Design and Implementation of an Intelligent Hybrid Assessment Framework for Supplier Risk

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Abstract. Against the backdrop of an ever-changing global economic environment and increasingly complex supply chains, supplier risk assessment has become a key component of enterprise supply chain management. This paper aims to address the issue of incomplete data utilization in traditional supplier assessment methods, especially in handling unstructured data and responding to market fluctuations. For this purpose, the paper proposes a multi-model hybrid scoring framework that combines machine learning and deep learning. This framework integrates these technologies to comprehensively assess supplier risks. Experimental results show that the framework designed in this paper is more accurate and effective in identifying suppliers of different risk levels compared to traditional methods, helping enterprises better navigate market changes and supply chain complexities, thereby maintaining a competitive edge.

Keywords: Supplier Risk, Random Forest, LSTM Network, Supply Chain Management, Artificial Intelligence

1. Introduction

In the current economic environment, effective supply chain management has become a key factor in corporate strategic planning. Effective and rational management of supplier selection is an important link in ensuring the stability and efficiency of a company's supply chain. However, the dynamic changes in the market and the complexity of the supply chain itself increase the difficulty of supplier risk assessment for companies. How to effectively assess suppliers has become a significant factor constraining corporate development. In traditional supplier assessment methods, companies mainly rely on quantitative data such as financial indicators, supply capacity, delivery time, and other variables to evaluate the merits and reliability of suppliers[1-3]. While these methods have advantages in objectivity and quantification, they also have obvious limitations. They often fail to fully capture the comprehensive situation of suppliers, especially in terms of adaptability and flexibility in response to market fluctuations and emergency events. Additionally, these traditional assessment methods ignore the use of unstructured data (such as the supplier's reputation, business qualifications, social evaluations, etc.), which often leads to an incomplete assessment of supplier risks.

With the development of artificial intelligence technology, machine learning (ML) and deep

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learning (DL) have been widely applied in the field of supply chain management. In the field of machine learning, by applying algorithms like Support Vector Machines (SVM)[4] and Random Forest[5], companies can deeply analyze the historical transaction data of suppliers to predict the timeliness of delivery and consistency in quality. Through the predictive results of the models, companies can more accurately identify potential risks of suppliers (such as delivery delays or product quality issues) and take corresponding preventive measures. In terms of deep learning, the continuous advancement of Natural Language Processing (NLP) technology[6] provides new ways to process and parse unstructured text data from suppliers. Companies can use deep neural networks, such as Convolutional Neural Networks (CNN)[7] and Long Short-Term Memory networks (LSTM)[8], to extract sentiment tendencies and thematic information from suppliers' social media dynamics, news reports, and customer feedback. This information helps assess the market reputation and business risks of suppliers, providing decision-makers with a more comprehensive perspective for risk assessment.

Based on the respective advantages of machine learning and deep learning algorithms in supplier risk assessment, this paper proposes a multi-model hybrid scoring framework. The core of this mechanism is to combine machine learning and deep learning technologies to form a comprehensive and dynamic intelligent supplier assessment framework. In this framework, machine learning algorithms are responsible for analyzing historical transaction data to predict delivery timeliness and quality consistency. Deep learning algorithms are used to process and analyze unstructured text data, such as suppliers' social media content, news reports, and customer feedback. Finally, the results of these two algorithms are integrated into the comprehensive assessment algorithm proposed in this paper. According to the final results of the comprehensive assessment algorithm, the market reputation and business risks of suppliers are evaluated, helping companies better cope with market uncertainties and supply chain complexities, thereby promoting the company's sustainable development and competitive advantage.

2. Related Research

2.1 Supplier Risk Factors and Grading

Supplier risk is a key component of supply chain management, primarily involving the identification, assessment, and management of potential negative impacts related to suppliers[9]. For high-quality development of enterprises, it is crucial to accurately identify, assess, and manage potential risks associated with suppliers. These risks encompass multiple dimensions, including the internal operational capabilities of suppliers, adaptability to market environments, financial health, and the adequacy of business qualifications[10-12]. A comprehensive classification of these factors not only helps to clarify the sources of risk but also lays the groundwork for developing effective risk mitigation strategies.。

To maintain the stability, efficiency, and sustainable development of their supply chains, enterprises must conduct in-depth analysis and effective management of potential risks posed by suppliers. As shown in Figure 1, specific types of supplier risks include financial risk, operational risk, market risk, legal risk, geopolitical risk, technological risk, and reputational risk. Through comprehensive identification and assessment of these risk types, companies can more accurately pinpoint potential sources of risk and thus take appropriate preventative measures to minimize the negative impact of these risks.

