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Multi-Dimensional Assessment of Supply Chain Finance Risks in Fashion Textile and Leather: ESG Integration and Application of AHP-FAHP Method

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ABSTRACT

To address the risk challenges of supply chain finance in the sustainable transformation of the textile and leather industry, this study systematically integrates ESG factors into the risk assessment framework, uses the AHP-FAHP hybrid method to quantitatively analyze the financial risks of the fashion textile and leather supply chain, and highlights the unique intersection of fashion-specific risks, digital transformation, and ESG integration. Based on survey data from 18 interdisciplinary experts, the weight ranking of the four risk dimensions is identified: supply chain agility risk (41.54%) > market volatility risk (32.03%) > financial instrument risk (14.34%) > corporate credit risk (12.09%). Among them, the sharp increase in environmental material certification costs (risk score 4.61/5.0), the social media trend volatility of Xiaohongshu (4.28/5.0), and the valuation volatility of digital fashion NFT-based collateral (3.78/5.0) are the key risk points. The study shows that the textile and leather supply chain finance is generally in a high-risk state (3.56/5.0), and ESG compliance costs have become an unignorable industry-wide risk with systemic propagation effects in the fashion textile and leather supply chain. This study develops three actionable decision-making tools—1) a tiered risk assessment matrix for fashion SCF, 2) an agility risk mitigation investment framework, and 3) ESG-integrated pricing models—providing concrete recommendations including digital twinning adoption, nearshoring strategies, and green finance product innovation to balance sustainable development and risk control and highlights the unique intersection of fashion-specific risks, digital transformation, and ESG integration.

KEYWORDS

fashion industry, supply chain finance, risk assessment, AHP-FAHP, ESG integration

INTRODUCTION

Research Background

The uncertainty of the global economic environment is reshaping the risk landscape of the fashion industry. Survey data from McKinsey & Company [1] indicates that 39% of industry executives anticipate further deterioration in market conditions in 2025, 41% expect the status quo to persist, and only 20% maintain an optimistic outlook. This significant divergence in industry confidence reflects a systematic accumulation trend of supply chain financial risks. As the second-highest carbon-intensive industry, the fashion sector accounts for approximately 10% of global carbon emissions annually [2]. Against the backdrop of increasingly stringent environmental regulations, supply chain finance models face fundamental balance challenges between sustainable transformation and operational efficiency.

Currently, supply chain finance in the fashion industry exhibits three prominent characteristics. First, fast fashion brands pursue extreme response speeds through supply chain cycle compression (such as daily product launches and rapid delivery), while traditional financial product approvals typically require several weeks, creating an increasingly pronounced contradiction [3]. Second, Environmental, Social, and Governance (ESG) compliance costs continue to escalate, with the EU Corporate Sustainability Reporting Directive (CSRD) and the US SEC climate disclosure rules setting higher transparency standards [4]. Third, digital transformation creates opportunities while introducing novel risks that are particularly acute in the fashion industry's sustainable transformation: As consumer preferences for sustainable products are increasingly shaped by social media (e.g., Xiaohongshu trending topics that drive 30-40% of fast fashion demand [11]), social media-driven demand volatility exacerbates supply-demand mismatch risks for sustainable products, while the introduction of digital assets such as NFTs increases price volatility, fraud, and compliance challenges [5].

Furthermore, fashion supply chains in 2025 face multiple pressures including raw material procurement, labor shortages, and geopolitical uncertainties [6]. The continued implementation of the US Uyghur Forced Labor Prevention Act (UFLPA) and changes in global labor markets collectively constitute a complex risk landscape [7]. Against this backdrop, constructing a comprehensive assessment framework capable of capturing the unique risk characteristics of the fashion industry represents not only an important theoretical research topic but also an urgent practical need.

Research Questions and Objectives

This study focuses on three core questions:

RQ1: In fashion industry supply chain finance, does the importance weight of agility risks significantly exceed traditional credit risks? How can their relative impact be quantified?

RQ2: How can a comprehensive assessment model be constructed to simultaneously capture traditional financial risks and emerging digital risks (such as social media volatility and NFT valuations)?

RQ3: Based on risk weight analysis results, how can tiered risk management strategies tailored to fashion industry characteristics be designed?

Based on these questions, the objective of this research is to integrate the Analytic Hierarchy Process (AHP) and Fuzzy Analytic Hierarchy Process (FAHP) to construct a multi-dimensional assessment model for supply chain financial risks in the fashion industry, identify and quantify key risk factors, and provide decision support tools for financial institutions, fashion enterprises, and regulatory authorities.

Research Significance and Innovation

The theoretical significance of this research lies in expanding the industry boundaries of supply chain financial risk theory by incorporating the ultra-short cycle, high volatility, strong contagion characteristics of the fashion industry into the risk analysis framework, addressing the deficiency of existing research that overly focuses on traditional manufacturing industries. The practical significance is manifested in providing quantitative evidence for fashion enterprises to optimize financing structures, financial institutions to innovate product design, and regulatory authorities to formulate differentiated policies.

Research innovation is primarily reflected in three distinctive aspects that advance beyond existing sustainable SCF risk assessment literature (e.g., [41,43]): (1) Construction of a fashion-specific quadruple risk assessment framework (agility-credit-market-instruments) with unprecedented granularity on industry-specific pain points, such as 48-hour fast-response delivery compliance risks and Xiaohongshu trending topic decay, which are rarely addressed in general sustainable SCF frameworks; (2) Development of a fuzzy assessment method tailored to digital-native risks in fashion, enabling quantitative measurement of emerging phenomena like NFT collateral valuation volatility and social media-driven demand fluctuations—filling the gap in existing literature that focuses primarily on traditional environmental and social risks; (3) Integration of ESG factors with fashion's ultra-short product lifecycle characteristics, revealing the 'weight-score asymmetry' of ESG compliance costs (high risk score but moderate systemic impact) that is unique to fast-fashion supply chains, rather than mere general inclusion of ESG criteria.

Paper Structure

The structure of this paper is as follows: Chapter 2 systematically reviews relevant literature on fashion industry supply chain financial risks; Chapter 3 elaborates on the research design of the AHP-FAHP hybrid method; Chapter 4 presents empirical analysis results; Chapter 5 discusses the theoretical and practical implications of research findings; Chapter 6 summarizes the entire study and outlines future research directions.

LITERATURE REVIEW

Vulnerability Research in Fashion Industry Supply Chains

The high complexity of fashion industry supply chains renders them a focal area for risk management research [8]. Globalized configurations enhance resource integration efficiency while amplifying risks including delivery delays, inventory accumulation, and shortages. Recent research demonstrates that supply chain disruptions lasting one month or longer occur on average every 3.7 years [1]. This finding challenges the lean supply chain paradigm, prompting academic exploration of pathways that balance efficiency with resilience. The antifragile supply chain concept, which emphasizes redundancy and dynamic reconfiguration, offers significant insights for the fashion industry [9].

