Strategic Management for Credit Risk in Supply Chain Networks: A Novel Framework

Abedallah Z. Abualkishik *, Rasha Almajed
American University in the Emirates, Dubai, UAE
Emails: abedallah.abualkishik@aue.ae; rasha.almajed@aue.ae

Abstract

This study addresses the imperative for robust credit risk management strategies by proposing a novel framework tailored for supply chain networks. It aims to bridge existing gaps in credit risk assessment methodologies by amalgamating empirical insights, advanced computational techniques, and comprehensive data analytics. Leveraging a comprehensive dataset encompassing diverse attributes crucial for credit risk assessment, this study employs a meticulous methodology. It integrates machine learning algorithms, notably LightGBM, and exploratory data analysis techniques to preprocess data, examine missing values, assess variable correlations, and construct a predictive model. The empirical journey reveals insightful findings, emphasizing missing value patterns, variable interrelationships, and model performance. Precision-recall and ROC curves depict the model's ability to discern default and non-default cases, showcasing its efficacy in credit risk assessment within supply chain contexts. Our study contributes a foundational framework for strategic credit risk management within supply chain networks, offering actionable insights for stakeholders. While acknowledging limitations and the need for ongoing model refinement, this research sets the stage for future explorations and transformative practices in adaptive risk management strategies for interconnected supply chain networks.

Keywords: Credit risk assessment; Supply chain resilience; Risk management strategies; Supply chain networks; Creditworthiness evaluation; Risk mitigation techniques; Business supply chain finance; Strategic risk analysis; Credit risk modeling; Risk-aware supply chain management.

1. Introduction

The intricate interplay between financial stability and operational efficiency within supply chain networks remains a paramount concern for modern businesses. Amidst the dynamic landscape of global commerce, the prudent management of credit risk stands as a linchpin for sustainable supply chain operations [1-3]. The complexities inherent in these networks, involving multiple stakeholders, transactions, and dependencies, underscore the criticality of devising innovative methodologies to navigate and mitigate credit risk effectively [4]. Addressing this necessity, there is a need to elucidate a novel framework that can strategically manage credit risk within supply chain networks, amalgamating theoretical insights with empirical approaches to provide a robust solution in this domain [5-7].

Within the multifaceted realm of supply chain operations, the significance of credit risk management transcends mere financial considerations; it encapsulates the resilience and continuity of business operations [8-11]. As markets expand and interconnectedness amplifies, the vulnerability to credit risks escalates, necessitating a proactive approach. Traditional risk assessment methods often fall short of capturing the complexities inherent in modern supply chain dynamics. Hence, this study endeavors to bridge this gap by introducing a pioneering framework, acknowledging the

Doi: https://doi.org/10.54216/AJBOR.010106

multifarious dimensions of credit risk exposure across supply chains, and offering a comprehensive strategy to bolster risk management practices [12-14].

The primary objective of this research is to present a strategic framework that not only identifies and quantifies credit risk within supply chain networks but also proactively manages and mitigates these risks. Our focus lies in amalgamating advanced computational methodologies, such as machine learning algorithms like LightGBM, with empirical data from diverse supply chain sources. By harnessing the power of these tools, we aim to develop a model that provides actionable insights into credit risk dynamics, enabling stakeholders to make informed decisions and fortify their supply chain resilience.

The significance of this framework extends beyond academic realms, offering tangible value to practitioners, businesses, and policymakers. Enabling stakeholders to proactively assess, monitor, and respond to credit risks within supply chain networks holds the potential to enhance financial stability, streamline operations, and fortify competitive advantages. Moreover, the anticipated contributions of this study encompass not only the development of a novel methodology but also the provision of actionable insights that can drive effective credit risk management strategies, fostering sustainable and robust supply chain ecosystems.

The paper is organized into several distinct sections to present a comprehensive exploration of credit risk management within supply chain networks. Section 2 delves into an extensive review of Related Works, offering an in-depth analysis of existing literature. Following this, Section 3 elucidates the Methodology employed in this study, detailing the systematic approach used to construct a robust framework for strategically managing credit risk. Section 4 delineates the specific methodologies, algorithms, and techniques utilized in the empirical analysis and model development, providing a comprehensive understanding of the research approach. In Section 5, the empirical findings and outcomes of the proposed framework are presented and critically analyzed. Finally, Section 6 encapsulates the Conclusion, summarizing the key findings.