Figure 1 Types of supplier risk

In supply chain management, enterprises implement a tiered risk level assessment method[13] to effectively manage potential risks from suppliers. This graded assessment method categorizes suppliers based on risk levels—high risk, medium risk, low risk—thereby supporting business decision-making. Low-risk suppliers typically require only routine monitoring and assessment. Medium-risk suppliers may need closer cooperation and frequent audits to ensure the maintenance of a stable supply chain. For high-risk suppliers, enterprises might need to adopt special management strategies or consider alternative supplier options to reduce the risk of supply chain disruptions or safety issues. This tiered assessment method allows companies to optimize resource allocation based on risk levels, thereby enhancing the overall effectiveness and adaptability of supply chain management.

2.2 Current State of Multi-Model Fusion Framework Research

With the rapid evolution of artificial intelligence technologies, multi-model fusion frameworks have gained significant attention in the data analytics landscape[14-15]. This advancement is a testament to AI's growing capability to handle complex and varied datasets efficiently[16]. Pioneering this development, Xu et al. [17] employed a novel approach combining hybrid feature selection with multi-model fusion, showcasing exceptional proficiency in analyzing intricate data environments. Parallelly, Wu et al. [18-19] have demonstrated the effectiveness of these frameworks in the domain of text processing, achieving high precision and efficiency in managing extensive textual data. This marks a significant milestone in the utilization of multi-model fusion techniques for processing high-dimensional data.

Expanding into areas such as medical diagnostics, fake news detection, and emotional analysis, the contributions of Ali et al. [20], Hasan et al. [21], Gupta and Parmar [22], and Yang et al. [23] highlight the versatility and effectiveness of multi-model fusion approaches. Furthermore, research by Zhang et al. [24], Koupil et al. [25], Mang and Chen [26], and Fan et al. [27] extends the application of these frameworks into emerging fields like geolocation prediction, data modeling, and economic analysis. Studies by Santhosh et al. [28], Tran et al. [29], Pipino et al. [30], and Xia et al. [31] further demonstrate the robust capability of multi-model fusion in large-scale and multi-variable data analysis, offering innovative solutions to complex technical challenges.

In summary, these studies collectively underscore the extensive application and significance of multi-model fusion frameworks in data analytics. They enhance the precision and efficiency of data analysis, offering new perspectives and methodologies for tackling complex data challenges. By integrating various models and techniques, multi-model fusion frameworks play a crucial role in augmenting data processing capabilities and decision-making accuracy, especially in environments characterized by high-dimensional and large-scale data.

2.3 Multi-Model Assessment Methods in Supplier Risk Assessment

In the field of supply chain management, multi-model integration methods are gradually becoming a research direction for supplier risk assessment[32]. This approach emphasizes integrating different assessment models and techniques to create a comprehensive and precise supplier risk assessment framework. The multi-model assessment method differs from traditional assessments that mainly focus on a single data source or technical approach. Instead, it employs a multi-angle, multi-dimensional approach to comprehensively analyze the capabilities and potential risks of suppliers. Ultimately, based on the results of the multi-model assessment, enterprises can obtain a more comprehensive view of supplier risk assessment, thereby more effectively predicting and mitigating potential supply disruptions or quality issues.

In the past, scholars and experts have adopted a dual-track strategy[33], merging qualitative and quantitative methods for supplier risk assessment. As shown in Figure 2, the core of this method lies in combining traditional quantitative and qualitative assessments to create a more comprehensive and precise risk assessment framework. Quantitative assessment focuses on using hard data, such as financial indicators, historical transaction records, and market performance, to provide an objective, quantified basis for assessment. On the other hand, qualitative assessment focuses on soft data like the supplier's business model, management quality, market reputation, etc., which often involve more subjective judgment and in-depth analysis, necessitating modifications and evaluations by industry experts. By integrating these two assessment methods, enterprises can comprehensively assess the capabilities and potential risks of suppliers from multiple perspectives, making the decision-making process more comprehensive and balanced.

