datasets. In the training data, supplier 1 shows on-time probabilities of 0.9301; in the test data, this reliability is confirmed with probabilities of 0.9294 (Table II). This strong track record reduces the risks associated with delayed or early deliveries. Supplier 2 also performs well, with a high probability of on-time deliveries in both datasets. The training data exhibits on-time probabilities of 0.9430, this reliability continues with probabilities of 0.9592 in test data, too. However, suppliers 3 and 4 also display a degree of consistency in their delivery performance probabilities, but they also show a higher probability of late deliveries. Late deliveries pose a substantial risk, as they can result in increased costs and operational disruptions. The critical factor for supplier selection in this context is consistently delivering on time. Given the potential cost and operational risks of early or late deliveries, supplier 1 is the preferred choice, and its on-time deliveries ensure cost-effectiveness and operational efficiency in SCM.

Supplier Risk Analysis and Profiling: From previous experiments, it is useful to classify suppliers based on the delivery performance (OT, L, and AH). However, knowing supplier risk based on the number of orders, order quantity, lead time, disruptive events, and past delivery performance can help organizations develop robust strategies for different suppliers. Further, to check supplier risk assessment, four Supplier Risk Models (SMLs), including KNN, DTC with Hyperparameter Tuning, Logistic Regression, RF, Bagging-DTC, and Neural Networks, each with distinct training and test scores, were tested (Table IV). KNN displayed a high training score of 0.7329, indicating a strong fit to the training data. However, it has a lower test score of 0.5709 and raises concerns about overfitting, suggesting potential overfitting. DTC achieved a perfect training score of 1.00, signalling overfit, and its low test score of 0.5702 suggests limited practicality for predicting supplier risk. With hyperparameter tuning, DTC-HPT produced a moderate training data score of 0.6452 and a slightly improved test score of 0.5952 compared to the base DTC. Although this can help mitigate overfitting and improve generalization, further fine-tuning is needed for optimal performance. Bagging-DTC emerges as the most suitable choice for supplier risk prediction among these models. It generates a significant training score of 0.7256 and a relatively high test score of 0.6509, indicating its applicability in real-world supplier risk prediction. This model balances overfitting and generalization, making it the preferred choice for supplier risk assessment. While DTC and KNN deliver superior performance for training datasets, their overfitting tendencies make Bagging-DTC the optimal selection.

Table IV Supervised ML model performance (Source: Author’s own work)

Model Parameters	Training	Test

	Accuracy Score	Accuracy Score
KNN (K = 11)	0.7329	0.5709
LogisticRegression (penalty: 'l1', solver: 'saga', C: 10)	0.5708	0.5848
DecisionTreeClassifier(max_depth=4, min_impurity_decrease=0.0025, min_samples_split=120)	0.6452	0.5952
RandomForestClassifier (bootstrap= True, max_depth= 10, min_impurity_decrease= 0.0005, min_samples_leaf= 2, min_samples_split= 5, n_estimators= 200)	0.7946	0.5938
BaggingClassifier(DecisionTreeClassifier(max_depth=20, min_impurity_decrease=0.0015, min_samples_split=30), n_estimators = 500, random_state = 10)	0.7256	0.6509
MLPClassifier(activation= 'relu', alpha= 0.01, hidden_layer_sizes= (100,), learning_rate = 'constant', max_iter= 500, solver= 'adam')	0.6679	0.6250



	precision	recall	f1-score	support
1	0.58	0.50	0.54	133
2	0.39	0.36	0.37	107
3	0.49	0.62	0.55	122
4	0.70	0.69	0.70	118
accuracy			0.54	480
macro avg	0.54	0.54	0.54	480
weighted avg	0.55	0.54	0.54	480

Figure X Bagging Model Performance (Source: Author's own work)

Further, prediction probabilities were obtained using the Bagging-DTC classifier to associate a risk score with each supplier based on previous performance and low-impact and high-impact events (Figure X). The supplier classification model's results highlight the accuracy of its predictions, providing insights into overall performance and the impact of misclassifications on supplier classes (Figure XI). In cases like #1017 and #290, where both the actual supplier classes and the algorithm's predictions are class 3, the model showcases its accuracy in supplier classification. These instances highlight the model's proficiency in classifying suppliers with precision. Conversely, in case #849, there's a disparity where the actual supplier is in class 2, but the algorithm misclassifies it as class 1. Such misclassifications could impact supplier selection decisions, potentially leading to suboptimal choices that may affect SC performance, emphasizing the need to minimize errors. In case #1101, the model effectively predicts the supplier's class, aligning with the actual class 2, contributing to more informed supplier selection decisions. Similarly, in case #1126, the algorithm's prediction aligns with the actual class 3, benefiting organizations that choose suppliers in line with specific SC requirements. In case #1342, there's another misclassification, where the actual supplier belongs to class 2 but is predicted as class 3. Addressing misclassifications like this is crucial to ensure supplier selection decisions align with SC objectives and performance expectations. Finally, in case #821, the actual supplier's class 3 classification aligns with the algorithm's prediction, underscoring the model's reliability in certain instances. Overall, the model demonstrates proficiency in accurately classifying suppliers, but the implications of misclassification in cases like #849 and #1342 emphasize the need for ongoing model refinement to minimize errors in supplier selection. This optimization is essential for making more effective and strategic supplier choices, ultimately enhancing SC performance.

