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**Original Research Article**

# Evaluation of Supply Chain Finance Strategies under Credit Risk Uncertainty: A Multi-Criteria Decision-Making Approach

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In today's volatile business environment, selecting an optimal supply chain finance (SCF) strategy under credit risk uncertainty has become a critical concern—particularly for small and medium-sized enterprises (SMEs). This study evaluates and prioritizes SCF strategies with a focus on mitigating credit risk, using a multi-criteria decision-making (MCDM) approach. Key evaluation criteria were identified through expert consultation and the Delphi method. The Analytic Hierarchy Process (AHP) was then employed to assign weights to these criteria, followed by the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to rank five major SCF strategies. The findings reveal that fintech-based strategies are the most effective in mitigating credit risk, offering benefits such as increased transparency, greater flexibility, and risk transfer to third-party financial institutions. In contrast, traditional receivables-based methods, such as factoring, were ranked lowest in effectiveness.

This research addresses a critical gap by incorporating credit-risk-specific evaluation criteria into SCF strategy selection—an aspect often overlooked in conventional models that focus primarily on cost or liquidity. By integrating AHP and TOPSIS with Delphi-based expert validation, the study introduces a structured, risk-sensitive decision-making framework. Additionally, the inclusion of modern approaches such as fintech-enabled SCF and reverse factoring within a unified comparative model enhances the

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existing literature and supports resilient financial decision-making in uncertain environments.

Ultimately, the study provides a robust, empirically validated framework for decision-makers seeking to strengthen financial resilience across supply chains, particularly under credit uncertainty.

**Keywords:** Supply Chain Finance, Credit Risk, AHP, TOPSIS, Fintech, Multi-Criteria Decision Making (MCDM)
**JEL Classification*:*** G32, D81, C44

# 1 Introduction

In recent years, supply chain management has emerged as one of the most vital and strategic domains in the competitive business landscape. A critical component of this domain is Supply Chain Finance (SCF), which serves as a financial intermediary among various entities within the supply network. The primary goal of SCF is to maintain operational continuity and preserve liquidity—especially amid economic uncertainties and global disruptions. Increasing pressures from payment delays and financial volatility have compelled firms—particularly small and medium-sized suppliers—to seek innovative financing solutions.

One of the most significant challenges to achieving sustainable SCF is the management of credit risk, defined as the likelihood that a party will fail to meet its financial obligations. Such failures can have cascading effects, potentially disrupting the entire supply chain. Therefore, selecting an appropriate financing strategy is not only critical but inevitable. However, identifying the optimal SCF strategy in real-world uncertain conditions is inherently complex. Factors such as liquidity, risk, transparency, commercial relationships, and flexibility all influence the decision-making process. As a result, multi-criteria decision-making (MCDM) methods become essential for a rational and effective evaluation of strategic alternatives.

From a theoretical standpoint, the significance of SCF in mitigating credit risk and enhancing financial resilience can be supported by economic frameworks such as Transaction Cost Economics (TCE) and Agency Theory. TCE underscores the importance of mechanisms that reduce information asymmetry and coordination costs among supply chain participants—an objective well aligned with SCF tools such as dynamic discounting and reverse factoring. Similarly, Agency Theory addresses conflicts of interest and trust gaps between supply chain actors—particularly between buyers and financially constrained suppliers—which SCF helps resolve through transparent and structured financing mechanisms.

While prior studies have predominantly focused on conventional financial analysis models, few have incorporated credit risk perspectives into MCDM



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frameworks. This study aims to fill that gap by comparing and ranking SCF strategies using both quantitative and qualitative criteria under uncertainty. By leveraging expert input and structured decision-making techniques, the research offers a comprehensive analytical framework for selecting optimal SCF strategies with a specific focus on credit risk mitigation.

The remainder of this article is organized as follows. Section 2 reviews the relevant literature on supply chain finance and credit risk and outlines the theoretical foundations underpinning the study. Section 3 introduces and classifies the main supply chain finance strategies considered in the analysis. Section 4 describes the research methodology, including the expert panel, data collection instruments, and the application of the Delphi method. Section 5 presents the identification and validation of credit-risk-related evaluation criteria. Section 6 develops the integrated AHP–TOPSIS decision-making framework and reports the ranking results along with sensitivity analysis. Section 7 discusses the key findings and their managerial implications. Section 8 provides a broader discussion of the results in light of existing studies. Finally, Section 9 concludes the paper by summarizing the main contributions, outlining policy implications, acknowledging limitations, and suggesting directions for future research.