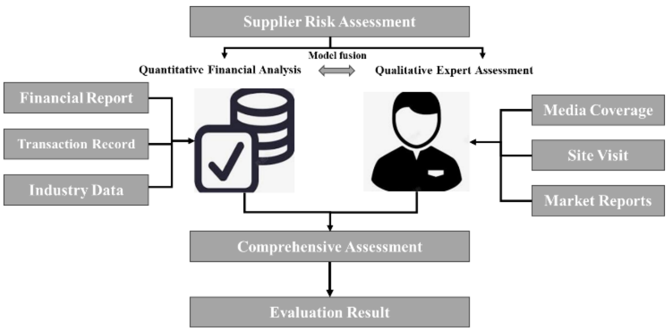

Figure 2. Traditional evaluation model

As the volume of supplier operational data rapidly increases and the supply chain environment becomes more complex, the traditional dual-track strategy faces certain limitations in handling large-scale data. To address this challenge, scholars have proposed a method that combines machine learning with manual assessment[34] to better cope with these challenges. As shown in Figure 3, in this theoretical approach, machine learning algorithms are used to process and analyze a large amount of complex supplier data, including real-time market information, suppliers' transaction history, and financial status. These algorithms can quickly identify patterns and trends, predict potential risk points, thereby providing decision-makers with timely, data-driven insights. At the same time, manual assessment still plays a crucial role in this process. The knowledge and experience of experts are vital for interpreting the outputs of machine learning models, understanding complex business environments, and providing strategic insights. Additionally, manual assessment can be used to verify and refine the results of machine learning models, ensuring the accuracy and practicality of the assessment. By combining the efficient data processing capability of machine learning with the deep business understanding of manual assessment, this integrated approach can more effectively handle supplier risk assessment in large-scale data environments. This not only improves the efficiency of risk management but also enhances the enterprise's awareness and ability to respond to potential risks in complex supply chain systems.

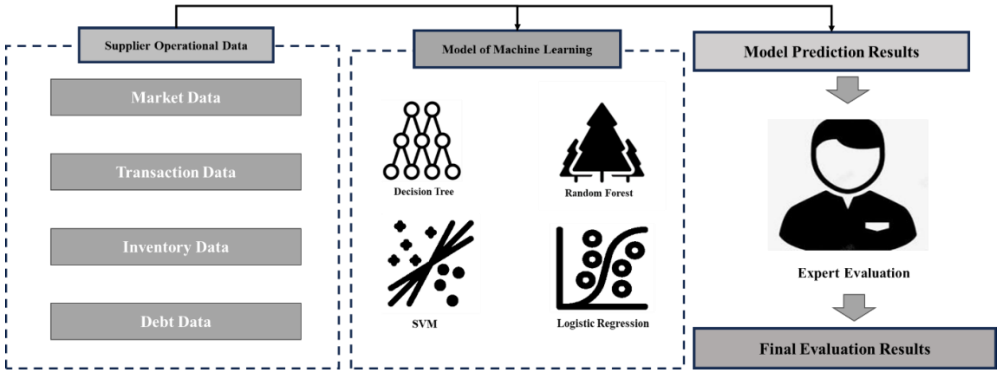

Figure 3 Machine Learning + expert evaluation

With the development of Natural Language Processing (NLP) technology, the paradigm of supplier risk assessment is evolving. NLP technology enables the automated processing and analysis of large volumes of unstructured text data[35]. By utilizing advanced methods such as sentiment analysis and topic detection[36], NLP can rapidly extract key information from sources like news reports, social media, and customer feedback, providing businesses with more comprehensive and real-time market analysis for assessing supplier risks[37]. At the same time, NLP technology compensates for the shortcomings of expert assessments in handling large-scale data and real-time data analysis, and also enhances the objectivity and accuracy of the overall assessment framework. The application of this technology, particularly in understanding and analyzing suppliers' market reputations and business risks, offers enterprises a more timely and precise perspective for risk assessment.