	Actual	S(1)	S(2)	S(3)	S(4)	Predicted Class
1017	3	0.0150	0.3860	0.5980	0.0010	3
290	3	0.1920	0.2345	0.5735	0.0000	3
1019	4	0.0000	0.1495	0.0000	0.8505	4
833	3	0.1080	0.0000	0.8920	0.0000	3
849	2	0.6480	0.3460	0.0060	0.0000	1
...	...	...	...	...	...	...
1101	2	0.0795	0.8255	0.0950	0.0000	2
1126	3	0.1985	0.0790	0.7225	0.0000	3
1456	4	0.0000	0.0295	0.0000	0.9705	4
1342	2	0.1360	0.2810	0.5830	0.0000	3
821	3	0.0855	0.2730	0.6415	0.0000	3

Figure XI Supplier Classification Model (Source: Author’s own work)

Managerial Implications and Contribution

The study offers several managerial implications of ML use in redefining supplier management and SCR. Selecting an appropriate supplier is a strategic decision for any organization. One of the significant implications of this research is the streamlining of SCR management through supervised ML. ML simplifies the complexity of risk management models by enabling the analysis of historical data and the prediction of outcomes. This leads to a more in-depth understanding of potential risks and facilitates more robust decision-making processes. Using the supervised ML models brings a digital data-driven decision-making dimension to SC risk management, where several scenarios with different datasets can be tested using existing ML libraries. Organizations can dynamically examine historical data, providing real-time advantages in decision-making. This adaptability is vital in an ever-changing SC landscape, giving organizations the agility to respond effectively to disruptions and opportunities using advanced digital data-driven techniques.

Beyond enhancing existing relationships, the methodologies explored in this study offer the potential to uncover high-value partnerships within the supplier network. This research emphasizes

ML's effectiveness and scalability and presents a practical approach that can be applied across various industries. It showcases the flexibility and power of ML in making proactive and informed decisions, ultimately contributing to more efficient resource allocation and robust SCM. Compared to prior literature on resilient and sustainable supplier selection, this study represents a new and advanced approach using ML for supplier prediction and selection.

The outcomes derived from this ML-based approach highlight the adaptability and efficacy of ML techniques in facilitating dynamic and proactive decision-making in supplier management. When companies possess a clear understanding of their suppliers' diverse profiles and can categorize them into manageable groups, they are better equipped to allocate resources with increased efficiency. Moreover, this methodology is versatile and applicable across various industrial scenarios, providing valuable insights for policymakers facing supplier selection decisions in diverse circumstances. Additionally, the findings of this study directly benefit humanitarian organizations operating in remote areas, aiding organizational policymakers in making informed decisions about which potential suppliers to incorporate into their SC. The methodology outlined in this study offers a valuable resource for decision-makers seeking to comprehend the impact of diverse supplier selection criteria and sub-criteria. This research establishes a benchmark for companies within the same industry, contributing significantly to the overall growth and future capabilities of the organization.

In the context of theoretical contributions, the methodologies outlined in this study extend existing knowledge in the data-driven decision-making domain using supervised ML approaches to SC problems. This study also demonstrates the effectiveness of supervised ML approaches in multi-class classification problems, which adds to the existing academic work on binary classification problems. Further, the study shows that ML needs to be applied in a flexible manner. The same algorithm can perform differently as the data, process, and underlying patterns can change. This requires training and testing different models with hyper-parameter tunning techniques to leverage the full potential of ML algorithms. The proposed methodology expands on the systems thinking principles and builds a closed-loop system, where future performance on the risks profiling model can be improved by further training the model with real-time datasets. The systems thinking aspect can also be explored based on the potential synergy between MCDM and supervised ML methods in enhancing supplier selection and risk management. While MCDM frameworks like AHP and BWM have traditionally been used to balance multiple criteria (e.g., cost, quality, delivery performance), ML introduces the ability to analyze large datasets and deliver probabilistic outcomes. This combined approach allows decision-makers to leverage structured decision-making models alongside predictive insights, thus improving both accuracy and scalability in supplier selection. Supervised ML models, by providing prediction probabilities, can serve as a baseline for refining MCDM frameworks, enabling a more dynamic, data-driven decision process. This integration could be especially useful for complex SC environments where supplier resilience and adaptability are crucial.