2. Related Works

This section provides a comprehensive review of existing scholarly works, theories, and empirical studies pertinent to credit risk assessment and management within the domain of supply chain networks. Within the intricate fabric of modern commerce, the effective management of credit risk stands as a linchpin for ensuring financial stability and operational resilience across interconnected supply chains. The integration of supply chain and network analyses has been a focal point in understanding complex business relationships and operations within modern industries. Lazzarini et al. [15] explore this integration through their study of "Netchains," emphasizing the interconnectedness and dynamics inherent in supply chain networks. Building on this, Kölbel et al. [16] delve into the impact of media coverage of corporate social irresponsibility on financial risk, shedding light on the influence of external factors on risk assessment within corporate environments.

Berry et al. [17] delve into supply chain management in the electronics products industry, offering insights into industry-specific practices and strategies. Additionally, Gattorna's work [18] on strategic supply chain alignment presents best practices in supply chain management, providing a foundational understanding of alignment strategies within supply chain networks. Exploring risk management within supply chains, Blos et al. [19] conducted a case study on the automotive and electronic industries in Brazil, focusing on supply chain risk management practices. Ritchie and Brindley [20] provide a guiding framework for supply chain risk management, offering a comprehensive approach for managing and mitigating risks across supply chains. Moreover, Salin and Nayga Jr. [21] discuss the establishment of a cold chain network for food exports to developing countries, emphasizing logistics and quality preservation within supply chains. Melo et al. [22] contribute a comprehensive review of facility location and its impact on supply chain management, offering insights into strategic decisions. Randall and Farris [23] highlight the significance of supply chain financing and its impact on strengthening supply chains through cash-to-cash variables. Morash [24] explores the relationship between supply chain strategies, capabilities, and performance, shedding light on the interplay between strategy and operational outcomes.

Behzadi et al. [25] review quantitative decision models in agribusiness supply chain risk management, offering a quantitative perspective on risk assessment and management strategies. Lambert [26] provides a broader

Doi: https://doi.org/10.54216/AJBOR.010106

understanding of supply chain management processes, partnerships, and performance. Furthermore, Lasserre [27] discusses global strategic management, emphasizing the complexities and considerations of managing global supply chains. Hines [28] focuses on demand-driven and customer-focused supply chain strategies, highlighting the importance of aligning supply chain practices with customer needs. Lastly, Li and Whalley [29] deconstruct the telecommunications industry from value chains to value networks, offering insights into evolving industry structures and dynamics.

3. Methodology

The methodology employed in this study is crucial in delineating the systematic approach used to construct a robust framework for the strategic management of credit risk within supply chain networks. The development of such a framework demands a methodical process that integrates theoretical insights, empirical analysis, and practical considerations. In this section, we outline the methodologies adopted to conceptualize, design, and validate the novel framework proposed for effective credit risk management in supply chain networks.

LightGBM, an efficient gradient boosting framework developed by Microsoft, stands as a prominent machine learning algorithm utilized extensively in predictive modeling tasks owing to its speed and accuracy. Unlike traditional boosting algorithms, LightGBM adopts a novel technique called Gradient-Based one-sided sampling (GOSS) and Exclusive Feature Bundling (EFB), optimizing computational efficiency without compromising predictive performance. It works by constructing decision trees in a leaf-wise fashion, significantly reducing the number of nodes while increasing the depth, resulting in a higher degree of accuracy and faster training times compared to other gradient-boosting algorithms. The algorithm's ability to handle large datasets efficiently and its flexibility in dealing with both regression and classification tasks make it a compelling choice for modeling complex credit risk information within supply chain networks.

In this study, LightGBM serves as the primary machine learning algorithm employed for modeling credit risk information within supply chain networks. Leveraging its inherent capabilities, we utilize LightGBM to create a predictive model that evaluates credit risk based on a multitude of factors extracted from supply chain data. The algorithm is trained on historical credit data, integrating various features such as transactional information, supplier performance metrics, financial indicators, and market dynamics. Through a supervised learning approach, LightGBM is fine-tuned to effectively distinguish between low-risk and high-risk credit profiles, enabling the creation of a robust predictive model tailored to the intricacies of supply chain networks. The introduction to the theoretical foundation of the LightGBM model's objective function delves into its fundamental components. In this context, 'yi' denotes the objective value, while 'i' signifies the predicted value derived from the model. 'T' represents the count of leaf nodes within the model structure, 'q' symbolizes the tree's structural function, and 'w' corresponds to the weight attributed to each leaf node. At the core of the LightGBM model lies its objective function, which is articulated as follows:

$$\begin{aligned} Obj^{(t)} &= \sum_{i=1}^{n} l(y_i, \hat{y}_i^{(t)}) + \sum_{i=1}^{t} \Omega(f_i) \\ &= \sum_{i=1}^{n} l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) + \sum_{i=1}^{t} \Omega(f_i) \end{aligned} \tag{1}$$