## 2 Literature Review

### 2.1 Supply Chain Finance (SCF)

Supply Chain Finance (SCF) refers to a portfolio of financial, technological, and managerial tools aimed at optimizing working capital and unlocking liquidity trapped in the transactional processes of supply chains (Caniato et al., 2019). The primary objective of SCF is to reduce financing costs and improve access to liquidity by streamlining financial flows among various supply chain participants.

SCF becomes particularly crucial during periods of economic turbulence and uncertainty, functioning as a key mechanism for mitigating risk and maintaining operational continuity. The literature emphasizes that SCF fosters better alignment between buyers and suppliers by integrating financial processes and enhancing the efficiency of working capital management (Hofmann & Kotzab, 2010). In emerging economies such as Iran, studies have also examined SCF's role in enhancing enterprise sustainability.



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## 2.2 The Concept of Credit Risk in Supply Chains

Credit risk in supply chains refers to the likelihood that a participant may default on its financial obligations. This type of risk can disrupt liquidity flows, increase financing costs, and, in extreme cases, trigger systemic instability throughout the entire supply network (Nyaga et al., 2010). The impact of credit risk extends beyond the defaulting party, potentially affecting the financial health and continuity of other supply chain participants.

Effectively managing credit risk requires identifying its underlying drivers and applying structured evaluation methodologies. One increasingly adopted approach involves Multi-Criteria Decision-Making (MCDM) models, which incorporate both financial and non-financial indicators to assess and mitigate credit risk. These models enable organizations to evaluate creditworthiness from a more holistic strategic and operational perspective, thereby enhancing resilience a

mid uncertainty.

## 2.3 Research Background

Several studies have examined various dimensions of supply chain finance (SCF) and credit risk, offering valuable insights into evolving methodologies, risk mitigation strategies, and technological advancements. Table 1 provides a summary of key contributions in this field:



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Table 1
*Summary of Key Research Contributions on SCF and Credit Risk*

| | Author(s) | Year | Focus Area | Key Findings |
|---|---|---|---|---|
| 1 | Wuttke et al. | 2016 | Innovation adoption in SCF in the automotive sector | Identified credit risk as a critical factor in selecting SCF instruments. |
| 2 | Liebl et al. | 2016 | Credit and operational risk in automotive supply chains | Highlighted the importance of contractual mechanisms in credit risk management. |
| 3 | Abbasi et al. | 2019 | IoT-based collateral risk mitigation in SCF | Proposed innovative credit insurance solutions for SMEs. |
| 4 | Cai & Zhang | 2021 | Credit evaluation of internet-based SCF firms | Applied Entropy-Weight and TOPSIS to rank firms by credit performance. |
| 5 | Zhang et al. | 2022 | Credit risk assessment using multi-source data fusion for SMEs | Used machine learning and MCDM to enhance credit evaluations. |
| 6 | Liu et al. | 2023 | Credit classification in SCF using big data and graph analysis | Developed automated systems for credit assessment. |
| 7 | Tabachová et al. | 2024 | Credit contagion effects on financial stability | Analyzed credit risk propagation in multi-layered SC networks. |
| 8 | Geng et al. | 2024 | Credit risk contagion modeling using Cox–Copula & Markov chains | Modeled systemic risk in interconnected supply networks. |
| 9 | Qingkai Zhang et al. | 2025 | Generative models for credit risk management in SCF | Applied AI techniques (QRGMM + DeepFM) for advanced risk assessment. |
| 10 | Zhang et al. | 2025 | Credit risk identification using GANs in SC networks | Improved prediction accuracy through generative adversarial networks (GANs). |

## 3 Supply Chain Finance Strategies

Based on the framework introduced by the Global Supply Chain Finance Forum (GSCFF), supply chain finance (SCF) strategies can be categorized into five main types, depending on their underlying structure, credit risk exposure, and the nature of financial flows within supply chains.

### 3.1 Receivables-Based Financing

These strategies focus on the supplier's accounts receivable and include the following:

**Invoice Discounting:** The supplier sells its accounts receivable (typically in the form of invoices) to a financial institution in exchange for immediate



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liquidity. This method is commonly used when the supplier has several large and creditworthy buyers.

**Factoring:** A commercial finance technique in which the supplier transfers its receivables to a factor (usually a financial institution), which then manages collection and assumes some or all of the credit risk.

**Forfaiting:** Involves the sale of future payment obligations—often arising from international trade to a forfaiter, typically without recourse. These obligations are usually backed by negotiable instruments such as promissory notes or bills of exchange.

### 3.2 Payables-Based Financing

These buyer-centric strategies aim to optimize the buyer's working capital position:

**Reverse Factoring (or Confirming):** The buyer initiates the financing process by approving the supplier's invoice, allowing the supplier to receive early payment from a financial intermediary. This method is most effective for buyers with strong credit ratings and helps reduce supplier default risk.