Conclusion

The primary aim is to explore how ML and digital technologies can revolutionize supplier selection criteria and enhance the adaptability of organizations in dynamic SC environments. The training and test dataset results show consistency among all suppliers and different classes when used for a multi-class classification problem. These results validate that there is no over or unfitting problem with the selected ML approach. Suppliers can improve overall SC visibility by knowing probabilities associated with alternatives (second best, etc.) and helping organizations optimize associated strategies with SC risk management. For example, Predicting the probabilities of delivery performance and the supplier's overall performance can help assess and mitigate SC risks using a data-driven decision-making approach. For suppliers with a high probability of late deliveries, the company may explore alternative suppliers or implement contingency plans to avoid disruptions, which can help negotiate more effectively with suppliers. Similarly, safety stock levels can be optimized for suppliers with higher OT or AH delivery probabilities. Conversely, maintaining higher safety stock may be necessary for suppliers with a higher probability of late deliveries. This can also help in operational performance optimization by developing more efficient production schedules. If a supplier is likely to deliver ahead of schedule, the company can adjust production plans to maximize efficiency. This can also lead to improved customer service levels. Knowing the supplier's delivery probabilities helps set realistic delivery commitments to customers. This ensures that the company can meet customer expectations and avoid disappointment due to delays.

However, the misclassifications in cases like #849 and #1342 underscore the limitations of relying solely on ML algorithms for supplier classification. The consequences of such errors, potentially leading to suboptimal supplier choices, emphasize the need for ongoing model refinement to enhance accuracy and minimize risks in supplier selection. The observed misclassifications emphasize the importance of integrating human knowledge into the supplier classification process. While ML provides insights, human judgment is essential for contextual understanding and strategic decision-making that is aligned with SC objectives. Organizations should implement strategies to mitigate the risks associated with misclassifications, including redundancy checks, human validation, and contingency plans to address inaccuracies and uphold SC performance. While the model exhibits proficiency, strategic supplier selection requires a collaborative approach integrating ML insights and human expertise. This hybrid model ensures decisions align with broader SC goals and minimizes the impact of misclassifications.

Furthermore, the study's findings have significant implications for disaster and humanitarian SCM. In these contexts, the stakes are even higher, as the timely delivery of supplies can be critical for saving lives and alleviating human suffering. The ML-based approach to supplier performance analysis and risk profiling can enhance the resilience of humanitarian SCs in several ways. The humanitarian SCs often operate under conditions of uncertainty and urgency. ML algorithms can analyze vast amounts of data to predict potential disruptions and identify resilient suppliers capable of maintaining performance under stress, thereby improving response times and efficiency during disasters. Effective resource allocation is crucial in disaster scenarios where resources are limited. By predicting supplier performance probabilities, humanitarian organizations can better allocate resources to ensure that critical supplies reach affected areas promptly. Humanitarian SCs involve multiple stakeholders, including governments, NGOs, and private sector partners. ML tools can facilitate better coordination and collaboration by providing a common platform for data-driven decision-making, enhancing the overall effectiveness of relief efforts. The ability to adapt to rapidly changing environments is essential in disaster relief operations. ML models can provide real-time insights into supplier performance and risk factors, enabling organizations to adapt strategies quickly to meet emerging needs.

Overall, the integration of ML in both commercial and humanitarian SCM represents a significant advancement towards building resilient and responsive supply networks. This paper offers a practical roadmap for organizations looking to thrive in a dynamic SC landscape, emphasizing the transformative power of ML and digital technologies in supplier management and SCR. Future research can explore more deeply the integration of MCDM models with supervised ML, highlighting how these approaches can work together to provide robust decision-support systems that are both scalable and adaptive to real-world supply chain challenges.

References

Abdulla, A. Baryannis, G., and Badi, I. (2019), "Weighting the Key Features Affecting Supplier Selection using Machine Learning Techniques", available at: https://www.preprints.org/manuscript/201912.0154 (accessed 23 December 2023)

Abubakar, A. Mahfouz, A. and Arisha, A. (2017), "Analysing Supply Chain Resilience: Integrating the Constructs in a Concept Mapping Framework via a Systematic Literature Review", *Supply Chain Management*, Vol. 22, No. 1, pp.16-39. https://doi.org/10.1108/scm-06-2016-0197

Alavi, B. Tavana, M. and Mina, H. (2021), "A Dynamic Decision Support System for Sustainable Supplier Selection in Circular Economy", *Sustainable Production and Consumption*, Vol. 27, pp.905–920.