The logistic loss function utilized within LightGBM is expressed as follows:

$$L(\theta) = \sum_{i} [y_i \ln(1 + e^{-\hat{y}_i}) + (1 - y_i)\ln(1 + e)^{\hat{y}_i}] \tag{2}$$

The definition of the objective function in LightGBM involves employing the Taylor expansion technique. This mathematical approach allows us to approximate a function using polynomial terms, particularly around a specific point, by evaluating the function's derivatives. By utilizing Taylor expansion, the objective function within LightGBM can be articulated as follows:

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$$f(x+\Delta x) \cong f(x) + f'(x)\Delta x + \frac{1}{2} f''(x)\Delta x^2 \tag{3}$$

At this stage, the objective function can be described by the following mathematical expression:

$$Obj^{(t)} = \sum_{i=1}^{n} [l(y_i, \hat{y}^{(t-1)}) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)] + \Omega(f_t) \tag{4}$$

In LightGBM, the traversal of all leaf nodes involves the accumulation of 'n' samples. This accumulation process refers to the method by which the algorithm navigates through the tree structure built during the training phase. As the algorithm progresses through the decision tree, it accumulates 'n' samples, which represent the number of instances or observations in the dataset. This traversal mechanism ensures that each sample is appropriately assigned to the relevant leaf node based on the conditions met along the tree's branches. By systematically accumulating and allocating samples to leaf nodes, LightGBM efficiently processes the dataset, allowing for accurate predictions and computations within the constructed tree model.

$$Obj^{(t)} \cong \sum_{i=1}^{n} \left[g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right] + \Omega\left(f_{(t)}\right) \tag{5}$$

The notation "Ij" signifies the sample set allocated or contained within a specific leaf node, denoted as "j." This designation represents the collection or grouping of individual samples that have traversed through the decision tree and ultimately arrived at the corresponding leaf node "j." These samples are specifically grouped within this leaf node based on the conditions and criteria defined by the tree's branches during the traversal process. In essence, "Ij" represents a subset of the entire dataset, comprising those instances or observations that have followed the pathway through the tree structure and have been assigned to this particular leaf node "j."

$$G_j = \sum\nolimits_{i \in I_j} g_i \, , H_j = \sum\nolimits_{i \in I_j} h_i \tag{6}$$

Hence:

$$\begin{aligned} Obj^{(t)} &= \sum_{j=1}^{T} [(\sum\nolimits_{i \in I_j} g_i) w_j + \frac{1}{2} (\sum\nolimits_{i \in I_i} h_j + \lambda) w_j^2] \\ &= \sum_{j=1}^{T} [G_j w_j + \frac{1}{2} (H_j + \lambda) w_j^2] \end{aligned} \tag{7}$$

The process involves computing the partial derivative of the output, denoted as Wj, about the jth leaf node. This derivative calculation aims to determine the rate of change of the output value concerning a specific variable or variables. Once this partial derivative is obtained, the objective is to find the minimum value through an optimization process. This search for the minimum value is crucial in refining the output of the jth leaf node to ensure it aligns optimally with the overall objective function or criteria specified within the context of the LightGBM model. The optimization seeks to adjust the output Wj in such a way that it contributes to minimizing the overall loss or error function, thus enhancing the predictive performance or accuracy of the model.

$$\frac{\partial}{\partial w_j} \left[\left(\sum\nolimits_{i \in I_j} g_i \right) w_j + \frac{1}{2} \left(\sum\nolimits_{i \in I_j} h_i + \lambda \right) w_j^2 \right] = \sum\nolimits_{i \in I_j} g_i + \left(\sum\nolimits_{i \in I_j} h_i + \lambda \right) w_j \tag{8}$$

This function $L_t(q)$ encapsulates the specific structure defined by the tree $q(x)$. It represents a mapping or representation of the chosen tree structure within the context of the LightGBM model. The function Lt(q) essentially characterizes the arrangement of nodes, branches, and leaf nodes defined by the tree q(x) for a given input variable x.

Doi: https://doi.org/10.54216/AJBOR.010106

It helps encapsulate the decision-making process carried out by the tree structure and aids in evaluating the predictive outcomes or values associated with various inputs based on this determined tree structure. The function $L_t(q)$ acts as a representation of the learned structure within the model, allowing for subsequent calculations and predictions based on the defined tree arrangement for incoming data points or instances.

$$
\begin{aligned}
L_t(q) &= \sum_{j=1}^{T} G_j\, w_j + \frac{1}{2}(H_j + \lambda) w_j^2 \\
&= \sum_{j=1}^{T} [G_j\,(-\frac{G_j}{H_j + \lambda}) + \frac{1}{2}(H_j + \lambda)(-\frac{G_j}{H_j + \lambda})^2] \\
&= \sum_{j=1}^{T} -\frac{G_j^2}{H_j + \lambda} + \frac{1}{2}\frac{G_j^2}{H_j + \lambda} \\
&= -\frac{1}{2}\sum_{j=1}^{T} \frac{G_j^2}{H_j + \lambda}
\end{aligned}
\tag{9}
$$