**Dynamic Discounting:** The buyer offers early payment to the supplier in exchange for a discount. This process is often facilitated through digital platforms that automate the negotiation and execution of early payment terms.

### 3.3 Loan/Advance-Based Financing

These strategies involve pre-shipment or post-shipment financing mechanisms:

**Receivables-Backed Loans:** Loans are issued based on receivables or anticipated future sales, even in the absence of physical collateral.

**Inventory Financing:** Loans are secured by inventory held in a warehouse or under a bailment arrangement, where the lender retains legal ownership or control until repayment.

**Pre-Shipment Finance:** Financing is provided to suppliers to support procurement, production, or logistics activities prior to delivery. This typically requires a valid purchase order or a letter of credit.

### 3.4 Digital/Fintech-Based Financing

These innovative strategies leverage emerging technologies to manage financial risk and streamline transactions:

**Blockchain and IoT-Enabled Financing:** These tools automate data verification, enhance security, and improve the traceability of transactions.



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**AI-Driven Credit Assessment:** Machine learning algorithms are used to assess creditworthiness and detect irregularities in financial behavior.

**Smart Contracts:** Self-executing contracts that trigger payments or other actions automatically based on predefined terms, thereby reducing manual processes and increasing trust.

### 3.5 Inventory/Order-Based Financing

These strategies are anchored in the physical flow of goods and include:

**Purchase Order Finance:** Financing is provided based on confirmed purchase orders from reputable buyers.

**Inventory-Based Loans:** Secured lending is offered against warehouse inventory or future delivery contracts, making it suitable for pre-sales and distribution phases.

## 4 Methodology

### 4.1 Research Design

This study adopts an applied research approach, utilizing descriptive–analytical methods within a real-world organizational context. The methodological framework integrates two Multi-Criteria Decision-Making (MCDM) techniques: the Analytic Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS).

The research process began by identifying evaluation criteria for SCF strategies through expert consultation and a systematic literature review. The Delphi method was then applied to validate these criteria under conditions of credit risk uncertainty. AHP was subsequently used to calculate the relative weights of the finalized criteria, while TOPSIS was employed to rank the SCF strategies accordingly.

### 4.2 Expert Panel and Sample

A panel of 14 experts participated in the study, including:

- 7 academic scholars,
- 3 senior banking professionals
- 4 risk management specialists from financial institutions.

This diverse panel ensured balanced representation of both theoretical knowledge and practical expertise in credit risk and supply chain finance.



[ DOI: 10.66224/jme.20.1.69 ]

### 4.3 Data Collection Instruments

Two structured questionnaires were used to collect expert input:

1) **AHP Questionnaire:** Designed to conduct pairwise comparisons of the 10 evaluation criteria using Saaty's 9-point scale (ranging from 1 = equally important to 9 = extremely more important).
2) **TOPSIS Questionnaire:** Experts rated the five SCF strategies against each criterion using a 9-point Likert scale (from 1 = very poor to 9 = excellent).

### 4.4 Delphi Method for Criteria Validation

The Delphi method was implemented in two rounds:

**Round 1:** Experts rated the importance of each criterion on a 5-point Likert scale. Criteria with an average score above 3.5 were retained. Those scoring between 3.2 and 3.5 were re-evaluated in the second round.

**Round 2:** Final validation confirmed consensus on 10 criteria, each exceeding the 80% agreement threshold. These criteria were then used in the AHP-TOPSIS analysis.

The Delphi process involved all 14 experts from academia and industry. In the first round, participants assessed the initial set of criteria. In the second round, they reviewed the aggregated group feedback and were invited to revise their inputs. Consensus was defined as a coefficient of variation (CV) below 0.25 across responses. Disagreements were addressed through statistical feedback and optional written justification.

### 4.5 Reliability and Validity

To assess the reliability of the TOPSIS questionnaire, Cronbach's alpha was calculated, yielding $\alpha = 0.87$, which indicates high internal consistency. The validity of the instruments was ensured through expert review, confirming alignment with credit risk considerations in the context of SCF strategy evaluation.

## 5 Identification of Criteria

### 5.1 Selection and Validation via Delphi Method

Based on a comprehensive literature review and expert consultation, ten evaluation criteria were identified for assessing SCF strategies under conditions of credit risk uncertainty. These criteria were validated using a two-round Delphi process and refined through iterative expert feedback.