Al-Ayed, S. I. and Al-Tit, A. A. (2023), "The Effect of Supply Chain Risk Management on Supply Chain Resilience: The intervening part of Internet-of-Things", *Uncertain Supply Chain Management*, Vol. 11, No. 1, pp.179–186. https://doi.org/10.5267/j.uscm.2022.10.009

Ali, H., & Zhang, J. (2023), "A Fuzzy Multi-Objective Decision-Making Model for Global Green Supplier Selection and Order Allocation Under Quantity Discounts", *Expert Systems with Applications*, Vol. 225, 120119. https://doi.org/10.1016/j.eswa.2023.120119

Ali, M. R. Nipu, S. M. A. and Khan, S. A. (2023), "A Decision Support System for Classifying Supplier Selection Criteria using Machine Learning and Random Forest Approach", *Decision Analytics Journal*, Vol. 7, pp.100238. https://doi.org/10.1016/j.dajour.2023.100238

Amindoust, A. (2018), "A resilient-sustainable based supplier selection model using a hybrid intelligent method", *Computers and Industrial Engineering*, Vol. 126, pp.122–135. https://doi.org/10.1016/j.cie.2018.09.031

Ayyildiz, E. and Taskin Gumus, A. (2021), "Interval-valued Pythagorean fuzzy AHP method-based supply chain performance evaluation by a new extension of SCOR model: SCOR 4.0", *Complex and Intelligent Systems*, Vol. 7, No. 1, pp.559–576. https://doi.org/10.1007/s40747-020-00221-9

Azadi, M., Jafarian, M., Saen, R. F., & Mirhedayatian, S. M. (2015), "A new fuzzy DEA model for evaluation of efficiency and effectiveness of suppliers in sustainable supply chain management context", *Computers & operations research*, Vol. 54, pp. 274-285. https://doi.org/10.1016/j.cor.2014.03.002

Azim, R. and Raja Yaacob, R. A. I. (2017), "Criteria for supplier selection: An application of AHP-SCOR integrated model (ASIM)", *International Journal of Supply Chain Management*, Vol. 6, No. 3, pp. 284–290. https://doi.org/10.59160/ijscm.v6i3.1885

Baryannis, G. Dani, S. and Antoniou, G. (2019), "Predicting supply chain risks using machine learning: The trade-off between performance and interpretability", *Future Generation Computer Systems*, Vol. 101, pp.993–1004. https://doi.org/10.1016/j.future.2019.07.059

Camur, M. C. Ravi, S. K. and Saleh, S. (2023), "Enhancing Supply Chain Resilience: A Machine Learning Approach for Predicting Product Availability Dates Under Disruption", *Expert Systems with Applications*, Vol. 247, pp. 123226. (arXiv:2304.14902). https://doi.org/10.1016/j.eswa.2024.123226

Cavalcante, I. M. Frazzon, E. M. Forcellini, F. A. and Ivanov, D. (2019), "A supervised machine learning approach to data-driven simulation of resilient supplier selection in digital manufacturing", *International Journal of Information Management*, Vol. 49, pp. 86–97. https://doi.org/10.1016/j.ijinfomgt.2019.03.004

Cerqueira-Streit, J. Endo, G. Guarnieri, P. and Batista, L. (2021), "Sustainable Supply Chain Management in the Route for a Circular Economy: An Integrative Literature Review", *Logistics*, Vol. 5, No. 4, p. 81. https://doi.org/10.3390/logistics5040081

Chaouni Benabdellah, A. Zekhnini, K. and Cherrafi, A. (2021), "Sustainable and Resilience Improvement Through the Design for Circular Digital Supply Chain", In A. Dolgui, A. Bernard, D. Lemoine, G. Von Cieminski, and D. Romero (Eds.), Advances in Production Management Systems. Artificial Intelligence for Sustainable and Resilient Production *Systems-Springer International Publishing*. Vol. 633, pp. 550–559. https://doi.org/10.1007/978-3-030-85910-7_58

Chopra, S., Sodhi, M., and Lücker, F. (2021), "Achieving supply chain efficiency and resilience by using multi-level commons", *Decision Sciences*, Vol. 52, No. 4, pp. 817-832. https://doi.org/10.1111/deci.12526

Christopher, M., and Holweg, M. (2017), "Supply chain 2.0 revisited: a framework for managing volatility-induced risk in the supply chain", *International Journal of Physical Distribution & Logistics Management*, Vol. 47, No. 1, pp. 2-17. https://doi.org/10.1108/IJPDLM-09-2016-0245