3. Framework Design

In the previous chapter, this article has already detailed the relevant concepts of supplier risk and multi-model assessment methods. This chapter will design and implement a supplier risk assessment framework based on machine learning and Natural Language Processing (NLP) technologies. The aim of this framework is to comprehensively utilize these algorithmic techniques to enhance the precision and efficiency of supplier risk assessments, while ensuring the comprehensiveness and reliability of the assessment results.

3.1 Construction of the Assessment Framework

Before constructing the intelligent hybrid assessment framework for supplier risk, this article first accurately defines the design goals and functional requirements of the framework. The core purpose of this preparatory stage is to establish the structure of the supplier risk framework. The main goal of framework design is to provide an accurate assessment of the current risk status of suppliers and to predict potential risks, thereby supporting enterprises to make timely strategic adjustments. In addition, the framework needs to integrate information from multi-dimensional data sources and use reasonable and effective analysis methods to ensure it can provide in-depth and extensive risk assessment.

As shown in Figure 3, to achieve these framework design goals, it is first necessary to establish a comprehensive supplier operations dataset. This article collects and integrates supplier risk data from multiple channels, including traditional structured data such as financial reports and historical transaction records, as well as unstructured data containing market dynamics and customer perceptions, such as social media activity, news reports, and customer feedback. The construction of this diversified dataset helps assess the current financial health and operational efficiency of suppliers and can also reveal other important market risk factors. Through this approach, the framework can meet the need for a comprehensive assessment of supplier risk in a dynamic market environment, ensuring that enterprises can make effective strategic decisions based on comprehensive data insights.

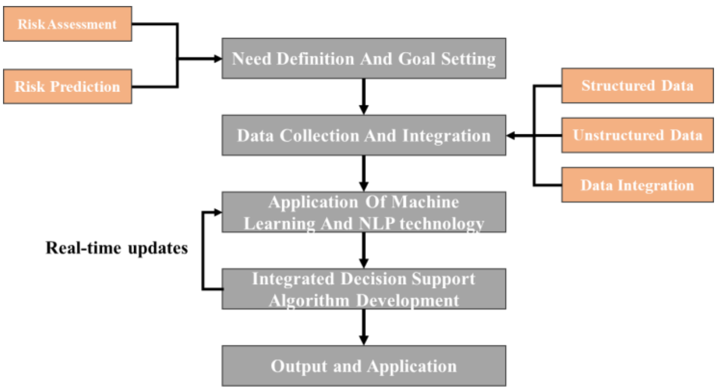

Figure 3 Process of intelligent hybrid assessment framework for supplier risk

In the second phase, the focus of the framework is on how to effectively utilize the collected dataset. In this stage, the article concentrates on applying machine learning and Natural Language Processing (NLP) technologies, aiming to extract in-depth analytical insights from the dataset established in the first phase. Specifically, machine learning algorithms are applied to analyze structured data, such as identifying risk patterns and trends from suppliers' financial reports and historical transaction records. Simultaneously, NLP technology is used to mine insights from unstructured data, like sentiment and thematic information in social media and customer feedback. The purpose of this approach is to transform the multi-dimensional data sources collected in the first phase into actionable risk assessment information, ensuring that the comprehensive risk assessment of suppliers is not limited to financial health and operational efficiency, but also includes in-depth analysis of market reputation and customer perception. Through such processing, we can ensure the maximum value is extracted from the dataset built in the first phase, providing a solid and comprehensive analytical foundation for the final integrated risk assessment.

The third phase involves the integrated application and consolidation of the results from the machine learning and Natural Language Processing (NLP) analyses conducted in the second phase. The core task of this stage is to implement an integrated decision support algorithm, whose main function is to consolidate different sources and types of analysis results into a unified, quantified supplier risk rating through a comprehensive scoring mechanism.