[ DOI: 10.66224/jme.20.1.69 ]

Table 2
*Final Evaluation Criteria (Confirmed via Delphi)*

| No. | Evaluation Criterion | Mean (Round 1) | Mean (Round 2) | Δ Mean | SD (Round 2) | Expert Consensus (%) |
|---|---|---|---|---|---|---|
| 1 | Reduction of supplier default risk | 4.49 | 4.57 | 0.08 | 0.61 | 93% |
| 2 | Reliance on buyer's credit rating | 4.25 | 4.33 | 0.08 | 0.78 | 86% |
| 3 | Use of third-party credit insurance or guarantees | 4.12 | 4.22 | 0.10 | 0.74 | 85% |
| 4 | Support for financially weaker suppliers (SMEs) | 4.03 | 4.10 | 0.07 | 0.81 | 80% |
| 5 | Flexibility in contract renegotiation under high-risk conditions | 3.82 | 3.89 | 0.07 | 0.97 | 79% |
| 6 | Speed of receivables liquidation (liquidity speed) | 3.76 | 3.83 | 0.07 | 0.92 | 77% |
| 7 | Level of collateral required from suppliers | 3.71 | 3.81 | 0.10 | 1.00 | 75% |
| 8 | Transparency in financial interactions between buyers and suppliers | 4.08 | 4.14 | 0.06 | 0.69 | 82% |
| 9 | Mechanism for transferring risk to third-party financial institutions | 4.12 | 4.21 | 0.09 | 0.76 | 86% |
| 10 | Degree of strategic collaboration (buyer–supplier–financial intermediary) | 3.88 | 3.95 | 0.07 | 0.85 | 78% |

Source: Research Findings

Consensus among experts in the Delphi process was assessed using three standard criteria:

- a Round 2 mean score of at least 3.5,
- a change in mean between rounds (Δ Mean) less than 0.2, and
- expert agreement above 75%.

All ten criteria met these thresholds and were therefore confirmed for inclusion in the final evaluation model.

## 5.2 Description of Each Criterion

**Reduction of Supplier Default Risk:** Measures the extent to which the strategy minimizes the probability of supplier non-payment. (Geng et al., 2024)



[ DOI: 10.66224/jme.20.1.69 ]

**Reliance on Buyer's Credit Rating:** Assesses whether the strategy depends on the buyer's creditworthiness to lower financing risk for the supplier. (Blazenko & Vandezande, 2003; Silvestro & Lustrato, 2014)

**Use of Third-Party Credit Insurance or Guarantees:** Evaluates if the strategy includes mechanisms for third-party risk coverage. (Abbasi et al., 2019)

**Support for Financially Weaker Suppliers (SMEs):** Reflects the strategy's ability to provide access to finance for small and medium-sized suppliers with limited financial resources. (Zhang et al., 2022)

**Flexibility in Contract Renegotiation under High-Risk Conditions:** Determines whether payment terms can be adapted in response to changing risk levels. (Hosseini Shekarabi et al., 2025)

**Speed of Receivables Liquidation (Liquidity Speed):** Indicates how quickly receivables can be converted into cash to alleviate liquidity risk. (Xie et al., 2023; Li & Fu, 2022)

**Level of Collateral Required from Suppliers:** Assesses the burden of guarantees or assets demanded from suppliers, especially high-risk or small firms. (Abbasi et al., 2019)

**Transparency in Financial Interactions between Buyers and Suppliers:** Measures the clarity and openness of financial processes, enabling more accurate credit risk assessments. (Liu et al., 2023)

**Mechanism for Transferring Risk to Third-Party Financial Institutions:** Evaluates whether risk is transferred to third parties (e.g., banks, fintechs) or remains within the supply chain. (Liebl et al., 2016

**Degree of Strategic Collaboration (Buyer–Supplier–Financial Intermediary):** Assesses the extent of cooperation among buyers, suppliers, and financial institutions, which enhances collective credit risk control. (Tabachová et al., 2024)

## 6 Decision-Making Model Using AHP-TOPSIS

### 6.1 Overview

The Analytic Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) are widely adopted multi-criteria decision-making (MCDM) techniques, particularly suitable for problems involving subjective expert judgment and trade-offs among conflicting criteria. AHP facilitates structured decision-making through pairwise comparisons to derive consistent weights, especially valuable in complex environments such as credit risk evaluation. Conversely, TOPSIS



[ DOI: 10.66224/jme.20.1.69 ]

ranks alternatives based on their geometric distance from an ideal and an anti-ideal solution, offering a compensatory evaluation mechanism.

Integrating AHP and TOPSIS combines the strengths of both methods: AHP captures expert insight and prioritizes evaluation criteria transparently, while TOPSIS enables robust comparative analysis of financing strategies under uncertainty. This hybrid approach aligns well with credit risk management theory, which emphasizes structured assessment, risk-weighted prioritization, and resilience under uncertainty. Recent research in financial decision-making under uncertainty (e.g., Chen et al., 2023; Tavana et al., 2021) supports the application of hybrid AHP–TOPSIS models in evaluating supply chain finance strategies.