Dohale, V. Gunasekaran, A. Akarte, M. and Verma, P. (2021), "An integrated Delphi-MCDM-Bayesian Network framework for production system selection", *International Journal of Production Economics*, Vol. 242, pp. 108296. https://doi.org/10.1016/j.ijpe.2021.108296

Duan, L. and Ventura, J. A. (2019), "A dynamic supplier selection and inventory management model for a serial supply chain with a novel supplier price break scheme and flexible time periods". *European Journal of Operational Research*, Vol. 272, No. 3, pp. 979–998. https://doi.org/10.1016/j.ejor.2018.07.031

El Baz, J. and Ruel, S. (2021), "Can supply chain risk management practices mitigate the disruption impacts on supply chains' resilience and robustness? Evidence from an empirical survey in a COVID-19 outbreak era", *International Journal of Production Economics*, Vol. 233, pp. 107972. https://doi.org/10.1016/j.ijpe.2020.107972

Es-Satty, A. Lemghari, R. and Okar, C. (2020), "Supply chain digitalization overview SCOR model implication", *2020 IEEE 13th International Colloquium of Logistics and Supply Chain Management (LOGISTIQUA)*, pp. 1–7. https://ieeexplore.ieee.org/abstract/document/9353936/

Eyika Gaida, I. W. Mittal, M. and Yadav, A. S. (2022), "Optimal Strategy for Supplier Selection in a Global Supply Chain Using Machine Learning Technique", *International Journal of Decision Support System Technology*, Vol. 14, No. 1, pp. 1–13. https://doi.org/10.4018/IJDSST.292449

Garg, R. K. (2021), "Structural equation modeling of E-supplier selection criteria in mechanical manufacturing industries", *Journal of Cleaner Production*, Vol. 311, pp. 127597. https://doi.org/10.1016/j.jclepro.2021.127597

Ghadimi, P. Wang, C. Lim, M. K. and Heavey, C. (2019), "Intelligent sustainable supplier selection using multi-agent technology: Theory and application for Industry 4.0 supply chains", *Computers and Industrial Engineering*, Vol. 127, pp. 588–600. https://doi.org/10.1016/j.cie.2018.10.050

Gökler, S. H. and Boran, S. (2023), "A novel resilient and sustainable supplier selection model based on D-AHP and DEMATEL methods", *Journal of Engineering Research.* https://doi.org/10.1016/j.jer.2023.07.015

Golmohammadi, D. (2011), "Neural network application for fuzzy multi-criteria decision making problems", *International Journal of Production Economics*, Vol. 131, Issue 2, pp. 490-504. https://doi.org/10.1016/j.ijpe.2011.01.015

Haldar, A. Ray, A. Banerjee, D. and Ghosh, S. (2014), "Resilient supplier selection under a fuzzy environment", *International Journal of Management Science and Engineering Management*, Vol. 9, No. 2, pp. 147–156. https://doi.org/10.1080/17509653.2013.869040

Hashemzahi, P. Azadnia, A. Galankashi, M. R. Helmi, S. A. and Rafiei, F. M. (2020), "Green supplier selection and order allocation: A nonlinear stochastic model", *International Journal of Value Chain Management*, Vol. 11, No. 2, pp. 111. https://doi.org/10.1504/IJVCM.2020.106821

Hosseini, S., and Barker, K. (2016), "A Bayesian network model for resilience-based supplier selection", *International Journal of Production Economics*, Vol. 180, pp. 68-87. https://doi.org/10.1016/j.ijpe.2016.07.007

Hu, S., Dong, Z. S., and Dai, R. (2024), "A machine learning based sample average approximation for supplier selection with option contract in humanitarian relief", *Transportation Research Part E: Logistics and Transportation Review*, Vol. 186, 103531. https://doi.org/10.1016/j.tre.2024.103531

Islam, S. Amin, S. H. and Wardley, L. J. (2022), "Supplier selection and order allocation planning using predictive analytics and multi-objective programming", *Computers and Industrial Engineering*, Vol. 174, pp. 108825. https://doi.org/10.1016/j.cie.2022.108825

Islam, S. Amin, S. H. and Wardley, L. J. (2024), "A supplier selection and order allocation planning framework by integrating deep learning, principal component analysis, and optimization techniques", *Expert Systems with Applications*, Vol. 235, pp. 121121. https://doi.org/10.1016/j.eswa.2023.121121

Ivanov, D. and Dolgui, A. (2021), "A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0", *Production Planning and Control*, Vol. 32, No. 9, pp. 775–788. https://doi.org/10.1080/09537287.2020.1768450