3.2 Implementation of the Assessment Framework

The previous section focused on designing the intelligent hybrid assessment framework for supplier risk. This section mainly transforms the theoretical and planning aspects of the design stage into an actual operational algorithm implementation, with the specific implementation steps of the framework illustrated in Figure 4.

In the process of implementing the framework, the first step involves data preprocessing of the collected structured supplier data (such as XLSX, CSV, DB, etc.) and unstructured supplier data (like DOCX, TXT, PDF, etc.) to ensure the collected data is suitable for subsequent risk analysis. Specific operations include standardizing structured data through data cleaning processes, which involves correcting format inconsistencies, filling missing values, removing outliers, and deleting duplicate records. For unstructured data, the process involves text normalization by removing irrelevant content such as headers, footers, and advertising text, and standardizing grammar to extract the core textual content for analysis. Moreover, to enhance the representativeness of the dataset and the depth of analysis, relevant external data sources are introduced to expand the original data. This can include market dynamics data, industry reports, etc., which are used to enhance the information volume and diversity of the original dataset.

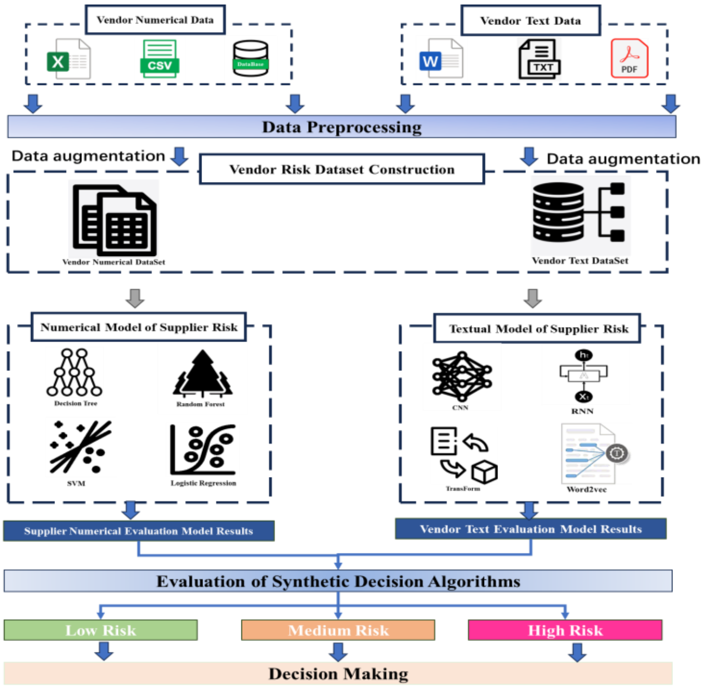

Figure 4 Implementation of an intelligent hybrid assessment framework for supplier risk

After preprocessing, the structured and unstructured supplier-related data are transformed into two main datasets: a supplier numerical dataset and a text dataset. The numerical dataset focuses on quantitative information, such as financial indicators and transaction history, while the text dataset contains qualitative information, like market dynamics and customer feedback. Based on the numerical dataset, this paper employs advanced machine learning technologies, such as Random Forest (RF) and Support Vector Machine (SVM), to build a numerical assessment model. This model can perform quantitative analysis of the supplier's financial health and operational efficiency, providing key risk indicators. For the text dataset, Natural Language Processing (NLP) technologies, such as Long Short-Term Memory networks (LSTM) and Word2vec, are used to construct a text assessment model. These technologies can deeply parse text content, extracting key information about the supplier's market reputation and customer perception. Through sentiment analysis and topic modeling, the text assessment model can complement the results of the numerical model, offering a more comprehensive perspective on risk.