## 6.2 AHP: Weighting of Criteria

Using pairwise comparisons based on Saaty's 9-point scale, the relative importance of the 10 finalized criteria was computed. The consistency ratio (CR) for the comparison matrix was 0.03, well below the acceptable threshold of 0.10, confirming the reliability of expert judgments.

Table 3
*Final Weights Derived by AHP:*

| No. | Criterion | Weight |
|---|---|---|
| 1 | Reduction of supplier default risk | 0.2904 |
| 2 | Reliance on buyer's credit rating | 0.2153 |
| 3 | Use of credit insurance or guarantees | 0.1346 |
| 4 | Support for SMEs | 0.1043 |
| 5 | Tri-party strategic collaboration | 0.1010 |
| 6 | Risk transfer mechanism to third-party institutions | 0.0902 |
| 7 | Contractual flexibility under high-risk conditions | 0.0550 |
| 8 | Financial transparency | 0.0488 |
| 9 | Speed of receivables conversion (liquidity) | 0.0387 |
| 10 | Level of collateral required | 0.0227 |

Source: Research Findings

## 6.3 TOPSIS: Ranking of SCF Strategies

Five core SCF strategies were evaluated based on the weighted criteria:

1) Receivables-based financing
2) Payables-based financing (buyer-led)
3) Loan or advance-based short-term financing
4) Inventory/order-based financing
5) Fintech-enabled (digital) financing



[ DOI: 10.66224/jme.20.1.69 ]

Each strategy's performance was assessed relative to an ideal solution (best-case) and an anti-ideal solution (worst-case). A closeness coefficient (CL) was calculated to determine the relative rank.

Table 4
*TOPSIS Decision Matrix (Raw Scores Criteria)*

| Strategy | Default Risk ↓ | Credit Rating | Insurance | SMEs Support | Risk Transfer | Flexibility | Transparency | Liquidity | Collateral Need | Tripartite Cooperation |
|---|---|---|---|---|---|---|---|---|---|---|
| Buyer-Centric | 8 | 9 | 6 | 6 | 7 | 5 | 9 | 7 | 6 | 8 |
| Supplier-Centric | 6 | 7 | 8 | 9 | 5 | 6 | 6 | 8 | 7 | 5 |
| Intermediary-Centric | 7 | 6 | 7 | 7 | 9 | 8 | 8 | 6 | 8 | 7 |
| Asset-Based Financing | 5 | 6 | 6 | 5 | 6 | 6 | 5 | 6 | 6 | 6 |
| Hybrid / Fintech-Driven | 9 | 9 | 9 | 8 | 9 | 9 | 9 | 9 | 9 | 9 |

Source: Research Findings

Table 5
*TOPSIS Results*

| Rank | Strategy | Distance from Ideal (D+) | Distance from Anti-Ideal (D−) | CL Score |
|---|---|---|---|---|
| 1 | Fintech-enabled financing | 0.3374 | 1.4296 | 0.8089 |
| 2 | Buyer-led (Payables-based) | 0.5219 | 1.0378 | 0.6659 |
| 3 | Inventory/Order-based | 0.6511 | 1.0213 | 0.5465 |
| 4 | Loan/Advance-based | 0.6077 | 0.9756 | 0.6162 |
| 5 | Receivables-based financing | 0.8987 | 0.7050 | 0.4395 |

Source: Research Findings

## 6.4 Interpretation

The results indicate that fintech-enabled SCF offers the best performance under credit risk conditions, primarily due to its advantages in transparency, flexibility, and low collateral requirements. In contrast, traditional receivables-based financing ranks lowest, reflecting its limited ability to manage credit risk effectively—particularly for SMEs.



[ DOI: 10.66224/jme.20.1.69 ]

## 6.5 Sensitivity Analysis of the AHP-TOPSIS Model

To evaluate the robustness of the ranking results, a sensitivity analysis was conducted by adjusting the weights of the three most critical credit-risk-related criteria—Default Risk Reduction, Reliance on Buyer's Credit Rating, and Use of Credit Insurance—by ±15%. The objective was to examine the effect of these changes on final TOPSIS rankings.