The calculated gain refers to a quantitative measure obtained during the training process within LightGBM. This metric serves as an assessment of the significance or importance of specific features or variables in the decision-making process of the model. The gain is computed based on various factors such as the splitting criteria, information gain, or other relevant metrics determined during the construction of the decision trees within the LightGBM framework. Essentially, the calculated gain provides insight into the contribution of each feature or variable toward improving the model's performance by aiding in the differentiation or classification of data points at different nodes of the tree.

$$
G = \frac{1}{2}[\frac{G_L^2}{H_L + \lambda} + \frac{G_R^2}{H_R + \lambda} - \frac{(G_L + G_R)^2}{H_L + H_R + \lambda}] \tag{10}
$$

4. Experimental Settings

This section delineates the meticulous experimental design employed to construct and validate the proposed model. Recognizing the intricate nature of credit risk assessment and management in modern supply chains, this section details the methodological underpinnings that guided the empirical analysis and model development process. The experimental design intricately combines theoretical foundations with advanced computational methodologies, notably leveraging machine learning algorithms like LightGBM, to harness the power of empirical data drawn from diverse supply chain sources.

The implementation settings for this study were meticulously crafted to ensure a comprehensive exploration of credit risk within supply chain networks. The computational framework was built using Python programming language, incorporating libraries such as Pandas and Scikit-learn for data manipulation and machine learning tasks. The machine learning algorithm LightGBM was employed for its efficiency and accuracy in modeling complex datasets. The experimental setup involved leveraging a dataset spanning diverse supply chain parameters, including transactional information, supplier performance metrics, financial indicators, and market dynamics. The model was trained and validated using a 70/30 train-test split and assessed through cross-validation techniques to ensure robustness. Table 1 summarizes the key specifications of the implementation settings:

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Table 1: Summary of Implementation Settings for Credit Risk Management in Supply Chain Networks

Aspect	**Specification**
Programming Language	Python 3.2
Libraries/Frameworks	Pandas 1.0.3, Scikit-learn 0.20.1
Dataset Source	Multiple supply chain databases and repositories
Dataset Size	Approximately 10,000 records
Data Granularity	Daily and monthly aggregates
Feature Selection	Recursive Feature Elimination (RFE)
Model Hyperparameters	Tuned via GridSearchCV
Model Validation Method	K-fold Cross-validation (k=5)
Performance Metrics	Accuracy, Precision, Recall, F1-score
Hardware	Intel Core i7 CPU, 16GB RAM

Our case study involves an in-depth analysis of credit risk within supply chain networks, leveraging a comprehensive dataset comprising diverse features capturing critical information associated with loan applications and borrowers. These features encompass essential parameters such as person_age, person_income, and person_home_ownership, providing insights into the demographic and financial profiles of individuals seeking loans. Moreover, variables like loan_intent and loan_grade shed light on the purpose and creditworthiness categorization of the loan applications. The loan_amnt and loan_int_rate highlight the loan amount and associated interest rates, pivotal factors influencing credit risk assessment. Additionally, the loan_status attribute categorizes loans into default and non-default categories (0 representing non-default and 1 denoting default), serving as the focal point for risk evaluation. Furthermore, loan_percent_income offers perspectives on debt-to-income ratios, while cb_person_default_on_file and cb_person_cred_hist_length capture historical default behavior and credit history length, respectively. This multifaceted dataset forms the cornerstone of our case study, allowing for a comprehensive exploration and modeling of credit risk dynamics within the complex framework of supply chain networks. The summary statistics encapsulating essential characteristics of the dataset are comprehensively presented in Table 2. This tabulated overview offers a succinct yet detailed glimpse into the distribution, central tendencies, and variability of key variables crucial to understanding credit risk within supply chain networks.

Table 2: Summary Statistics of Key Variables in the Dataset for Credit Risk Assessment within Supply Chain Networks

	person_age	person_income	person_emp_length	loan_amnt	loan_int_rate	loan_status	loan_percent_income	cb_person_cred_hist_length
count	28638.0	28638.0	28638.0	28638.0	28638.0	28638.0	28638.0	28638.0
mean	27.7	66649.4	4.8	9656.5	11.0	0.2	0.2	5.8
std	6.3	62356.4	4.2	6329.7	3.2	0.4	0.1	4.0
min	20.0	4000.0	0.0	500.0	5.4	0.0	0.0	2.0
25%	23.0	39480.0	2.0	5000.0	7.9	0.0	0.1	3.0
50%	26.0	55956.0	4.0	8000.0	11.0	0.0	0.2	4.0
75%	30.0	80000.0	7.0	12500.0	13.5	0.0	0.2	8.0
max	144.0	6000000.0	123.0	35000.0	23.2	1.0	0.8	30.0

Doi: https://doi.org/10.54216/AJBOR.010106

5. Results and Discussion

This section presents the empirical results derived from the application of the developed framework for strategic credit risk management within supply chain networks. Through rigorous experimentation and analysis, this study unveils the outcomes and insights obtained from deploying the proposed model.