Based on the results of the supplier numerical assessment model and text assessment model, this paper adopts a comprehensive decision algorithm to assess the risk level of suppliers. In implementing the comprehensive decision algorithm, a multivariate linear regression analysis is first conducted on the numerical dataset (D_{numeric}) and text dataset (D_{text}), using historical risk levels as the dependent variable, thereby obtaining the regression coefficients β_{numeric} and β_{text} Next, the information entropy H_{numeric} and H_{text} for each dataset is calculated, and the information entropy weights are calculated using the following formulas (1) and (2):

$$W_{\text{entropy,numeric}} = -\frac{H_{\text{mumeric}}}{H_{\text{numeric}} + H_{\text{text}}} \tag{1}$$

$$W_{\text{entropy,text}} = -\frac{H_{\text{text}}}{H_{\text{numeric}} + H_{\text{text}}} \tag{2}$$

Then, the regression coefficients and information entropy weights are combined to calculate the final weighted coefficients W_{numeric} 和 W_{text} as shown in the following formulas(3)(4):

$$W_{\text{numeric}} = \alpha\left(\frac{\beta_{\text{numeric}}}{\beta_{\text{numeric}} + \beta_{\text{text}}}\right) + (1-\alpha)W_{\text{entropy,numeric}} \tag{3}$$

$$W_{\text{text}} = \alpha\left(\frac{\beta_{\text{text}}}{\beta_{\text{numeric}} + \beta_{\text{text}}}\right) + (1-\alpha)W_{\text{entropy,text}} \tag{4}$$

In this context,, α is a tuning factor ranging between 0 and 1, used to balance the influence of the regression coefficients and the information entropy weights. The specific implementation principle of the comprehensive decision-making algorithm is shown in Table 1. This algorithm aims to aggregate the outputs of the numerical and text models to arrive at a comprehensive judgment regarding the supplier's risk level.

Table 1 Principle of comprehensive decision algorithm

Algorithm: Advanced Comprehensive Decision Algorithm for Suppler Risk Assessment

Input:

suppliers: List of suppliers
numericData: {NumericDatal, NumericData2,..., NumericDataN} for each supplier
textData:{TextDatal, TextData2,..., TextDataN} for each supplier numericWeight w1 textWeight w2
riskThresholds: {HighRiskThreshold, MediumRiskThreshold}

Process:

Initialize supplierRiskScores as an empty list
For each supplier **in** suppliers:
mumericScore =ApplyMachineLeamningModel(mumericData[supplier]) textScore = ApplyNLPModel(textData[supplier])
combinedScore = w1 * numericScore +w2* textScore
riskLevel = **"Low"**
If combinedScore > riskThresholds["HighRiskThreshold"]:
riskLevel = **"High"**
Else If combinedScore > riskThresholds["MediumRiskThreshold"]: riskLevel = **"Medium"**
supplierRiskScores.append({"Supplier": supplier, "RiskLevel": riskLevel, "Score": combinedScore })
Sort supplierRiskScores by Score in descending order

Output: supplierRiskScores

In the final stage of the comprehensive decision-making algorithm, the framework provides an assessment of the supplier's risk level by integrating and analyzing the outputs from both the numerical and text assessment models. The output of the algorithm includes the risk level and a composite score for each supplier. With this information, businesses can more accurately identify key risk points and vulnerabilities within the supply chain. The quantified risk ratings enable enterprises to allocate resources and formulate risk mitigation strategies according to the priority of risk levels

4. Experiment

The experiments related to this article were conducted in an environment configured with the Ubuntu 22.04 operating system, an 8-core CPU, NVIDIA GeForce RTX 3080, and 16GB of system memory. The programming language used was Python 3. Data cleaning and preprocessing for numerical data were performed using Pandas, while the training and application of the Random Forest model were implemented using Scikit-learn. The PyTorch framework was utilized to build and train the LSTM model.

The analysis of the three models – Random Forest, LSTM, and the comprehensive decision algorithm (referred to as 'Ours' in the study) – reveals significant findings in the context of supplier risk assessment accuracy. According to the data presented in Table 2, the comprehensive decision algorithm demonstrates superior performance. Specifically, it achieves the highest accuracy rates across all risk categories: **high risk (98.75%)**, **medium risk (99.27%)**, and **low risk (98.81%)**. This outperforms both the Random Forest model (with accuracy rates of 91.54% for high risk, 90.22% for medium risk, and 93.62% for low risk) and the LSTM model (95.11% for high risk, 89.47% for medium risk, and 96.14% for low risk). The results underscore the effectiveness of the comprehensive decision algorithm in assessing supplier risk levels with a high degree.