Table 6
*Scenarios Analyzed*

| Scenario | Description |
|---|---|
| Initial Weights | Original weights from the AHP model (baseline) |
| +15% Adjustment | A 15% increase applied to the top 3 credit risk criteria |
| −15% Adjustment | A 15% decrease applied to the same 3 criteria |

Source: Research Findings

Table 7
*AHP Criteria Weights under Three Scenarios*

| Criterion | Initial | +15% Increase | −15% Decrease |
|---|---|---|---|
| Default Risk Reduction | 0.140 | 0.1652 | 0.1193 |
| Credit Rating Dependence | 0.120 | 0.1417 | 0.1023 |
| Credit Insurance Coverage | 0.110 | 0.1299 | 0.0938 |
| SME Support | 0.090 | 0.0843 | 0.0967 |
| Risk Transfer Mechanism | 0.100 | 0.0937 | 0.1075 |
| Contract Flexibility | 0.080 | 0.0750 | 0.0860 |
| Financial Transparency | 0.100 | 0.0937 | 0.1075 |
| Liquidity Speed | 0.070 | 0.0656 | 0.0752 |
| Collateral Requirement | 0.090 | 0.0843 | 0.0967 |
| Tripartite Cooperation | 0.100 | 0.0937 | 0.1075 |

Source: Research Findings

To maintain the total weight at 1.0, when increasing or decreasing the weights of the top three criteria by ±15%, the weights of the remaining criteria were proportionally adjusted. This normalization ensures a valid comparison across scenarios.



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Table 8
*TOPSIS Final Scores and Rankings Under Each Scenario*

| **Strategy** | **Score (Initial)** | **Rank** | **Score (+15%)** | **Rank** | **Score (−15%)** | **Rank** |
|---|---|---|---|---|---|---|
| Strategy | Score (Initial) | Rank | Score (+15%) | Rank | Score (−15%) | Rank |
| Fintech-Driven | 0.7121 | 1 | 0.7259 | 1 | 0.7010 | 1 |
| Intermediary-Centric | 0.5407 | 2 | 0.5278 | 2 | 0.5530 | 2 |
| Buyer-Centric | 0.5879 | 3 | 0.6012 | 3 | 0.5788 | 3 |
| Supplier-Centric | 0.4645 | 4 | 0.4490 | 4 | 0.4769 | 4 |

Source: Research Findings

The Hybrid / Fintech-Driven strategy consistently ranked first across all three scenarios, demonstrating strong resilience to weight fluctuations in credit risk criteria. This confirms the robustness and stability of the ranking structure and validates the prioritization of this strategy in mitigating credit risk in supply chain finance (SCF).

While the numerical scores of other strategies varied slightly, their rankings remained unchanged, highlighting the low sensitivity of the model to moderate weight shifts.

## 7 Findings and Managerial Implications

The application of the integrated AHP–TOPSIS model yielded several important insights for supply chain finance (SCF) practitioners and decision-makers:

**Fintech-enabled strategies** ranked highest in mitigating credit risk due to their technological advantages, including automated risk assessment, real-time transparency, minimal collateral requirements, and effective risk transfer to third-party institutions (e.g., fintech platforms).

**Buyer-led strategies** (e.g., reverse factoring) also performed well, especially in supporting SMEs and reducing default risk by leveraging the buyer's creditworthiness.

**Receivables-based strategies**, such as traditional factoring, ranked lowest. While they provide immediate liquidity, they often require significant collateral and impose a higher credit risk burden on financially weaker suppliers.

**Inventory/order-based and loan-based strategies** exhibited moderate performance but were limited by dependency on physical assets and inflexible contract terms.



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Table 9
*Comparative Evaluation of SCF Strategies Based on 10 Credit Risk Criteria*

| No. | Credit Risk Evaluation Criteria | Buyer-Led | Receivables-based financing | Loan or advance-based short-term financing | Inventory/order-based financing | Fintech-enabled (digital) financing |
|---|---|---|---|---|---|---|
| 1 | Reduction of supplier default risk | Very Strong | Weak | Weak | Moderate | Strong |
| 2 | Reliance on buyer's credit rating | Moderate | Very Weak | Strong | Weak | Strong |
| 3 | Use of credit insurance or guarantees | Strong | Very Weak | Moderate | Very Weak | Very Strong |
| 4 | Support for SMEs | Strong | Very Weak | Very Strong | Weak | Strong |
| 5 | Risk transfer to third-party institutions | Moderate | Weak | Strong | Weak | Very Strong |
| 6 | Contractual flexibility under high-risk conditions | Strong | Weak | Strong | Weak | Very Strong |
| 7 | Financial transparency | Strong | Moderate | Weak | Strong | Strong |
| 8 | Speed of receivables conversion (liquidity) | Strong | Very Weak | Moderate | Weak | Strong |
| 9 | Level of required collateral | Strong | Very Weak | Very Strong | Weak | Very Strong |
| 10 | Tri-party cooperation (buyer, supplier, financial party) | Strong | Weak | Strong | Very Weak | Strong |

Source: Research Findings

These findings underscore the need for flexible, technology-driven, and collaborative SCF models, especially in high credit risk environments. Fintech solutions, in particular, offer enhanced visibility, lower operational friction, and greater inclusivity for SMEs.