Jabbarzadeh, A., Fahimnia, B., and Sabouhi, F. (2018), "Resilient and sustainable supply chain design: sustainability analysis under disruption risks", *International Journal of Production Research*, Vol. 56, No. 17, pp. 5945-5968. https://doi.org/10.1080/00207543.2018.1461950

Jabbarzadeh, A., Haughton, M., and Khosrojerdi, A. (2018), "Closed-loop supply chain network design under disruption risks: A robust approach with real world application", *Computers & industrial engineering*, Vol. 116, pp. 178-191. https://doi.org/10.1016/j.cie.2017.12.025

Kamalahmadi, M., & Parast, M. M. (2017), "An assessment of supply chain disruption mitigation strategies", *International Journal of Production Economics*, Vol. 184, pp. 210-230. https://doi.org/10.1016/j.ijpe.2016.12.011

Kazancoglu, Y. Ozkan-Ozen, Y. D. Sagnak, M. Kazancoglu, I. and Dora, M. (2023), "Framework for a sustainable supply chain to overcome risks in transition to a circular economy through Industry 4.0", *Production Planning and Control*, Vol. 34, No. 10, pp. 902–917. https://doi.org/10.1080/09537287.2021.1980910

Khan, M. M. Bashar, I. Minhaj, G. M. Wasi, A. I. and Hossain, N. U. I. (2023), "Resilient and sustainable supplier selection: An integration of SCOR 4.0 and machine learning approach", *Sustainable and Resilient Infrastructure*, Vol. 8, No. 5, pp. 453–469. https://doi.org/10.1080/23789689.2023.2165782

Kıotaran, M. S. Eşme, E. Torğul, B. and Paksoy, T. (2020), "Supplier Selection with Machine Learning Algorithms", *In Logistics 4.0*, pp. 103–125. CRC Press. https://www.researchgate.net/profile/Sercan-Demir-2/publication/347639069_Logistics_40_SCM_in_Industry_40_Era/links/6044bf3192851c077f21b009/Logistics-40-SCM-in-Industry-40-Era.pdf#page=110

Kuo, R. J., Hong, S. Y., and Huang, Y. (2010), "Integration of particle swarm optimization-based fuzzy neural network and artificial neural network for supplier selection", *Applied Mathematical Modelling*, Vol. 34, Issue 12, pp. 3976-3990. https://doi.org/10.1016/j.apm.2010.03.033

Kusi-Sarpong, S. Gupta, H. Khan, S. A. Chiappetta Jabbour, C. J. Rehman, S. T. and Kusi-Sarpong, H. (2023), "Sustainable supplier selection based on industry 4.0 initiatives within the context of circular economy implementation in supply chain operations", *Production Planning and Control*, Vol. 34, No. 10, pp. 999–1019. https://doi.org/10.1080/09537287.2021.1980906

Lin, R. H., Chuang, C. L., Liou, J. J., & Wu, G. D. (2009), "An integrated method for finding key suppliers in SCM", *Expert Systems with Applications*, Vol. 36, No. 3, pp. 6461-6465. https://doi.org/10.1016/j.eswa.2008.07.078

Liu, Q. Huang, H. Zeng, Z. Chen, L. and Ming, J. (2023), "An optimal supplier selection method for uncertain sustainable supply chains", *European Journal of Industrial Engineering*, Vol. 17, No. 3, pp. 431. https://doi.org/10.1504/EJIE.2023.130598

Machuca, J. A. Marin-Garcia, J. A. and Alfalla-Luque, R. (2020), "The country context in Triple-A supply chains: An advanced PLS–SEM research study in emerging vs developed countries", *Industrial Management and Data Systems*, Vol. 121, No. 2, pp. 228–267. https://doi.org/10.1108/IMDS-09-2020-0536

Marin-Garcia, J. A. Machuca, J. A. D. and Alfalla-Luque, R. (2023). "In search of a suitable way to deploy Triple-A capabilities through assessment of AAA models' competitive advantage predictive capacity". *International Journal of Physical Distribution and Logistics Management*, Vol. 53, No. 7/8, pp. 860–885. https://doi.org/10.1108/IJPDLM-03-2022-0091

Mohammed, A. Harris, I. Soroka, A. Mohamed, N. and Ramjaun, T. (2018), "Evaluating Green and Resilient Supplier Performance: AHP-Fuzzy Topsis Decision-Making Approach", *Proceedings of the 7th International Conference on Operations Research and Enterprise Systems*, pp. 209–216. https://doi.org/10.5220/0006619902090216

Nasri, S. A. Ehsani, B. Hosseininezhad, S. J. and Safaie, N. (2023), "A sustainable supplier selection method using integrated Fuzzy DEMATEL–ANP–DEA approach (case study:

