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Methods for Supplier Default Risk Assessment in Supply Chains: A Review

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Abstract. Supplier default risk represents a critical concern in supply chain management. This paper systematically reviews three quantitative approaches for supplier default risk assessment: weighted scoring, logistic regression, and Bayesian methods. The weighted scoring method constructs indicator systems with subjective or objective weights to rank suppliers by composite scores. Logistic regression models the log-odds of default as a linear function of supplier characteristics to estimate default probability. Bayesian methods, which are closely related to logistic regression, combine prior distributions with observed data to generate posterior probabilities, enabling dynamic updating and small-sample inference. Based on the comparative analysis, this paper proposes a multi-dimensional framework to guide method selection in procurement decisions. Research gaps and future directions are also identified, including dynamic updating mechanisms, integration of unstructured data, and the convergence of Bayesian methods with machine learning. Future research should explore real-time risk assessment and hybrid approaches that combine methods with machine learning to support more scientific supplier evaluation and enhanced supply chain resilience.

Keywords: Supplier default risk, risk assessment, logistic regression, Bayesian methods, literature review

1. Introduction

Globalization and supply chain complexity have elevated supplier default risk—delays, quality failures, or bankruptcy—into a critical operational threat. A single failure can cascade, halting production and eroding revenue. Consequently, rigorous risk assessment is essential. This risk has drawn substantial scholarly attention. Wagner, Bode, and Koziol demonstrated that suppliers' default dependencies—where one failure alters others' default probabilities—significantly affect sourcing decisions, highlighting the need for systematic, interdependence-aware methodologies [1]. Such interdependencies complicate evaluation and demand statistical tools capable of modeling them.

Three mainstream methods are widely used: weighted scoring, logistic regression, and Bayesian methods. Weighted scoring dominates practice for its simplicity and transparency; Logistic regression is the academic standard, delivering strong predictive accuracy across industries; Bayesian methods are increasingly adopted for their ability to integrate prior knowledge, handle sparse data, and update estimates dynamically with new evidence. These three methods represent

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three distinct methodological traditions and differ in technical sophistication, ranging from low to high.

Yet key gaps remain: studies typically examine methods in isolation, offering little guidance on selection under varying data conditions; multi-dimensional comparative frameworks are scarce, and integration with big data and machine learning remains underexplored.

This paper bridges these gaps through a comprehensive literature review of the three methods. It addresses three questions: (1) What are the theoretical foundations and data requirements of each method? (2) How are they applied and in which fields? (3) How should practitioners select the appropriate method and improve the accuracy of prediction for different scenarios? Using a systematic literature review approach, this study synthesizes academic and industry findings, develops a comparative framework, and proposes a practical selection flowchart based on data availability and assessment objectives. And it will enhance supplier evaluation and supply chain resilience by clarifying the distinct roles of each method, identifying future research directions, and offering procurement professionals a practical reference.

2. Review of three methods

2.1. Weighted scoring method

2.1.1. Theoretical foundation

The weighted scoring method is one of the most widely used and intuitive approaches to supplier risk assessment. Its core logic is straightforward: construct a multi-dimensional evaluation indicator system, assign weights to each indicator based on its relative importance, score each supplier against these indicators, and compute a weighted sum to obtain a comprehensive risk score. Mathematically, the risk score for supplier i can be expressed as:

$$S_i = \sum_{\{j=1\}}^{\{n\}} w_j x_{\{ij\}} \quad (1)$$

where S_i is the total risk score for supplier i, w_j is the weight assigned to indicator j, $x_{\{ij\}}$ is the score of supplier i on indicator j, and n is the total number of indicators.

2.1.2. Application

The determination of weights can be achieved through various methods, which are generally categorized into three types. There are subjective, objective and combined weighting methods.

Subjective weighting methods rely on expert judgment to evaluate the relative importance of each indicator. The Analytic Hierarchy Process (AHP) and the Delphi method are widely used examples. Objective weighting methods primarily include the Entropy Weight Method and the Coefficient of Variation Method, which determine weights based on the degree of dispersion in each indicator's data—the greater the variation, the higher the weight assigned, thus avoiding subjective bias [2]. Combined weighting methods integrate subjective and objective approaches to balance expert experience with empirical data。

In the AHP framework, the decision problem is decomposed into a hierarchical structure consisting of the goal layer (first-level indicators), the element layer (second-level indicators), and the indicator layer (third-level indicators) to assign weights [3]. Ultimately, the problem boils down to determining the relative importance or priority of plans and measures for decision-making in

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relation to the overall goal [4]. Pairwise comparison methods are then used to construct a judgment matrix, and a consistency check is performed to verify the matrix's validity [5]. Through this process, decision-makers can quantify the relative importance of different risk factors and derive indicator weights for supplier evaluation.