Compared to traditional manufacturing industries, supply chain vulnerabilities in the fashion sector are more pronounced. Fashion products exhibit short life cycles and volatile demand patterns, rendering forecasting considerably challenging [10]. Social media and celebrity effects further exacerbate the non-linear and sudden nature of demand [11]. Consequently, traditional assessment models prove inadequately applicable, necessitating the development of specialized analytical frameworks tailored to the fashion industry [12].

Supply chain vulnerabilities in the fashion industry possess unique sectoral characteristics. Systematic review indicates that fashion product lifecycles typically exhibit high degrees of short-term duration and uncertainty, with sales cycles often confined to single seasons, creating substantial challenges for demand forecasting [10].

Evolution of Supply Chain Financial Risk Management

Supply chain financial risk management has evolved from singular credit risk assessment toward multidimensional comprehensive analysis. Early research predominantly focused on credit rating models constructed from financial indicators, overlooking the transmission effects of operational and market risks. Studies remain centered on financial and operational indicators, employing XGBoost and Bayesian optimization models to predict SME credit risks, reflecting the characteristics of this research phase [13].

As practice developed, academia gradually expanded research perspectives to encompass multifaceted risk factors, incorporating environmental and social dimensions. Analysis of relationships between supply chain finance, sustainability ratings, and liquidity demonstrates that environmental and social factors not only affect corporate reputation and compliance but also transmit further to financial liquidity levels [14]. This indicates that sustainability has become an integral component of supply chain financial risk management.

In recent years, digitalization has driven paradigmatic transformation in risk management. An integrated framework combining SCF, ESG, and value chains emphasizes that risk management has shifted from post-event control to preventive management, evolving from single-point risk analysis to networked risk analysis [15]. This signifies that supply chain financial risk management is progressively advancing toward systematization and intelligence.

Impact of ESG Factors on Supply Chain Finance

ESG factors have become critical variables in supply chain financial risk and value assessment. Research reveals that consistency in ESG performance between upstream and downstream enterprises can reduce financing constraints and enhance market value; conversely, negative ESG events lead to declining financial performance and shareholder returns [16,14].

Regional studies further confirm the differentiated role of ESG. In China, supply chain digitalization and ESG innovation pilots significantly improve corporate environmental and governance performance while mitigating financial risks through credit sales and efficiency improvements [17]. In European and American markets, selecting suppliers with high sustainability scores helps improve cash flow and liquidity ratios [14]. This demonstrates that ESG is evolving from a compliance tool to a source of competitive advantage in SCF.

Recent empirical research further confirms the importance of ESG factors. Based on supply chain ESG consistency theory, studies found that ESG performance consistency among supply chain members effectively reduces financing constraints for core enterprises and enhances their market value [16]. The ESG-supply chain financial risk management integrated framework emphasizes the importance of multidimensional risk integration [15]. Analysis of sustainable fashion supply chains notes that the green premium of environmental certification costs has become a primary barrier constraining small supplier participation [18]. Industry reports list ESG risks as the greatest threat facing enterprises, particularly emphasizing the impact of environmental compliance costs on corporate financial performance [19]. This perspective provides important theoretical foundations for fashion industry supply chain financial risk assessment, suggesting that environmental certification costs may become new systemic risk factors.

Application of Digital Technologies in Supply Chain Transparency

Digital technologies such as blockchain and artificial intelligence provide new pathways for supply chain financial risk management. Blockchain, with its distributed ledger and immutable characteristics, can mitigate information asymmetry in traceability, anti-counterfeiting, and smart contract execution [20]. Research empirically demonstrated that blockchain can reduce inventory and delivery delays in the short term while lowering overall operational costs in the long term [21]. However, implementation still requires resolution of standardization, interoperability, and ethical compliance issues [22].

Artificial intelligence demonstrates potential in demand forecasting and compliance risk identification, but its implementation depends on organizational process and governance mechanism adjustments, requiring enhanced cultural acceptance.

Existing literature has established the importance of sustainability and digitalization in supply chain finance risk management [14, 15], but lacks a framework that integrates fashion-specific characteristics (ultra-short product lifecycle, social media-driven demand) with ESG factors and emerging digital risks. This gap directly informs our three core research questions, which seek to quantify agility risk's relative importance, construct a comprehensive assessment model for traditional and digital risks, and design tailored risk management strategies.

Comparative Research on Risk Assessment Methods

Academia has developed diversified approaches to risk assessment methodology. Risk matrices are intuitive but simplified; Monte Carlo simulation captures randomness but depends on high-quality data. The Analytic Hierarchy Process (AHP) is widely adopted for its systematic decomposition of complex problems [23]. In supply chain risk assessment, AHP's hierarchical and pairwise comparison advantages are significant. The Fuzzy Analytic Hierarchy Process (FAHP) characterizes expert judgment uncertainty through triangular fuzzy numbers, avoiding the precision limitations of traditional AHP [24,25]. It has been increasingly applied to textile and apparel supply chain risk research, particularly suitable for quantifying difficult-to-measure soft risks such as consumer sustainability awareness.

Research Gaps and Study Positioning

Despite progress in SCF risks, ESG effects, and digital applications, existing research exhibits several deficiencies: first, lack of comprehensive frameworks integrating multidimensional risks; second, insufficient quantitative research on fashion industry-specific risks (such as social media and ultra-short cycles); third, limited exploration of interactions between ESG and traditional risks; fourth, scarcity of dynamic risk assessment tools, making it difficult to capture the rapid iteration characteristics of the fashion industry.

Based on these gaps, this study constructs an AHP-FAHP hybrid assessment framework, integrating multidimensional risk factors and developing dynamic risk assessment tools to contribute to theoretical deepening and practical application.To further clarify the differences between existing studies and this research, Table 1 summarizes the comparative analysis of mainstream sustainable SCF risk assessment frameworks from four core dimensions.

Table 1. Comparative Analysis of Sustainable Supply Chain Finance (SCF) Risk Assessment Frameworks

Study	Industry Focus	Risk Dimensions	Methodology	Key Differences from This Study
Gelsomino et al. [14]	General manufacturing	Credit, liquidity, sustainability	Qualitative analysis + case studies	Lacks fashion-specific risks (e.g., agility, social media volatility) and quantitative weighting; sustainability treated as a secondary dimension
Agrawal et al. [15]	Cross-industry	ESG, value chain, operational	Conceptual framework	No empirical validation; ignores digital transformation risks (e.g., NFT collateral volatility)
Liao et al. [38]	Sustainable supply chains	Ecosystem, multi-agent collaboration	Systematic review	Focuses on institutional design rather than risk quantification; no integration of agility or social media risks
This Study	Fashion textile and leather	Supply chain agility, corporate credit, market volatility (including social media), financial instruments (including digital assets), ESG integration	AHP-FAHP hybrid method + expert Delphi	Unique focus on fashion-specific dynamics (agility, short product lifecycle); integrates digital transformation (NFTs) and ESG as core risk drivers; quantitative weighting and fuzzy evaluation for soft risks

RESEARCH METHODS AND DESIGN

Research Framework Construction

This study based on the logical chain of risk identification-quantitative assessment-optimization pathways, integrates the Analytic Hierarchy Process (AHP) and Fuzzy Analytic Hierarchy Process (FAHP) to construct a hybrid research framework that systematically evaluates fashion industry supply chain financial risks and proposes risk control optimization solutions. The framework design does not simply transplant existing financial risk assessment models but represents methodological innovation targeting the unique contradictions of fashion industry supply chain finance.