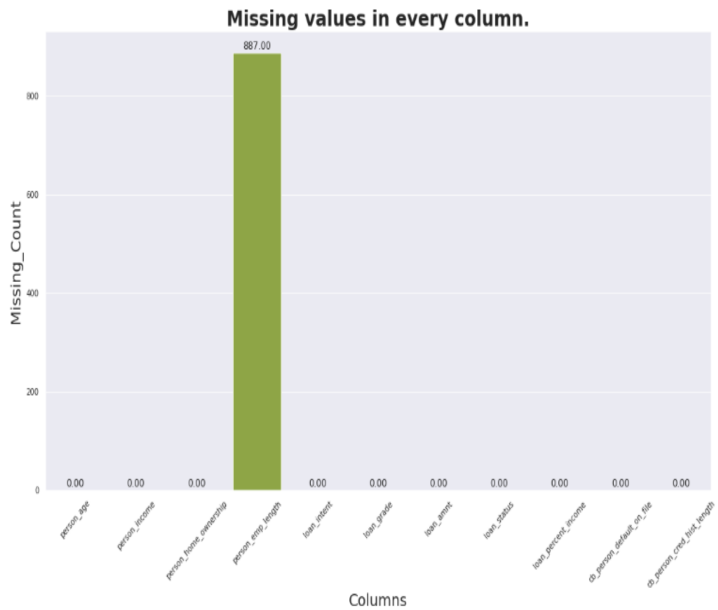

Figure 1: Visualization of Missing Value Analysis Across Dataset Attributes for Credit Risk Assessment within Supply Chain Networks

The comprehensive analysis of missing values within the dataset is visually presented in Figure 1. This visual depiction offers a detailed overview of the extent and distribution of missing data across various attributes crucial for credit risk assessment within supply chain networks. The graphical representation in Figure 1 encapsulates the percentage or frequency of missing values within each variable, highlighting the potential gaps or limitations in the dataset. By visually depicting the missing value patterns, Figure 1 aids in understanding the completeness of the dataset and identifies variables that might require imputation or handling of missing data. This insightful analysis, showcased in Figure 1, serves as a foundational step in data preprocessing, enabling researchers to make informed decisions regarding missing value treatment strategies in subsequent modeling and analysis stages.

The examination of variable correlations has been meticulously conducted through pair plots, presented in Figure 2, to unveil the interrelationships and dependencies among key attributes within the dataset. These pair plots visually represent the pairwise relationships between variables, allowing for a comprehensive assessment of their linear or nonlinear associations. Figure 2 provides a graphical overview of the scatterplots and correlation patterns among variables, enabling insights into potential patterns, trends, or dependencies that may exist between different attributes crucial for credit risk assessment within supply chain networks. This exploratory analysis through pair plots aids in