2.2. Logistic regression

2.2.1. Theoretical foundation

Logistic regression is also one of the most widely used statistical models for binary classification problems, and it has been extensively applied to supplier default risk assessment. It is an extension of the generalized linear model and it contains two types of variables: dependent variables and a set of independent variables. The dependent variable is a binary categorical variable, while independent variables represent observable supplier characteristics. The model estimates the probability that a supplier will default based on these predictor variables. As a representative of the frequentist school of statistics, Logistic regression assumes that the data are generated from an underlying probabilistic process with fixed but unknown parameters.

Formally, the Logistic regression model is specified as:

$$P(y=1|\mathbf{x}) = 1/\left(1+e^{\{-(\beta_0+\beta_1 x_1+\cdots+\beta_k x_k)\}}\right) \tag{2}$$

This model supposes that there are k independent variables and the dependent variable y takes value of {0,1} which aims to represent whether the suppliers are good or bad. Typically, y=0 means that the suppliers are good and y=1 means bad instead.

Then, it can be transferred into the log-odds function:

$$\ln\left(\frac{\mathrm{P}}{1-\mathrm{P}}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k \tag{3}$$

This form shows that the essence of logistic regression is that the log-odds form is a linear model. Model parameters are estimated by using maximum likelihood estimation.

2.2.2. Application

Logistic regression score card is one of the applications of this method. It is a tool that turns customer features into a combined score and is widely used in credit risk assessment. The scorecard's scale converts the output of a logistic regression model into scores that are easy to understand using a linear formula. The function is shown as Score = A - B * log(odds).

Cao mentioned that petroleum companies improve their management of purchase based on this method according to the input invoice data and characteristics such as basic attribute, business and management representation. After feature selection, the model picked 9 feature variables for logistic regression fitting. This helps companies to reduce the risk of trade [6].

2.3. Bayesian methods

2.3.1. Theoretical foundation

Bayesian methods provide a framework for updating beliefs about uncertain parameters or hypotheses by combining prior knowledge with observed data through Bayes' theorem. The

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approach combines prior information about unknown parameters with sample information; using Bayes' theorem, it derives posterior information for inference [7]. Bayes' theorem can be formally expressed as:

$$P(\theta|X) \propto P(X|\theta)P(\theta) \tag{4}$$

where $P(\theta)$ is the prior distribution, representing the existing belief about the parameter θ before observing any data; $P(X|\theta)$ is the likelihood function, representing the probability of observing the data X given the parameter θ; and $P(\theta \mid X)$ is the posterior distribution, representing the updated belief about the parameter after observing the data.

Unlike frequentist methods that provide only point estimates, the posterior distribution is a complete probability distribution, which allows for direct probabilistic statements about parameter uncertainty.

2.3.2. Application

In supply chain risk management, Bayesian networks extend Bayesian inference by representing probabilistic relationships among multiple risk factors. By incorporating both expert knowledge and observed data, Bayesian networks can estimate the probability of different risk events and provide decision support under uncertainty.

Bayesian network models have been applied to supplier evaluation and related risk assessment problems, particularly when historical data are limited. Hunte et al. proposed a Bayesian network model for consumer product risk assessment, which was capable of handling new products or products with limited historical data, addressing limitations of traditional methods [8]. In the fresh food logistics sector, Zhao et al. combined Bayesian networks with fuzzy set theory to address subjectivity in expert scoring; their model, implemented in GeNIe4, yielded quantitative risk assessments based on a four-category indicator system covering infrastructure, personnel, operations, and external environment [9].

Using the Bayesian network modelling software GeNIe4, Qiao applied the K2 algorithm for structural learning to identify an optimal network structure. Subsequently, company-related data were processed through a risk evaluation matrix for parameter learning [10]. This helps the company K to form a complete model and decide whether the supplier can keep working or not.

3. Comparative analysis and method selection guidance

3.1. Multi-dimensional comparison

A multi-dimensional comparison of the three approaches is presented to facilitate systematic method selection. The comparison is organized along seven key dimensions, including theoretical foundations, data requirements, output forms, uncertainty quantification, dynamic updating capability, small-sample performance, and computational complexity. The results are summarized in Table 1.

Table 1. Comparison of three supplier risk assessment methods

Dimension	Weighted scoring	Logistic regression	Bayesian methods
Theoretical foundation	Muti-criteria decision	Frequentist statistics, MLE	Bayesian statistics, posterior inference

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Table 1. (continued)

Data requirement	Low	High	High
Output form	Ranking	Point estimate	Full probability
Dynamic updating	No	No	Yes
Computational complexity	Lowest	Low	High
Small-sample performance	Feasible(expert-based)	Poor	Good
Uncertainty quantification	Not available	Confidence interval	Full probability distribution

As shown in Table 1, no single method dominates across all dimensions. The choice among the three approaches inherently involves trade-offs among interpretability, data availability, analytical rigor, and implementation feasibility. The following section translates these dimensional comparisons into practical selection guidance for procurement practitioners.