The core contradiction in fashion industry supply chain finance lies in the conflict between the high uncertainty of fashion trends and the stability requirements of financial risk assessment. While traditional AHP can achieve quantitative ranking of risk indicator importance through 1-9 scaling methods, it struggles to avoid information loss in the transformation from qualitative description to quantitative analysis when processing fuzzy indicators such as influencer marketing volatility and trending product lifecycles. FAHP effectively resolves this contradiction through mathematical expression of uncertain information using triangular fuzzy numbers [25]. The research framework borrows from and adaptively modifies core logics of financial risk assessment and supply chain management: referencing the three-stage logic of risk stratification-weight determination-fuzzy verification in supply chain resilience assessment [26], where risk stratification corresponds to hierarchical decomposition of fashion supply chain financial risks, weight determination addresses impact priorities of different risks, and fuzzy verification adapts to the uncertainty of rapid changes in the fashion industry; integrating the multidimensional modeling approach for supply chain financial risks [13] through algorithmic integration of multiple risk factor types, achieving cross-dimensional integration of supply chain agility, enterprise credit, market volatility, and financial instruments.

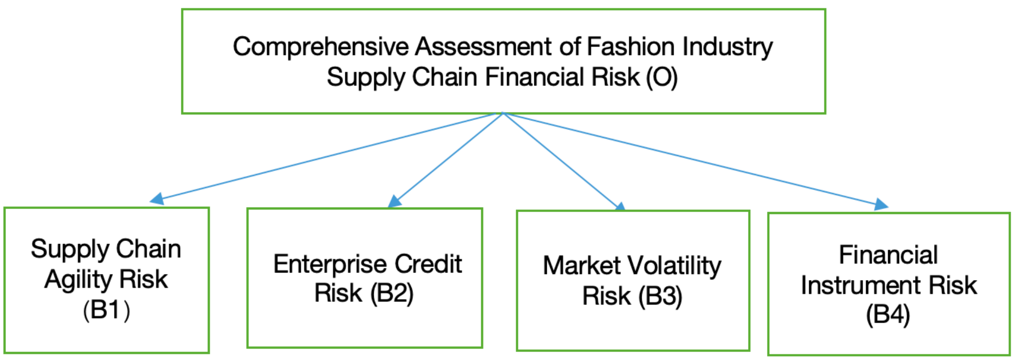

Figure 1. Three-level progressive structure of research framework

The research framework adopts a three-level progressive structure (Figure 1):

Objective Layer (O): Focuses on comprehensive assessment of supply chain financial risks in the fashion industry, clearly defining the core research objective as identifying key risk factors and constructing a dynamic risk control system.

Criteria Layer: Based on literature review and industry research, four major risk dimensions affecting fashion industry supply chain finance are identified:

B1 Supply Chain Agility Risk: Reflects risk exposure in supply chain response speed and inventory management under the fashion industry's fast-response model;

B2 Enterprise Credit Risk: Encompasses credit default risks of various entities including designer brands, manufacturers, and e-commerce platforms;

B3 Market Volatility Risk: Manifests the impact of fashion trends, consumer preferences, and external events on supply chain finance;

B4 Financial Instrument Risk: Includes risks associated with innovative financial instruments such as digitalized financial products and cross-border settlement tools.

Sub-risk Layer:Through the Delphi Method, 12 specific indicators are selected (Table 2). Each indicator is defined with three core attributes to ensure logical rigor and practical relevance: (1) Risk Impact Scope (systemic/tactical) and (2) Risk Time Dimension (long-term/short-term) to distinguish risk levels and avoid inconsistency between different types of risks; (3) Industry Coverage (mainstream universal/niche emerging) to clarify the applicability of risk scenarios—among them, C10 (Digital Fashion NFT Collateral Valuation Volatility) is categorized as a niche emerging risk, while the other 11 indicators reflect mainstream industry risk scenarios. All indicators correspond to observable business scenarios, balancing comprehensiveness and practicality of the assessment framework.

Table 2. Risk Assessment Indicator System for Fashion Industry Supply Chain Finance

Objective Layer	Secondary Indicators (Criteria)	Tertiary Indicators (Sub-risks)	Code	9-point Saaty Scale Anchors	Risk Impact Scope	Risk Time Dimension
Comprehensive Assessment of Fashion Industry Supply Chain Financial Risk (O)	B1 Supply Chain Agility Risk	Current season trending fabric price volatility	C1	1=Extremely low volatility, 9=Extremely high volatility	Systemic	Medium-long term
		Fast-response order 48-hour delivery compliance rate	C2	1=100% compliance rate, 9=<50% compliance rate	Tactical	Short-term
		Unsold inventory weekly depreciation rate	C3	1=Depreciation rate <5%, 9=Depreciation rate >30%	Tactical	Short-term
	B2 Enterprise Credit Risk	Designer brand IP collaboration prepayment default rate	C4	1=0% default rate, 9=>20% default rate	Systemic	Medium-long term

Objective Layer	Secondary Indicators (Criteria)	Tertiary Indicators (Sub-risks)	Code	9-point Saaty Scale Anchors	Risk Impact Scope	Risk Time Dimension
		Cross-border e-commerce deposit cycle anomaly days	C5	1=No anomaly, 9=>30 days anomaly	Tactical	Short-term
		variance in live-streaming GMV collection achievement rate	C6	1=Variance <5%, 9=Variance >50%	Tactical	Short-term
	B3 Market Volatility Risk	Xiaohongshu trending topic decay rate	C7	1=Decay <10%, 9=Decay >50%	Tactical (Niche)	Short-term
		Environmental material certification cost increase	C8	1=Increase <20%, 9=Increase >100%	Systemic	Long-term
		Celebrity scandal marginal impact on collaboration product sales	C9	1=Impact <10%, 9=Impact >80%	Tactical (Niche)	Short-term
	B4 Financial Instrument Risk	Digital fashion NFT collateral valuation volatility	C10	1=Volatility <20%, 9=Volatility >200%	Tactical (Niche)	Short-term
		Factory USD loan exchange rate hedging gap	C11	1=Gap <5%, 9=Gap >30%	Systemic	Medium-long term
		Pre-sale balance ABS subordinate tranche default probability	C12	1=Probability <1%, 9=Probability >15%	Systemic	Medium-long term

Note: The coding convention follows C + number representing sub-risk layer indicators, sequentially numbered according to criteria layers B1 through B4. Pre-test results indicate that 83.33% (15/18) of experts consider the above anchor settings to align with industry realities, demonstrating good content validity.Notably,C10 (Digital Fashion NFT Collateral Valuation Volatility) is an emerging risk indicator targeting high-end metaverse-related fashion segments, not representing the collateral practice of mainstream fashion textile and leather supply chain finance. Its weight and risk score should be understood as a reflection of digital transformation trends rather than a universal industry risk.