Petroleum Industry)”, *Environment, Development and Sustainability*, Vol. 25, No. 11, pp. 12791–12827. https://doi.org/10.1007/s10668-022-02590-2

Nazari-Shirkouhi, S. Tavakoli, M. Govindan, K. and Mousakhani, S. (2023), “A hybrid approach using Z-number DEA model and Artificial Neural Network for Resilient supplier Selection”, *Expert Systems with Applications*, Vol. 222, pp. 119746. https://doi.org/10.1016/j.eswa.2023.119746

Pramanik, D. Haldar, A. Mondal, S. C. Naskar, S. K. and Ray, A. (2017), “Resilient supplier selection using AHP-TOPSIS-QFD under a fuzzy environment”, *International Journal of Management Science and Engineering Management*, Vol. 12, No. 1, pp. 45–54. https://doi.org/10.1080/17509653.2015.1101719

Rezaei, A. Rahiminezhad Galankashi, M. Mansoorzadeh, S. and Mokhatab Rafiei, F. (2020), “Supplier Selection and Order Allocation with Lean Manufacturing Criteria: An Integrated MCDM and Bi-objective Modelling Approach”, *Engineering Management Journal*, Vol. 32, No. 4, pp. 253–271. https://doi.org/10.1080/10429247.2020.1753490

Sedamaki, K. and Kattepur, A. (2022), “Supply Chain Delay Mitigation via Supplier Risk Index Assessment and Reinforcement Learning”, *2022 IEEE 1st International Conference on Data, Decision and Systems (ICDDS)*, pp. 1–6. https://doi.org/10.1109/ICDDS56399.2022.10037409

Sepehri, S. (2020), “Supplier selection and relationship management: An application of machine learning techniques”, http://dr.library.brocku.ca/handle/10464/14831

Steinberg, F. Burggräf, P. Wagner, J. Heinbach, B. Saßmannshausen, T. and Brintrup, A. (2023), “A novel machine learning model for predicting late supplier deliveries of low-volume-high-variety products with application in a German machinery industry”, *Supply Chain Analytics*, Vol. 1, pp. 100003. https://doi.org/10.1016/j.sca.2023.100003

Tavana, M., Fallahpour, A., Di Caprio, D., and Santos-Arteaga, F. J. (2016), “A hybrid intelligent fuzzy predictive model with simulation for supplier evaluation and selection”, *Expert Systems with Applications*, Vol. 61, pp. 129–144. https://doi.org/10.1016/j.eswa.2016.05.027

Teller, C., Kotzab, H., Grant, D. B., and Holweg, C. (2016), “The importance of key supplier relationship management in supply chains”, *International Journal of Retail & Distribution Management*, Vol. 44, No. 2, pp. 109-123. https://doi.org/10.1108/IJRDM-05-2015-0072

Wang, C.-N. Tsou, M. C., Wang, C. H. Tinh Nguyen, V. and Ngo Thi Phuong, P. (2022), “Improving Supply Chain Performance Through Supplier Selection and Order Allocation Problem”, *Computers, Materials and Continua*, Vol. 70, No. 1, pp. 1667–1681. https://doi.org/10.32604/cmc.2022.019833

Wilson, V. H. NS, A. P. Shankharan, A. Kapoor, S. and Rajan A, J. (2020), “Ranking of supplier performance using machine learning algorithm of random forest”, *International Journal of Advanced Research in Engineering and Technology (IJARET)*, Vol. 11, No. 5. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3628378

Yazdi, A. K. Wanke, P. F. Hanne, T. Abdi, F. and Sarfaraz, A. H. (2022), "Supplier selection in the oil and gas industry: A comprehensive approach for Multi-Criteria Decision Analysis", *Socio-Economic Planning Sciences*, Vol. 79, pp. 101142. https://doi.org/10.1016/j.seps.2021.101142

Zangaro, F. Minner, S. and Battini, D. (2021), "A supervised machine learning approach for the optimisation of the assembly line feeding mode selection", *International Journal of Production Research*, Vol. 59, No. 16, pp. 4881–4902. https://doi.org/10.1080/00207543.2020.1851793

Zhaoa, P. Jia, S. and Xuea, Y. (2021), "Resilient-sustainable supplier selection and order allocation under multi-tier supplier network". Available at: Research gate. https://www.researchgate.net/profile/Shoufeng-Ji/publication/355788632_Resilient-sustainable_supplier_selection_and_order_allocation_under_multi-tier_supplier_network/links/617e09c4eef53e51e10c4b17/Resilient-sustainable-supplier-selection-and-order-allocation-under-multi-tier-supplier-network.pdf (accessed 29 March 2024)