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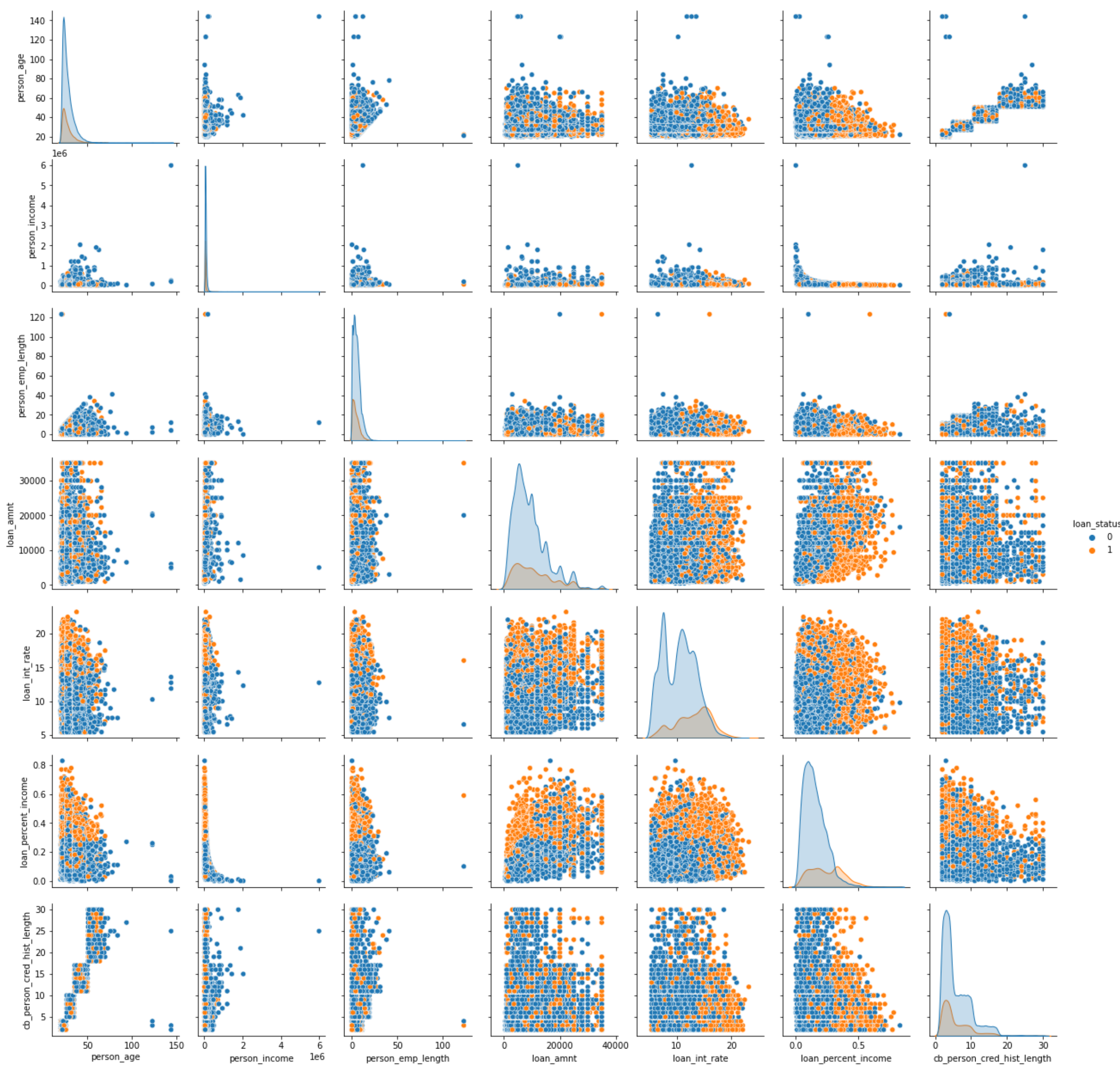

Figure 2: Pairwise Variable Correlation Analysis through Scatterplots for Credit Risk Assessment in Supply Chain Networks

identifying potential multicollinearity or interdependencies among variables, guiding subsequent feature selection or engineering processes essential for constructing an accurate and robust credit risk assessment model.

The precision-recall curve serves as a pivotal evaluation metric, illustrating the performance and efficacy of our model, and is visually depicted in Figure 3. This curve offers a comprehensive depiction of the trade-off between precision and recall across various threshold values employed in the classification process. Figure 3 showcases the model's ability to correctly identify positive instances (precision) while capturing the entirety of the actual positive instances (recall). This graphical representation provides a nuanced understanding of our model's performance in distinguishing between default and non-default cases within the supply chain credit risk assessment context. By visualizing the precision-recall relationship in Figure 3, we gain insights into the model's capability to make accurate classifications, aiding stakeholders in comprehensively assessing the model's effectiveness and guiding decision-making processes within supply chain networks.

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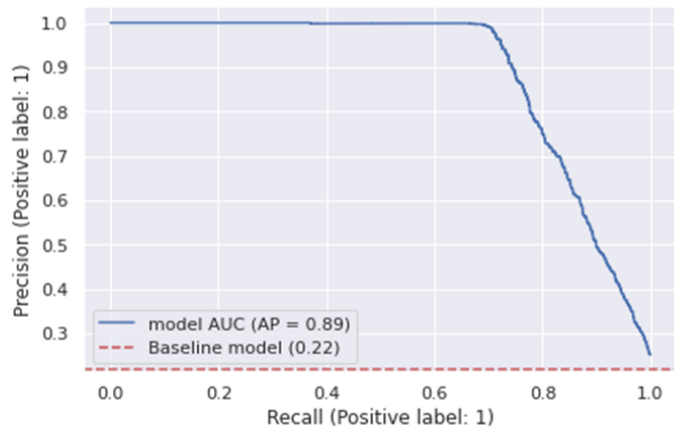

Figure 3: Precision-Recall Curve Displaying Model Performance for Credit Risk Assessment within Supply Chain