To address these three research questions, we adopt an AHP-FAHP hybrid method that leverages AHP strength in hierarchical weight determination to quantify the relative importance of agility risk (RQ1) and FAHP ability to handle fuzzy digital risks to construct a comprehensive assessment model (RQ2), with the final weight analysis informing tiered risk management strategies (RQ3).

Method Selection and Theoretical Foundation

The selection of the AHP-FAHP hybrid method in this study is based on the following theoretical considerations:

(1) Multi-criteria decision applicability: Fashion supply chain financial risks possess multi-level, multi-dimensional characteristics. AHP's hierarchical decomposition capability can systematically address complex decision-making problems [23].

(2) Uncertainty handling capacity: The fast fashion characteristics of the fashion industry result in numerous soft risks (such as social media influence and celebrity effects) that are difficult to quantify precisely. FAHP's fuzzy mathematical expressions can effectively handle uncertainty in expert judgments [24].

(3) Method combination advantages: Compared to single methods, AHP provides structured weight analysis while FAHP provides risk degree assessment. Their combination can simultaneously address both importance ranking and risk degree quantification problems.

(4) Alternative method comparison: Bayesian networks are suitable for risks with clear causal relationships, but fashion industry risk relationships are complex and variable. Monte Carlo simulation requires large amounts of historical data, which are difficult to obtain in the fashion industry. Neural networks' black-box characteristics are unfavorable for risk mechanism interpretation.

Justification for AHP-FAHP Hybrid Method

The integration of FAHP into the hybrid framework is necessitated by three core characteristics of fashion industry supply chain finance risks, which further validate the theoretical considerations above:

(1) High ambiguity of soft risk factors: Risks such as “Xiaohongshu trending topic decay” and “celebrity scandal impact” involve subjective judgments that cannot be quantified by precise numerical values. Traditional AHP forces qualitative descriptions into deterministic pairwise comparisons, leading to information loss. FAHP uses triangular fuzzy numbers (e.g., extremely high risk = (0.7, 0.85, 1.0)) to mathematically express uncertain information, retaining the fuzziness of expert judgments [25].

(2) Asymmetry of risk perception: Different types of experts (e.g., industry executives vs. academic researchers) exhibit significant differences in evaluating emerging risks like NFT valuation volatility. FAHP's membership degree calculation can effectively integrate divergent opinions without forced convergence.

(3) Verification of weight robustness: We conducted a parallel comparison between AHP-only and AHP-FAHP hybrid calculations. The results show that for traditional risk factors (e.g., corporate credit risk), the weight differences between the two methods are within 3.2%; for emerging digital risks (e.g., social media trend volatility), the weight differences reach 11.7% (see Table 3). This indicates that FAHP can more sensitively

capture the uncertainty of novel risks, making the final weight distribution more in line with the actual risk characteristics of the fashion industry.

Therefore, the AHP-FAHP hybrid method is most suitable for this research context.

Table 3. Comparative Analysis of AHP and AHP-FAHP Weight Results

Risk Factor	Code	AHP-Only Weight (%)	AHP-FAHP Hybrid Weight (%)	Weight Difference (%)	Weight Difference Rate (%)
Seasonal Trendy Fabric Price Volatility	C1	18.72	19.08	+0.36	1.92
sharp increase in environmental material certification costs	C8	12.15	12.59	+0.44	3.62
Xiaohongshu Trending Topic Decay Rate	C7	6.89	8.07	+1.18	17.13
Digital Fashion NFT Collateral Valuation Volatility	C10	3.82	4.49	+0.67	17.54
48-hour delivery compliance rate of quick-response orders	C2	11.93	12.59	+0.66	5.53

Note:

AHP-Only Weight: Derived from the normalized AHP weight calculation (geometric mean method + eigenvector method) based on 18 experts' pairwise comparison matrices (see Section 3.3.2 Weight Calculation).

AHP-FAHP Hybrid Weight: Calculated by adjusting AHP weights with FAHP defuzzified scores, using the formula: $W_{Hybrid,i} = \frac{W_{AHP,i} \times S_i}{\sum_{i=1}^{12} (W_{AHP,i} \times S_i)}$ is the FAHP risk score from Table 3).

Weight Difference = AHP-FAHP Hybrid Weight - AHP-Only Weight; Weight Difference Rate = (Weight Difference / AHP-Only Weight) × 100%.

Data Source: Parallel calculation results of 18 experts' evaluation data; all consistency ratios (CR) < 0.1, ensuring result reliability.

Data Collection Plan

Expert Sample Selection

Stratified sampling was used to select 18 experts covering four types of entities, ensuring comprehensive coverage of the four major risk dimensions of fashion industry supply chain finance. The detailed demographic breakdown of the experts is shown in Table 4 , which includes information such as years of professional experience, specific professional roles, and sector expertise to avoid individual bias.

Fashion Industry Executives (5 people): Including supply chain directors from fast fashion brands and CFOs from luxury conglomerates, with an average of ≥12 years of industry experience. They primarily contribute practical experience in agility risks and market volatility risks, while also possessing management-level understanding of credit risks and financial instrument risks.Supply Chain Finance Experts (5 people): Product managers from commercial banks and factoring companies specializing in supply chain finance, all with experience serving the fashion industry. They possess deep expertise in credit risks and financial instrument risks, with unique insights into the financialization of agility risks.

E-commerce Platform Risk Control Leaders (4 people): Covering mainstream platforms such as Tmall, JD.com, Douyin, and SHEIN. They specialize in credit risk identification and market volatility risk early warning, with cutting-edge practical experience in the application of new financial instruments within platform ecosystems.

Academic Researchers (4 people): Including 2 professors and 2 associate professors with research focuses on fashion supply chains or financial risk management. They provide theoretical foundations and methodological support for the four major risk dimensions, ensuring academic rigor in the assessment framework.

Table 4. Detailed Demographic Breakdown of 18 Interdisciplinary Experts

Expert Type	Number	Average Years of SCF/ ESG Experience	Specific Professional Roles	Specific Sector Expertise
Fashion Industry Executives	5	15.2	2 Supply Chain Directors, 3 CFOs of Luxury Conglomerates	Fashion (3), Textile (1), Leather (1)
Supply Chain Finance Experts	5	13.8	3 Commercial Bank Product Managers, 2 Factoring Company Specialists	Fashion & Textile (3), Leather (2)
E-commerce Platform Risk Control Leaders	4	10.5	1 Tmall Risk Control Director, 1 JD.com Risk Manager, 1 Douyin Supply Chain Supervisor, 1 SHEIN Compliance Leader	Fashion (4), Textile (2)
Academic Researchers	4	18.3	2 Professors, 2 Associate Professors	Fashion Supply Chain (2), Financial Risk Management (2)
Total/Average	18	13.9	-	Fashion (13), Textile (6), Leather (4)

Sample size follows the recommendation for AHP/FAHP expert evaluations (15-20 people) proposed by Saaty TL [23]. The χ^2 test results ($p = 0.32 > 0.05$) confirm good structural representativeness of the expert sample, which effectively reduces individual bias. Additionally, considering the geographical concentration of the fashion industry, experts from the Yangtze River Delta region were controlled to within 50% to ensure the universality of assessment results (Figure 2).