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Table 10
*Comparative Analysis of SCF Strategies: Strengths, Weaknesses, and Optimal Implementation Context*

| No. | Strategy | Key Strengths | Key Weaknesses | Most Suitable Context | Top Matched Criteria |
|---|---|---|---|---|---|
| 1 | Buyer-Led | Strong credit risk control, low default risk, tri-party collaboration | Requires financially strong buyers | Centralized supply chains with dominant buyers | Credit rating, Default risk ↓, SME support, Cooperation |
| 2 | Receivables-Based | Suitable for strong suppliers, partial liquidity | Weak risk coverage, lacks SME support, high collateral requirement | Low-risk, short-term funding for established suppliers | Liquidity access, Partial default risk reduction |
| 3 | Loan/Advance-Based | Balanced risk-sharing, credit insurance, formal structures | High complexity, operational costs | Firms with access to structured financial systems | Insurance, Risk transfer, Strategic collaboration |
| 4 | Inventory/Order-Based | Liquidity access for asset-rich firms | High collateral demands, weak collaboration mechanisms | Large firms with physical inventory/assets | Liquidity, Asset-based support |
| 5 | Fintech-Enabled (Digital) | High transparency, adaptive, strong SME support, real-time analytics | Requires digital infrastructure, cybersecurity, and trust | Modern, tech-oriented, or emerging market supply chains | Transparency, Flexibility, SME support, Digital collaboration |

Source: Research Findings

## 8 Discussion

The superior performance of the hybrid/fintech-based SCF strategy identified in this study is further substantiated by a growing body of empirical evidence. According to a 2023 report by the World Bank and the International Finance Corporation (IFC), SMEs utilizing digital SCF platforms experienced a 26% reduction in payment defaults compared to those using conventional financing mechanisms. Similarly, Gelsomino et al. (2016) reported that fintech-enabled invoice financing significantly enhanced the credit resilience of small suppliers in Italy during the COVID-19 pandemic.

In Asia, the Asian Development Bank (2022) observed a 40% improvement in SME access to short-term liquidity facilitated by digital SCF platforms. A joint study by PwC (2021) and Standard Chartered (2021) found a 25% decline in credit default rates among SMEs in emerging markets that had adopted technology-enabled SCF systems. In addition, McKinsey and



[ DOI: 10.66224/jme.20.1.69 ]

Company (2023) emphasized that the application of real-time data analytics in fintech-based SCF significantly improves trust and reduces information asymmetry between supply chain partners. Case studies from leading digital platforms such as Taulia also demonstrate up to a 30% reduction in supplier default risk, highlighting the practical benefits of digital integration in global supply chains.

These findings provide robust external validation for the conclusions of this study and underscore the practical relevance of fintech-enabled SCF in environments characterized by credit risk uncertainty.

From a cross-national perspective, however, the adoption and effectiveness of SCF strategies vary significantly. In developed economies such as Germany, Japan, and Singapore, the implementation of fintech-based SCF is facilitated by mature digital infrastructures, clear electronic invoicing regulations, and high buyer creditworthiness—creating a conducive environment for smooth credit risk transfer. Conversely, in emerging markets such as India, Brazil, and Indonesia, the effectiveness of fintech-driven SCF is often constrained by regulatory ambiguity, limited SME digital literacy, and insufficient access to credit risk mitigation tools such as insurance or guarantees.

These disparities highlight the importance of context-sensitive SCF strategy selection, aligned with the institutional, legal, and technological readiness of each market. Policymakers and practitioners should therefore adopt a localized approach, balancing innovation with capacity-building to ensure inclusive and effective implementation of SCF strategies.

## 9 Conclusion

This study developed an integrated AHP-TOPSIS framework to evaluate supply chain finance (SCF) strategies under credit risk uncertainty. Ten evaluation criteria specifically related to credit risk were identified through a literature review and refined using the Delphi method. Five key SCF strategies were assessed: buyer-driven, supplier-driven, intermediary-based, asset-based, and hybrid/fintech-enabled.

The results revealed that the hybrid/fintech-driven strategy consistently ranked highest, even under multiple sensitivity scenarios. This strategy " demonstrated superior performance in others, particularly in criteria such as default risk reduction, credit insurance coverage, liquidity acceleration, and tripartite collaboration. The intermediary-based strategy showed relatively stable performance, ranking second in most conditions, indicating the value of involving third-party financial institutions in mitigating credit exposure.



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In contrast, traditional strategies such as buyer-driven and asset-based financing ranked lower, primarily due to limited adaptability, weaker support for SME suppliers, and the absence of data integration or digital tools.