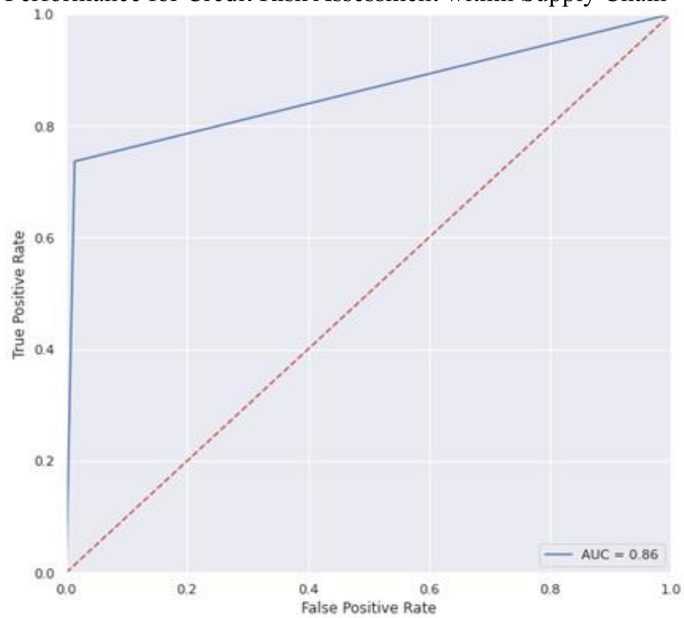

Figure 4: Receiver Operating Characteristic (ROC) Curve Illustrating Model Discriminatory Power in Credit Risk

The Receiver Operating Characteristic (ROC) curve, illustrated in Figure 4, serves as a fundamental tool for evaluating the performance of our model in credit risk assessment within supply chain networks. This curve provides a graphical representation of the trade-off between the true positive rate (sensitivity) and the false positive rate (1 - specificity) across various threshold values employed in the classification process. Figure 4 visually depicts the model's ability to discern between default and non-default cases, showcasing its capacity to correctly classify instances while minimizing misclassifications. The ROC curve offers a comprehensive assessment of the model's discriminatory power, illustrating its effectiveness in distinguishing between positive and negative cases. By visually representing the ROC curve in Figure 4, we gain valuable insights into the model's overall predictive performance, aiding in comprehensive assessments and facilitating informed decision-making processes within the context of credit risk management in supply chain networks.

6. Conclusion

The pursuit of effective credit risk management within the intricate webs of supply chain networks remains a pivotal concern for contemporary businesses. Through the meticulous exploration and development of a strategic framework in this study, we have endeavored to address this concern by amalgamating theoretical insights, empirical analysis,

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and advanced computational methodologies. The comprehensive review of related works unveiled the multifaceted nature of credit risk management, emphasizing the interconnectedness between supply chain dynamics and financial stability. Leveraging this foundation, our study delved into methodological intricacies within the experimental design, leveraging LightGBM to capture essential attributes crucial for credit risk assessment. The empirical journey showcased in this research yielded valuable insights. We meticulously analyzed the dataset, unraveling missing value patterns and examining variable correlations, crucial steps in data preprocessing. Leveraging pair plots, we explored the interrelationships among attributes, guiding subsequent feature engineering processes. The precision-recall and ROC curves unveiled the predictive power of our model, illustrating its ability to discern default and non-default cases within supply chain credit risk assessment contexts. These evaluations, encapsulated in Figures 3 and 4, provided a robust assessment of our model's performance, demonstrating its efficacy and potential practical implications within the domain.