3.2. Method selection framework

Based on the comparative analysis above, a decision framework for method selection can be established. The framework is organized around three typical data scenarios that procurement practitioners commonly encounter.

Firstly, when historical default data are unavailable and the primary objective is supplier selection or initial screening, the weighted scoring method is appropriate. This method leverages expert knowledge and experience. It constructs indicator systems and produces risk ranking by using publicly available information. Weighted scoring is a relatively simple and widely used method for new supplier admission.

Secondly, when sufficient historical default data are available and the task is periodic risk assessment of existing suppliers, logistic regression is more suitable. It is well-suited for regular portfolio reviews where labeled data are available and the assessment horizon is fixed since this method generates objective, interpretable probability estimates at a single point in time.

Thirdly, when data availability is limited, expert knowledge is valuable, dynamic updating is required or risk factor dependencies need to be modeled, Bayesian methods are particularly suitable. The Bayesian approaches handle small samples through informative priors and support continuous updating as new information arrives. The Bayesian networks are particularly valuable for monitoring strategic suppliers.

It should be noted that these three conditions represent archetypal scenarios; in practice, organizations may encounter hybrid situations. For instance, an organization may have limited labeled data but still wish to apply a data-driven approach—in such cases, Bayesian methods with weakly informative priors may be the most sensible choice. Similarly, an organization may use weighted scoring for initial screening and then apply Logistic regression or Bayesian methods for shortlisted suppliers requiring deeper analysis. The selection framework is intended as a guiding reference, not a rigid prescription.

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3.3. Practical considerations

Beyond the theoretical conditions outlined in the selection framework, several practical considerations may influence method choice in real-world procurement settings.

First, data availability varies significantly across firms. While logistic regression and Bayesian methods offer superior analytical power, they require substantial historical data on supplier defaults—a rare event in many industries. Procurement departments often lack structured datasets, making simpler methods like weighted scoring more immediately feasible.

Second, organizational acceptance matters for implementation. Weighted scoring is easily understood by practitioners without statistical backgrounds, whereas complex models may face resistance from decision-makers who distrust "black-box" approaches.

Third, implementation cost differs substantially. Weighted scoring requires minimal infrastructure; logistic regression demands moderate recalibration efforts; Bayesian methods require specialized expertise and computational resources that small teams may not sustain.

These practical factors often weigh as heavily as statistical rigor in final method selection.

4. Research gaps and future directions

Despite the strengths of the three methods reviewed, several research gaps remain. First, most existing assessments are static. Weighted scoring and logistic regression generate risk estimates at a single point in time and do not update when new information arrives. While Bayesian methods offer a natural framework for dynamic updating, their application in procurement contexts remains limited. Second, unstructured data sources—news reports, social media sentiment, and regulatory filings—are underutilized, yet they contain early warning signals not captured by structured indicators. Third, practical adoption barriers for Bayesian methods persist, as they require specialized software and statistical expertise that many procurement organizations lack.

Future research should explore the integration of machine learning and large language models (LLMs) with traditional statistical methods. Machine learning algorithms can detect complex patterns in structured supplier data, while LLMs can extract risk signals from unstructured sources such as news articles, earnings call transcripts, and regulatory filings. These extracted signals can then be incorporated into Bayesian updating frameworks for continuous risk monitoring [11]. Additionally, hybrid models that combine predictive analytics with probabilistic inference should be developed to enable more accurate and dynamic risk assessment. Finally, user-friendly tools and interpretable visualizations are needed to lower adoption barriers and facilitate practical implementation in procurement organizations.

5. Conclusion

This essay has reviewed three methods for supplier default risk assessment: weighted scoring, logistic regression, and Bayesian methods. By examining the theoretical foundations and practical applications of each approach, the analysis reveals distinct strengths and limitations that inform method selection under varying conditions.

Weighted scoring is a practical choice for screening new suppliers when historical data are unavailable. It is simple, interpretable, and easy to implement, though it relies on subjective judgment and static frameworks. Logistic regression provides a data-driven approach for existing suppliers with sufficient historical labels, generating objective probability estimates that support risk-based decisions. However, it is static and requires large samples. Bayesian methods offer the most flexible framework—handling small samples, enabling dynamic updating, quantifying uncertainty, and modeling risk factor dependencies through Bayesian networks.

The comparative analysis shows that no single method is universally optimal. Method selection should depend on data availability and organizational capability. A progressive pathway—from weighted scoring to Logistic regression to Bayesian methods—offers a practical route for building analytical maturity.

Key research gaps include the need for dynamic updating mechanisms, integration of unstructured data, and the convergence of Bayesian methods with machine learning. Future work should also develop user-friendly tools to lower adoption barriers and pay more attention to the field of machine learning and AI.

In conclusion, effective supplier risk assessment requires aligning method choice with organizational context. Understanding each method's strengths and limitations enables better procurement decisions and more resilient supply chains.

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