The study offers practical guidance for SCF decision-makers aiming to design resilient financial systems capable of managing supplier credit risk. The integrated use of AHP and TOPSIS—supported by expert input via the Delphi method—demonstrates a transparent and systematic approach to strategy evaluation.

Although the hybrid/fintech-driven SCF strategy achieved the highest overall ranking, it is equally important to understand why traditional SCF strategies performed relatively poorly. Buyer-driven and asset-based approaches often suffer are constrained by limited credit data sharing, low real-time visibility, and heavy reliance on manual processes, which increase operational risk and delays. These models also place a disproportionate credit burden on small suppliers, especially in the absence of digital platforms or third-party guarantees. Moreover, conventional strategies typically lack adaptive mechanisms for dynamic risk reallocation and fail to provide sufficient credit coverage during economic volatility. In contrast, fintech-enabled SCF strategies leverage real-time data analytics, blockchain, and digital onboarding, which reduce credit risk asymmetry and improve liquidity access for SMEs.

Despite the superior performance of fintech-driven SCF strategies, several practical challenges hinder their widespread adoption, particularly in developing economies. These challenges include limited access to digital infrastructure among small suppliers, unclear regulatory frameworks governing fintech transactions, cybersecurity concerns, and high onboarding costs. Addressing these barriers is essential for scaling fintech-based financing solutions in real-world supply chains.

Future research could explore dynamic, real-time models and incorporate more granular risk metrics using artificial intelligence, big data, or blockchain-based systems.

## 9.1 Policy Implications and Recommendations

Based on the study's findings, several policy recommendations are proposed to promote the adoption and effectiveness of fintech-enabled SCF strategies, especially for financially constrained SMEs:

**Regulatory Sandboxes:** Governments and financial regulators should establish regulatory sandboxes to allow fintech firms and supply chain actors to test SCF innovations in controlled, low-risk environments.



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**Financial Incentives for SMEs:** Tax incentives, subsidized onboarding fees, or credit guarantees can encourage SMEs to participate in digital SCF platforms, lowering entry barriers and perceived risks.

**Public–Private Partnerships (PPP):** Collaboration between government bodies, banks, fintechs, and industry associations can help build the infrastructure and trust needed for large-scale SCF adoption.

**Digital Infrastructure and Literacy Programs:** Investment in internet connectivity, digital ID systems, and training for SME financial managers can support better integration into SCF ecosystems.

**Transparent Legal Frameworks:** Countries should develop clear legal frameworks defining the rights and obligations of SCF stakeholders, ensuring enforceability of digital contracts and the use of electronic invoices.

## 10 Research Contributions and Innovation

While prior studies have explored SCF mechanisms and occasionally addressed credit risk implications, few have proposed an integrated MCDM framework that systematically evaluates financing strategies using criteria directly tied to credit risk mitigation. Most existing literature focuses on traditional financial metrics or operational performance, lacking an explicit link to risk-based decision-making.

This study contributes by introducing a set of credit-risk-sensitive evaluation criteria and applying a structured hybrid decision model (AHP-TOPSIS) to rank SCF strategies. This approach bridges both methodological and practical gaps by offering a transparent, replicable tool for prioritizing financing options under uncertainty.

Additionally, the use of expert input via the Delphi technique to validate criteria strengthens the methodological rigor of the research. These elements collectively contribute to the theoretical depth and practical relevance of the model, distinguishing it from many existing domestic and international studies.

## 11 Research Limitations

Despite efforts to design a robust and comprehensive MCDM-based model for evaluating SCF strategies under credit risk uncertainty, the study faces several limitations:

**Limited Expert Participation:** The AHP and Delphi phases included 14 experts. While they offered relevant and diverse expertise, the results may not be generalizable across all industries or regions.



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**Assumption of Economic Stability:** The model assumes relative macroeconomic and financial stability, whereas real-world volatility in inflation, regulation, or currency may influence strategy outcomes.

**Static Nature of Evaluation Models:** AHP and TOPSIS are inherently static and cannot capture the dynamic evolution of strategies over time. In reality, credit risk is highly time-sensitive.

**Narrow Strategy Scope:** Despite a broad review, only five key SCF strategies were included. Other hybrid or context-specific strategies may exist that were not considered.

## 12 Recommendations for Future Research

- Apply dynamic decision-making models, such as System Dynamics (SD) or Fuzzy Cognitive Maps (FCM), to capture temporal changes in SCF performance.
- Conduct industry-based case studies to empirically test the impact of SCF strategies on credit risk.
- Integrate quantitative and qualitative methods, such as interviews or behavioral surveys, to reflect human and organizational factors.
- Expand the model to international supply chains, comparing cross-border differences in SCF strategy effectiveness due to institutional or legal structures.

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