Table 2 Recognition accuracy of three models

Accuracy / Algorithm	High Risk	Medium Risk	Low Risk
Random Forest	91.54	90.22	93.62
LSTM	95.11	89.47	96.14
Ours	**98.75**	**99.27**	**98.81**

To comprehensively evaluate the practical effectiveness of the supplier risk intelligent hybrid assessment framework proposed in this article, a comparative analysis was conducted with the two mainstream supplier risk assessment methods mentioned earlier. As shown in Figure 5, the experimental results clearly demonstrate that compared to traditional multi-model assessment methods and the combination of machine learning with expert assessment, the framework proposed in this article exhibited higher recognition accuracy. This significant performance advantage proves the remarkable effectiveness of the framework in accurately assessing supplier risks, offering a more effective tool for supply chain risk management.

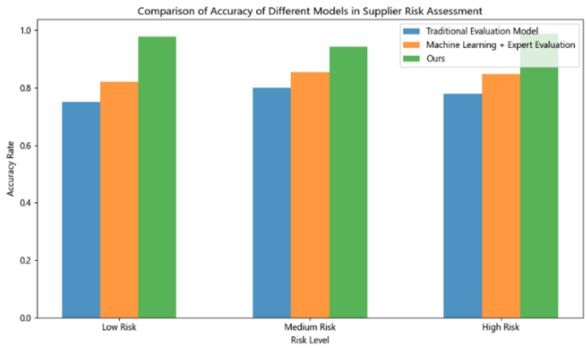

Figure 5 Comparison of accuracy rates of different models in supplier risk assessment

Based on the assessment framework that was practically trained, this article conducted a risk assessment of five potential suppliers (Suppliers A to E) with whom the enterprise might collaborate in the future. The results of the assessment, as shown in Figure 6, indicate that Suppliers A and D have lower risk scores, making them ideal partners for the enterprise. Suppliers B and C have moderate risk scores and are potential candidates for collaboration. However, Supplier E has a higher risk score, indicating significant risks, and is therefore not suitable for collaboration with the enterprise.

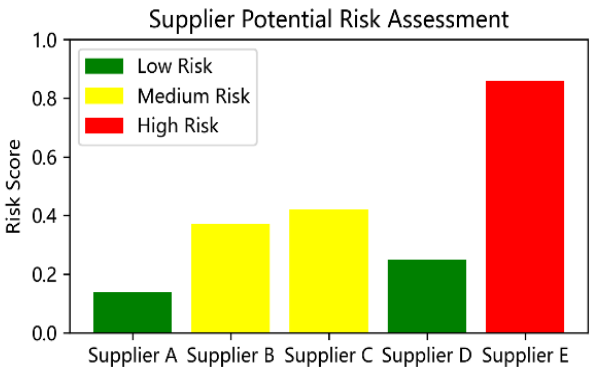

Figure 6 Potential supplier risk assessment results

5. Conclusions

This paper has successfully designed and implemented a novel supplier risk intelligent hybrid assessment framework that integrates machine learning and Natural Language Processing (NLP) technologies. The core feature of the framework is that it combines traditional quantitative assessment methods with qualitative analysis using modern artificial intelligence techniques, providing a comprehensive, flexible, and efficient solution for supplier risk assessment.

Experimental results show that the comprehensive decision algorithm proposed in this article has significant accuracy in assessing supplier risk levels, especially excelling in identifying high-risk and low-risk suppliers. This achievement proves that, compared to traditional methods of supplier risk assessment, the multi-source and multi-method comprehensive assessment framework proposed in this article is more effective. With the rapid progress in data science and artificial intelligence, future work may integrate emerging technologies (such as blockchain and IoT) into the assessment framework proposed in this article to improve transparency, traceability, and efficiency in supply chain management. Future research could explore the application of the framework in different industries and market environments, as well as how to adjust and optimize the model according to specific business needs and market changes. In summary, this study not only provides a new perspective in the field of supplier risk assessment theoretically but also demonstrates its strong application potential in practice. The implementation of this intelligent hybrid assessment framework will help enterprises manage and mitigate supply chain risks more effectively, thereby promoting their sustainable development and competitive advantage in a highly competitive market.

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