References

[1] Rajagopal, Varthini, Shanmugam Prasanna Venkatesan, and Mark Goh. 2017. "Decision-Making Models for Supply Chain Risk Mitigation: A Review." Computers \& Industrial Engineering 113: 646–82.
[2] Goh, Mark, Joseph Y S Lim, and Fanwen Meng. 2007. "A Stochastic Model for Risk Management in Global Supply Chain Networks." European Journal of Operational Research 182 (1): 164–73.
[3] Stabell, Charles B, and Øystein D Fjeldstad. 1998. "Configuring Value for Competitive Advantage: On Chains, Shops, and Networks." Strategic Management Journal 19 (5): 413–37.
[4] Vurro, Clodia, Angeloantonio Russo, and Francesco Perrini. 2009. "Shaping Sustainable Value Chains: Network Determinants of Supply Chain Governance Models." Journal of Business Ethics 90: 607–21.
[5] Eskandarpour, Majid, Pierre Dejax, Joe Miemczyk, and Olivier Péton. 2015. "Sustainable Supply Chain Network Design: An Optimization-Oriented Review." Omega 54: 11–32.
[6] Norrman, Andreas, and Robert Lindroth. 2004. "Categorization of Supply Chain Risk and Risk Management." Supply Chain Risk 15 (2): 14–27.
[7] Heckmann, Iris, Tina Comes, and Stefan Nickel. 2015. "A Critical Review on Supply Chain Risk--Definition, Measure and Modeling." Omega 52: 119–32.
[8] Lin, Fu-Ren, and Michael J Shaw. 1998. "Reengineering the Order Fulfillment Process in Supply Chain Networks." International Journal of Flexible Manufacturing Systems 10: 197–229.
[9] Hugos, Michael H. 2018. Essentials of Supply Chain Management. John Wiley \& Sons.
[10] Croxton, Keely L, Sebastian J Garcia-Dastugue, Douglas M Lambert, and Dale S Rogers. 2001. "The Supply Chain Management Processes." The International Journal of Logistics Management 12 (2): 13–36.
[11] Baryannis, George, Sahar Validi, Samir Dani, and Grigoris Antoniou. 2019. "Supply Chain Risk Management and Artificial Intelligence: State of the Art and Future Research Directions." International Journal of Production Research 57 (7): 2179–2202.
[12] Tang, Ou, and S Nurmaya Musa. 2011. "Identifying Risk Issues and Research Advancements in Supply Chain Risk Management." International Journal of Production Economics 133 (1): 25–34.
[13] Hofmann, Erik, and Herbert Kotzab. 2010. "A Supply Chain-Oriented Approach of Working Capital Management." Journal of Business Logistics 31 (2): 305–30.
[14] Tang, Christopher S. 2006. "Robust Strategies for Mitigating Supply Chain Disruptions." International Journal of Logistics: Research and Applications 9 (1): 33–45.
[15] Lazzarini, Sergio, Fabio Chaddad, and Michael Cook. 2001. "Integrating Supply Chain and Network Analyses: The Study of Netchains." Journal on Chain and Network Science 1 (1): 7–22.
[16] Kölbel, Julian F, Timo Busch, and Leonhardt M Jancso. 2017. "How Media Coverage of Corporate Social Irresponsibility Increases Financial Risk." Strategic Management Journal 38 (11): 2266–84.
[17] Berry, Danny, Denis R Towill, and Nick Wadsley. 1994. "Supply Chain Management in the Electronics Products Industry." International Journal of Physical Distribution \& Logistics Management 24 (10): 20–32.
[18] Gattorna, John. 2017. Strategic Supply Chain Alignment: Best Practice in Supply Chain Management. Routledge.
[19] Blos, Mauricio F, Mohammed Quaddus, H M Wee, and Kenji Watanabe. 2009. "Supply Chain Risk Management (SCRM): A Case Study on the Automotive and Electronic Industries in Brazil." Supply Chain Management: An International Journal 14 (4): 247–52.

Doi: https://doi.org/10.54216/AJBOR.010106

[20] Ritchie, Bob, and Clare Brindley. 2007. "Supply Chain Risk Management and Performance: A Guiding Framework for Future Development." International Journal of Operations \& Production Management 27 (3): 303–22.
[21] Salin, Victoria, and Rodolfo M Nayga Jr. 2003. "A Cold Chain Network for Food Exports to Developing Countries." International Journal of Physical Distribution \& Logistics Management 33 (10): 918–33.
[22] Melo, T, S Nickel, and F Gama. 2007. "Facility Location and Supply Chain Management--a Comprehensive Review."
[23] Randall, Wesley S, and M Theodore Farris. 2009. "Supply Chain Financing: Using Cash-to-Cash Variables to Strengthen the Supply Chain." International Journal of Physical Distribution \& Logistics Management 39 (8): 669–89.
[24] Morash, Edward A. 2001. "Supply Chain Strategies, Capabilities, and Performance." Transportation Journal, 37–54.
[25] Behzadi, Golnar, Michael Justin O'Sullivan, Tava Lennon Olsen, and Abraham Zhang. 2018. "Agribusiness Supply Chain Risk Management: A Review of Quantitative Decision Models." Omega 79: 21–42.
[26] Lambert, Douglas M. 2008. Supply Chain Management: Processes, Partnerships, Performance. Supply Chain Management Inst.
[27] Lasserre, Philippe. 2017. Global Strategic Management. Bloomsbury Publishing.
[28] Hines, Tony. 2014. Supply Chain Strategies: Demand Driven and Customer Focused. Routledge.
[29] Li, Feng, and Jason Whalley. 2002. "Deconstruction of the Telecommunications Industry: From Value Chains to Value Networks." Telecommunications Policy 26 (9–10): 451–72.

Doi: https://doi.org/10.54216/AJBOR.010106