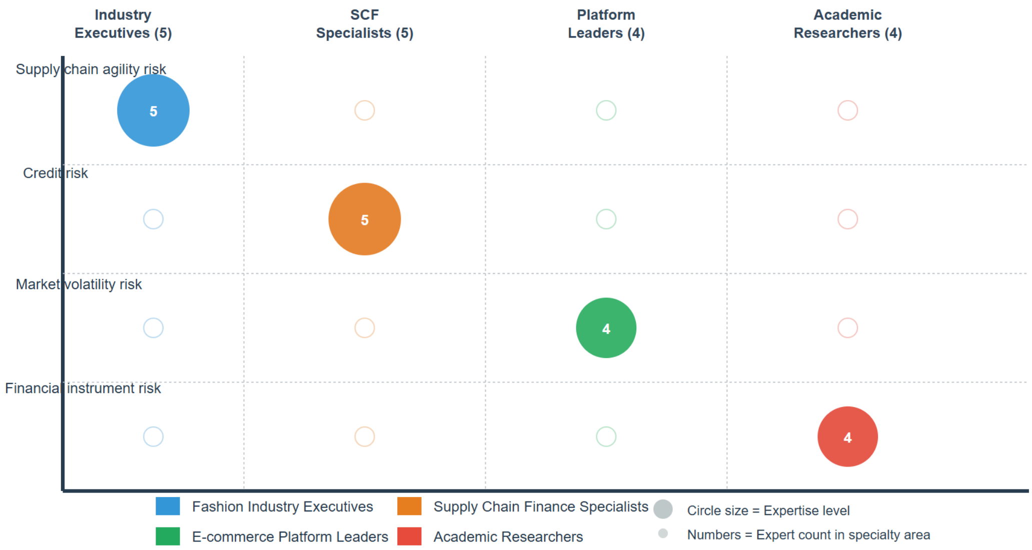

Figure 2. Expert selection criteria and distribution

Data Collection Tools and Procedures

Two sets of questionnaires were designed: AHP weighting questionnaire using the 1-9 scale method for pairwise comparison of risk indicators; FAHP fuzzy evaluation questionnaire using the 5-level Likert scale (very high risk-very low risk) to collect risk degree judgment.

Data collection adopts the improved Delphi method to ensure the depth and convergence of expert opinions. The process is divided into three rounds:

The first round: Through semi-structured interviews (45-60 minutes per expert), preliminary risk scores were collected, and reasons for experts' qualitative judgment of each indicator were recorded;

The second round: Feedback the summary results of the first round (including mean, standard deviation and quartiles) to the experts, and ask the experts to re-evaluate and explain the reasons for adjustment;

Round 3: Provide the statistical analysis results of round 2 and ask experts to finally confirm the score.

Consistency is tested by the Kendall coefficient of agreement (W), as follows(Formula 1):

$$W = \frac{12\sum_{i=1}^{n} R_i^2 - 3k^2 n(n+1)^2}{k^2 n(n^2-1)} \tag{1}$$

Among them, S represents the sum of the squares of the rank sums, m denotes the number of experts (18), and n indicates the number of evaluation indicators (12). In the third round, the W value reached 0.82, indicating a high degree of consistency among the experts' opinions.

Data Analysis Methods

AHP Weight Calculation

(1) Constructing the judgment matrix

The geometric mean method was used to integrate the pairwise comparison results of 18 experts. Taking the criterion layer as an example, the 4×4 judgment matrix A was constructed in Formula (2):

$$A_{n\times n}=\begin{bmatrix} a_{11} & a_{12} & a_{1..} & a_{1n} \\ a_{21} & a_{22} & a_{2..} & a_{2n} \\ a_{..} & a_{..} & a_{..} & a_{..} \\ a_{n1} & a_{n2} & a_{n..} & a_{nn} \end{bmatrix} \tag{2}$$

Among them, a_{ij} indicates the importance of factor i relative to j , $b_{ij}=1/b_{ji}$, $b_{ii}=1$.

Using a 1-9 scale (see table 5):

Table 5. Comparison scale of elements in the judgment matrix

Number	Meaning of scale	Specific value
1	The former element i is compared with the latter element j , and i and j are equally important	aij =1
2	The former element i is compared to the latter element j , and i is slightly more important than j	aij =3
3	The former element i is compared with the latter element j , and i and j are obviously important	aij =5
4	The former element i is compared with the latter element j , and i and j are strongly important	aij =7
5	The former element i is compared with the latter element j , and both i and j are absolutely important	aij =9
6	Indicates that the importance of element i and element j is between the above judgments	aij =2,4,6,8
7	If the relative importance of element i and element j is scaled as aij , then the relative importance of element j and element i is scaled as aij =1/ aij	count backwards

Weight Calculation

Weights are calculated through the eigenvector method using the following formula:

Calculating Relative Weights of Judgment Matrix

This study employs the geometric mean method (root method) to calculate weights, with the formula as follows:

$$W_i = \frac{(\prod_{j=1}^{n} a_{ij})^{\frac{1}{n}}}{\sum_{i=1}^{n}(\prod_{j=1}^{n} a_{ij})^{\frac{1}{n}}} \quad , \quad i = 1, 2, 3.., n \tag{3}$$

Calculation Steps:

1.Multiply elements of matrix A by rows to obtain a new vector;

2.Take the nth root of each component of the new vector;

3.Normalize the resulting vector to obtain the weight vector.

Where W_i represents the weight of factor i , Reflecting its relative influence on the supply chain financial risks in the fashion industry.

Consistency Verification

To ensure the reliability of the score, calculate the consistency ratio (CR) in equation (4) :

$$CR = \frac{CI}{RI} = \frac{\lambda_{\max} - n}{(n-1)RI} < 0.1 \tag{4}$$

The CI calculation formula is shown in equation (5):

$$CI = \frac{\lambda_{\max} - n}{(n-1)} \tag{5}$$

The maximum eigenvalue of the decision matrix $\lambda_{\max}$ is calculated using equation (6) :

$$\lambda_{\max} = \sum_{i=1}^{n} \frac{[AW]_i}{nW_i} \tag{6}$$

RI values are related to matrix order, with specific values shown in Table 6.