Zheng, G. Kong, L. and Brintrup, A. (2023), "Federated machine learning for privacy preserving, collective supply chain risk prediction", *International Journal of Production Research*, Vol. 61, No. 23, pp. 8115–8132. https://doi.org/10.1080/00207543.2022.2164628

Zimmer, K., Fröhling, M., and Schultmann, F. (2016), "Sustainable supplier management–a review of models supporting sustainable supplier selection, monitoring and development", *International Journal of Production Research*, Vol. 54, No. 5, pp. 1412-1442. https://doi.org/10.1080/00207543.2015.1079340

Appendix A:

Table – AI Experiment Details for Hyperparameter Tunning (Source: Author's own work)

Supervised ML Model	**Supplier Classification Best Parameters**	**Supplier Risk Profiling Best Parameters**	**Range of Parameters for Hyper tunning**
KNN	n-neighbours = 7	n-neighbours = 11	knn = KNeighborsClassifier() grid_search = GridSearchCV(estimator=knn, param_grid=param_grid, cv=5, scoring='accuracy') A range of values was tested from 1 to 30 with 5 cross-validations. Model performance doesn't change significantly for K > 7
Logistic Regression	LogisticRegression (penalty="l2", C = 1e42, solver="liblinear")	LogisticRegression (penalty: 'l1', solver: 'saga', C: 10)	penalties = ['l1', 'l2','elasticnet'], solvers = ['lbfgs', 'liblinear', 'newton-cg', 'newton-cholesky', 'sag', 'saga'], C_values = [1e-4, 1e-3, 1e-2, 1e-1, 1, 10, 100, 1e3, 1e4, 1e5, 1e6, 1e7, 1e8, 1e9, 1e10, 1e11, 1e12, 1e13, 1e14, 1e15, 1e16, 1e17, 1e18, 1e19, 1e20, 1e21, 1e22, 1e23, 1e24, 1e25, 1e26, 1e27, 1e28, 1e29, 1e30, 1e31, 1e32, 1e33, 1e34, 1e35, 1e36, 1e37, 1e38, 1e39, 1e40, 1e41, 1e42]
Decision Tree Classifier	DecisionTreeClassifier (max_depth=4, min_impurity_decrease=0.005, min_samples_split =5)	DecisionTreeClassifier(max_depth=4, min_impurity_decrease=0.0025, min_samples_split=120)	GS_parm ={"max_depth":range(1,40), min_impurity_decrease":[0.00025,0.0005,0.001,0.0025,0.005,0.01,0.025,0.05], "min_samples_split":[5,10,15,20,25,30,35,40,60,80,100,120] }
Random Forest Classifier	RandomForestClassifier (max_depth=10, min_impurity_decrease=0.00025,	RandomForestClassifier (bootstrap= True, max_depth= 10, min_impurity_decrease= 0.0005, min_samples_leaf=	param_grid = {'n_estimators': [1, 100, 200], 'max_depth': [10, 20, 30], 'min_samples_split': [2, 5, 10], 'min_samples_leaf': [1, 2, 4], "min_impurity_decrease":[0.00025,0.0005,0.001,0.0025,0.005,0.01,0.025,0.05], 'bootstrap': [True, False]}

	min_samples_split=41, n_estimators=200)	2, min_samples_split= 5, n_estimators= 200)	
Bagging Classifier	BaggingClassifier (estimator=DecisionTreeClassifier(max_depth=5, min_impurity_decrease=0.0015, min_samples_split=40), n_estimators=500, random_state=26)	BaggingClassifier(DecisionTreeClassifier(max_depth=20, min_impurity_decrease=0.0015, min_samples_split=30), n_estimators = 500, random_state = 10)	param_grid = {'n_estimators': [10, 50, 100, 200], 'max_samples': [0.5, 0.7, 1.0], 'max_features': [0.5, 0.7, 1.0], 'bootstrap': [True, False], 'bootstrap_features': [True, False]}
MLP Classifier	MLPClassifier(activation = 'relu', alpha= 0.0001, hidden_layer_sizes= (50, 50), learning_rate = 'constant', max_iter= 500, solver= 'adam')	MLPClassifier(activation= 'relu', alpha= 0.01, hidden_layer_sizes= (100,), learning_rate = 'constant', max_iter= 500, solver= 'adam')	param_grid = {'hidden_layer_sizes': [(50, 50), (100,), (100, 50), (50, 100)], 'activation': ['tanh', 'relu'], 'solver': ['sgd', 'adam'], 'alpha': [0.0001, 0.001, 0.01], 'learning_rate': ['constant', 'adaptive'], 'max_iter': [200, 500]}