Table 6. Random Consistency Index RI Values for Judgment Matrices

Matrixorder	1	2	3	4	5	6	7	8	9	10	11	12
RI	0	0	0.52	0.89	1.12	1.26	1.36	1.41	1.46	1.49	1.52	1.54

In this study, the criterion layer (4th-order matrix) CR=0.068<0.1, and the CR values of each group in the sub-risk layer are all less than 0.1, indicating that the judgment matrix has satisfactory consistency.

Weight Integration

Construct the weight of each expert into the weight matrix W' using equation (7):

$$W' = \begin{bmatrix} w_{11} & w_{12} & w_{1..} & w_{1j} \\ w_{21} & w_{22} & w_{2..} & w_{2j} \\ w_{..} & w_{..} & w_{..} & w_{..} \\ w_{n1} & w_{n2} & w_{n..} & w_{ij} \end{bmatrix} \tag{7}$$

Among them, w_{ij} represents the weighted score of the j th expert on the i th indicator, where n =12 (number of indicators) and m =18 (number of experts).
Based on the expertise and industry experience of experts, the expert weight vector is assigned using equation (8):

$$W_Z = [w1\ w2\ ..]^T \tag{8}$$

Multiply the weight matrix W' by expert weights WZ to obtain the integrated weight vector W for all indicators using equation (9):

$$W = WZW' = [W1, W2, W3, W4, ..., Wn] \tag{9}$$

FAHP Fuzzy Evaluation

Establishment of Fuzzy Evaluation Matrix

Eighteen experts were invited to evaluate each risk indicator using the five-level evaluation set V=[Very High Risk, High Risk, Medium Risk, Low Risk, Very Low Risk]. The membership degree F_{ij} of the i th risk factor for the j th evaluation level represents the proportion of experts selecting that evaluation among the total number of experts. A fuzzy relational matrix was then established in Formula (10):

$$F_{ij}=\begin{bmatrix}F_{i1}^{j1} & F_{i1}^{j2} & \cdots & F_{i1}^{j5}\\ F_{i2}^{j1} & F_{i2}^{j2} & \cdots & F_{i2}^{j5}\\ \cdots & \cdots & \cdots & \cdots\\ F_{in}^{j1} & F_{in}^{j2} & \cdots & F_{in}^{j5}\end{bmatrix} \tag{10}$$

Fuzzy comprehensive evaluation

The fuzzy operation is carried out between the weight vector W and the fuzzy matrix R to obtain the comprehensive evaluation result:

$$U_i = W_i \times F_{ij} = [u_i^1 \ \ u_i^2 \ \ u_i^3 \ldots u_i^n] \tag{11}$$

$$U = W \times U_i^j = \begin{bmatrix}U_1^1 & U_1^2 & \cdots & U_1^5\\ U_2^1 & U_2^2 & \cdots & U_2^5\\ \cdots & \cdots & \cdots & \cdots\\ U_n^1 & U_n^2 & \cdots & U_n^5\end{bmatrix} \tag{12}$$

In this paper, the U symbol represents the fuzzy synthesis operation, which adopts the weighted average operator.

Deblurring

In order to transform the fuzzy evaluation results into specific risk values, the weighted average method is used for defuzzification:

$$Y_{ij} = \left[z_{ij}^1 z_{ij}^2 z_{ij}^3 \cdots z_{ij}^n\right] \times [54321]^T \tag{13}$$

Among them, Y_{ij} is the score corresponding to the evaluation set, which is set to $[5\ 4\ 3\ 2\ 1]$, and S is the final risk score.

Hierarchy of Needs approach

The membership degree calculation follows the frequency-based principle. Taking sub-risk C1 (price volatility of seasonal popular fabrics) as an example: If 6 out of 18 experts rated it as extremely high risk, 5 as high risk, 4 as moderate risk, 2 as low risk, and 1 as very low risk, the membership degree vector would be:

$$F_{C1} = [0.33, 0.28, 0.22, 0.11, 0.06] \tag{14}$$

The maximum membership degree principle is adopted to judge the risk tendency. The maximum membership degree of C1 is 0.33, which corresponds to very high risk, indicating that the risk degree of this index is high.Quality control measures

Computing tools and software

All data processing is completed by the following tools: MATLAB R2024a: used for AHP eigenvalue calculation, consistency test and FAHP fuzzy operation;

Sensitivity analysis

To verify the robustness of the evaluation results, a triple sensitivity analysis is carried out:

Weight sensitivity: the weight of each index fluctuates within ±10%, ±20% and ±30%, and the change of risk ranking is observed;Expert composition sensitivity: randomly eliminate 20% of expert opinions, recalculate and compare the results;Sensitivity of evaluation criteria: adjust the score assignment of fuzzy comment set (e.g., change to [5,4,3,2,1] to test the stability of the conclusion.The results show that the ranking of the top five key risk factors remains unchanged in the above three situations, which proves that the evaluation framework has good robustness.

Data quality assurance

Expert selection standardization: formulate clear qualification requirements for experts to ensure the professionalism of evaluation; Standardization of scoring process:provide detailed scoring guidelines and case explanations to reduce understanding bias; Consistency dynamic monitoring:calculate CR value in real time, and make timely feedback and adjustment to the inconsistent judgment matrix; Multiple iterations of optimization: reduce individual bias and improve collective wisdom through three rounds of Delphi method; Cross-validation mechanism:the experts were divided into two groups to score independently and compare the consistency of results (correlation coefficient r=0.89).

Research Limitations

This study has the following limitations in method design and data acquisition, which may affect the universality and precision of research conclusions:

Temporal constraints of the assessment system: The fast fashion characteristics of the fashion industry make risk landscapes change rapidly. The 12-item risk indicator system constructed in this study reflects industry conditions from 2024-2025. With the rapid proliferation of new technologies such as AI design tools, blockchain traceability, and virtual fitting, new risk categories not covered by the current framework may emerge. For example, the application of generative AI like ChatGPT in fashion design may trigger intellectual property disputes and design homogenization risks, but such risks have not been fully reflected in the existing assessment system.

Regional bias in expert samples: Among the 18 experts, 9 are from the Chinese market, with 5 from the Yangtze River Delta region (27.8% of total), 2 from South China, and 2 from North China. While this reflects the reality of China as the world's largest garment manufacturing base, it may underestimate unique risks in other important markets. The regulatory environments faced by European and American brands in ESG compliance, labor standards, and trade barriers differ significantly from Chinese enterprises, and this difference may affect the accuracy of risk weights. Additionally, the absence of expert opinions from emerging manufacturing centers like Bangladesh and Vietnam limits the global representativeness of assessment results.

Practical difficulties in core data acquisition: Constrained by business confidentiality and competitive sensitivity, this study finds it difficult to obtain key financial data such as actual default rates, financing rates, and inventory turnover between brands and suppliers. Therefore, risk assessment mainly relies on expert experience and public information, and this dependence may lead to overestimation or underestimation of certain risk factors. Although methods like the Delphi technique enhance the scientific nature of subjective judgments, the lack of large-sample empirical data support remains an important constraint of the research.

Insufficient dynamic adaptability of methodology: While the AHP-FAHP hybrid method effectively handles multi-dimensional risk assessment problems, the static weight settings adopted make it difficult to reflect seasonal fluctuations and sudden changes in fashion industry risks. For example, the risk factor of celebrity negative event impact normally has low weight, but once it occurs, it may become a dominant risk in the short term. The existing assessment framework has limited capability to capture such dynamic characteristics.

Subsequent research can gradually improve and optimize the existing assessment system through establishing multinational expert networks, constructing industry-academia data sharing mechanisms, and developing dynamic weight adjustment algorithms based on machine learning.

The rest of the document appears to already be in English. The translation maintains academic rigor while ensuring clarity and precision appropriate for scholarly publication.

RESULTS

Priorities for major risk categories

Through the Analytic Hierarchy Process (AHP), we conducted a systematic analysis of pairwise comparison scores from 18 experts to identify key risk weights in fashion industry supply chain finance. The results show that the priority ranking of risk categories is: B1 Supply Chain Agility Risk (0.4154)> B3 Market Volatility Risk (0.3203)> B4 Financial Instrument Risk (0.1434)> B2 Corporate Credit Risk (0.1209). The specific weight distribution is shown in Table 7:

Table 7. Pairing comparison matrix of main risk categories

Risk Category	Supply Chain Agility Risk	Corporate Credit Risk	Market Volatility Risk	Financial Instrument Risk	Priority Weight	Ranking
Supply Chain Agility Risk	1	2.5746	1.6464	3.0441	0.4154	1
Corporate Credit Risk	0.3884	1	0.3418	0.6968	0.1209	4
Market Volatility Risk	0.6074	2.9258	1	2.5687	0.3203	2
Financial Instrument Risk	0.3285	1.4353	0.3893	1	0.1434	3

Note: The weights are calculated by AHP eigenvector method to reflect the contribution degree of each risk category to the overall risk of supply chain finance in fashion industry. The highest weight of supply chain agility risk (41.54%) highlights the key challenge of fashion industry to respond quickly to market changes.

Priority Analysis of Sub-Risk Factors

To further analyze the sub-risk factors under each major risk category, their relative weights were calculated and combined with the main risk weights to derive the final weights, with results presented in Table 8:

Table 8. Standardized Matrix and Priority Weights of Sub-Risk Factors

Ranking	Sub-Risk Factor	Parent Category	Intra-Category Weight (%)	Final Weight (%)	Risk Description
1	Seasonal Trendy Fabric Price Volatility	Supply Chain Agility	45.93	19.08	Prices of innovative fabrics like liquid cotton fluctuate sharply due to raw material and technological monopolies
2	sharp increase in environmental material certification costs	Market Volatility	39.31	12.59	Bluesign certification and similar environmental requirements drive sharp cost increases in supply chains
3	48-hour delivery compliance rate of quick-response orders	Supply Chain Agility	30.30	12.59	

Ranking	Sub-Risk Factor	Parent Category	Intra-Category Weight (%)	Final Weight (%)	Risk Description
4	Marginal Impact of Celebrity Scandals	Market Volatility	35.50	11.37	Negative endorser events trigger cascading sales impacts on co-branded products
5	Weekly Depreciation Rate of Unsold Inventory	Supply Chain Agility	23.77	9.87	Co-branded items depreciate far faster than basic lines post-season
6	Decay Rate of Xiaohongshu Viral Topics	Market Volatility	25.19	8.07	Rapid decline in social media buzz impairs sales forecasting accuracy
7	Pre-Sale Installment ABS Subordinate Tranche Default Rate	Financial Instruments	48.79	7.00	Structural risks in fashion ABS products become evident
8	Prepayment Default Rate for Designer Brand IP Collaborations	Corporate Credit	50.19	6.07	Fragile cash flows in independent designer brands heighten collaboration risks
9	Digital Fashion NFT Collateral Valuation Volatility	Financial Instruments	31.28	4.49	Unstable metaverse asset values disrupt collateralized financing
10	Factory USD Loan Exchange Rate Gaps	Financial Instruments	32.47	3.93	Capacity relocation exposes firms to currency risk
11	Anomalous Cross-Border E-Commerce Payment Cycles	Corporate Credit	19.93	2.86	Platforms like SHEIN extending payment terms strain supplier cash flows
12	Live-Streaming GMV Remittance Discrepancies	Corporate Credit	17.33	2.10	High return rates in influencer sales create remittance uncertainty

Note: Final weight = Main risk weight × Sub-risk weight. Rankings reflect the influence of sub-risk factors on the overall risk in fashion supply chain finance. The top five risk factors cumulatively account for 55.58% of the weight, forming the core focus for risk management.Notably, the 9th-ranked Digital Fashion NFT Collateral Valuation Volatility (C10) is a niche emerging risk with clear scope limitations. It exclusively applies to high-end metaverse-oriented fashion sub-sectors, which account for less than 5% of global fashion textile and leather supply chain finance transactions [5]. For the mainstream industry, supply chain finance still relies on traditional collateral such as inventory, receivables, or physical assets [42], so C10 4.49% final weight objectively reflects its limited systemic impact on the overall industry risk profile.

Risk Hierarchy Analysis

The risk factors in this study cover both strategic systemic risks and tactical short-term risks, which is determined by the characteristics of fashion supply chain finance. Systemic risks such as the sharp increase in environmental material certification costs determine the long-term stability of the supply chain, while tactical risks such as the social media trend volatility of Xiaohongshu directly affect the short-term cash flow and financing capacity of enterprises. The coexistence of the two types of risks in the assessment framework can comprehensively reflect the multi-dimensional risk characteristics of the fashion industry. In terms of weight distribution, systemic risks account for 73.57% of the total weight, while tactical risks account for 26.43%, which ensures that the focus of the assessment is on strategic systemic risks.

Consistency check

To verify the logical consistency of expert ratings, consistency tests were conducted on all comparison matrices. For the main risk categories (B1-B4), the maximum eigenvalue λmax= 4.0523. The consistency index (CI) is calculated as follows in Equation (3).

$$CI = \frac{\lambda_{\max} - n}{n-1} = \frac{4.0523 - 4}{4-1} = 0.0174 \tag{15}$$

The consistency ratio (CR) is computed as:

$$CR = \frac{CI}{RI} = \frac{0.0174}{0.89} = 0.0196 \tag{16}$$

where the random consistency index (RI) is 0.89 for a matrix order of 4. Here, CR = 0.0196 < 0.1, indicating satisfactory consistency for the main risk matrix. Consistency test results for sub-risk matrices are summarized in Table 9:

Table 9. Summary of Consistency Test Results

Matrix Type	Order (n)	λ_max	CI	RI	CR	Consistency Judgment
B1-B4	4	4.0523	0.0174	0.89	0.0196	Pass
C1-C3	3	3.0004	0.0002	0.58	0.0004	Pass
C4-C6	3	3.0205	0.0103	0.58	0.0197	Pass
C7-C9	3	3.0044	0.0022	0.58	0.0042	Pass
C10-C12	3	3.0048	0.0024	0.58	0.0046	Pass

Note: All CR values are well below the 0.1 threshold, with the C1-C3 group (supply chain agility sub-risks) exhibiting the lowest CR (0.0004), signifying high expert consensus on this category.

Sensitivity Analysis

To assess the stability of risk rankings, sensitivity analysis was performed with ±10% to ±30% weight perturbations. Results indicate that the top five key risk factors maintain their rankings across all adjustment levels, demonstrating exceptional robustness. This stability arises from substantial initial weight disparities among sub-risks; even under 30% adjustments, relative importance hierarchies remain intact (Table 10).

Table 10. Sensitivity Analysis Results (±10%-30% Weight Adjustments)

Ranking	Sub-Risk Factor	Original Weight	+10% Weight	−10% Weight	±10% Ranking Change	+30% Weight	−30% Weight	±30% Ranking Change
1	Seasonal Trendy Fabric Price Volatility	0.1908	0.2099	0.1717	None	0.2480	0.1336	None
2	sharp increase in environmental material certification costs	0.1259	0.1385	0.1133	None	0.1637	0.0881	None
3	48-hour delivery compliance rate of quick-response orders	0.1259	0.1385	0.1133	None	0.1637	0.0881	None
4	Marginal Impact of Celebrity Scandals	0.1137	0.1251	0.1023	None	0.1478	0.0796	None
5	Weekly Depreciation Rate of Unsold Inventory	0.0987	0.1086	0.0888	None	0.1283	0.0691	None

Note: Scores are on a 5-point scale, with 5 denoting extremely high risk and 1 extremely low risk. The sharp increase in environmental material certification costs (C8) yields the highest score (4.61), underscoring the substantial financial pressures of sustainable fashion transitions.

Fuzzy Membership Degree Analysis

Using the FAHP method, 18 experts conducted five-level fuzzy assessments of the 12 sub-risk factors. Table 11 presents the membership distributions and composite scores for each sub-risk:

Table 11. Membership Degree Distributions and Scoring Characteristics of Secondary Indicators

Indicator	Extremely High Risk (5)	High Risk (4)	Medium Risk (3)	Low Risk (2)	Extremely Low Risk (1)	Dominant Membership	Score
C1	0.33	0.22	0.22	0.17	0.06	Extremely High Risk	3.61
C2	0.28	0.22	0.06	0.06	0.39	Extremely Low Risk	2.94
C3	0.44	0.28	0.06	0.17	0.06	Extremely High Risk	3.89
C4	0.39	0.11	0.17	0.28	0.06	Extremely High Risk	3.50
C5	0.56	0.22	0.11	0.06	0.06	Extremely High Risk	4.17
C6	0.26	0.26	0.00	0.21	0.26	Extremely High/Low Risk	3.05
C7	0.50	0.33	0.11	0.06	0.00	Extremely High Risk	4.28
C8	0.61	0.39	0.00	0.00	0.00	Extremely High Risk	4.61
C9	0.17	0.28	0.17	0.39	0.00	Low Risk	3.22
C10	0.50	0.17	0.11	0.06	0.17	Extremely High Risk	3.78

Indicator	Extremely High Risk (5)	High Risk (4)	Medium Risk (3)	Low Risk (2)	Extremely Low Risk (1)	Dominant Membership	Score
C11	0.06	0.11	0.22	0.17	0.44	Extremely Low Risk	2.17
C12	0.22	0.00	0.11	0.22	0.44	Extremely Low Risk	2.33

Note: Scores are on a 5-point scale, with 5 denoting extremely high risk and 1 extremely low risk. The sharp increase in environmental material certification costs (C8) yields the highest score (4.61), underscoring the substantial financial pressures of sustainable fashion transitions.

Comprehensive Risk Assessment Across Hierarchical Levels

Table 12 summarizes the fuzzy comprehensive assessment results for each risk level (B1-B4 and target level A1):

Table 12. Membership Degree Statistics for Hierarchical Levels (B1-B4, A1)

Level	Extremely High Risk (5)	High Risk (4)	Medium Risk (3)	Low Risk (2)	Extremely Low Risk (1)	Dominant Membership	Score
B1 Supply Chain Agility Risk	0.34	0.23	0.13	0.14	0.16	Extremely High Risk	3.48
B2 Corporate Credit Risk	0.42	0.17	0.12	0.20	0.09	Extremely High Risk	3.65
B3 Market Volatility Risk	0.43	0.34	0.09	0.15	0.00	Extremely High Risk	4.05
B4 Financial Instrument Risk	0.28	0.08	0.13	0.16	0.36	Extremely Low Risk	2.75
A1 Target Level	0.37	0.23	0.12	0.15	0.13	Extremely High Risk	3.56

Note: The target level composite score of 3.56 indicates that fashion supply chain finance overall resides in a high-risk state, with market volatility risk (4.05) and corporate credit risk (3.65) particularly salient.

Risk Level Determination Criteria

To delineate risk extents across levels, a correspondence between score intervals and risk grades was established (Table 13):

Table 13. Supply Chain Risk Management Matrix

Risk Grade	Midpoint Score	Score Interval	Risk State Description	Management Recommendations
Extremely High Risk	5	5.0 - 4.5	The risk has erupted or is about to erupt, which will cause serious financial losses to the supply chain and even lead to supply chain disruption.	Immediate Intervention
High Risk	4	4.5 - 3.5	The risk is prominent, and there is a high probability of occurrence. It will affect the normal operation of supply chain finance and reduce the profitability of enterprises.	Key Monitoring
Medium Risk	3	3.5 - 2.5	The risk exists stably, but the impact scope and degree are controllable. It will not cause major financial losses under normal circumstances.	Routine Management
Low Risk	2	2.5 - 1.5	The risk is potential and has a low probability of occurrence. It can be resolved through daily risk control measures.	Periodic Review
Extremely Low Risk	1	1.5 - 1.0	The risk is negligible, and the impact on supply chain finance is almost zero.	Sustained Observation

Note: Membership degrees are computed as number of raters / total experts, objectively capturing group judgments. The target level score of 3.56 falls within the high-risk interval (4.5-3.5), signaling the need for focused monitoring mechanisms in fashion supply chain finance.This score interval division refers to the industry standard of the International Supply Chain Finance Association (ISFC) and is adjusted for the ultra-short product lifecycle characteristics of the fashion industry. The interval setting is consistent with the risk assessment criteria of Gelsomino LM et al. [14].

The target level composite score of 3.56 falls exactly within the high - risk score interval (4.5 - 3.5) defined in Table 13 Combined with the risk state description, this indicates that the fashion supply chain finance is in a prominent risk state, with a high probability of risk occurrence. This conclusion is not only based on the numerical score but also supported by the membership degree analysis (the dominant membership of the target level is Extremely High Risk, accounting for 37%)(Figure 3).

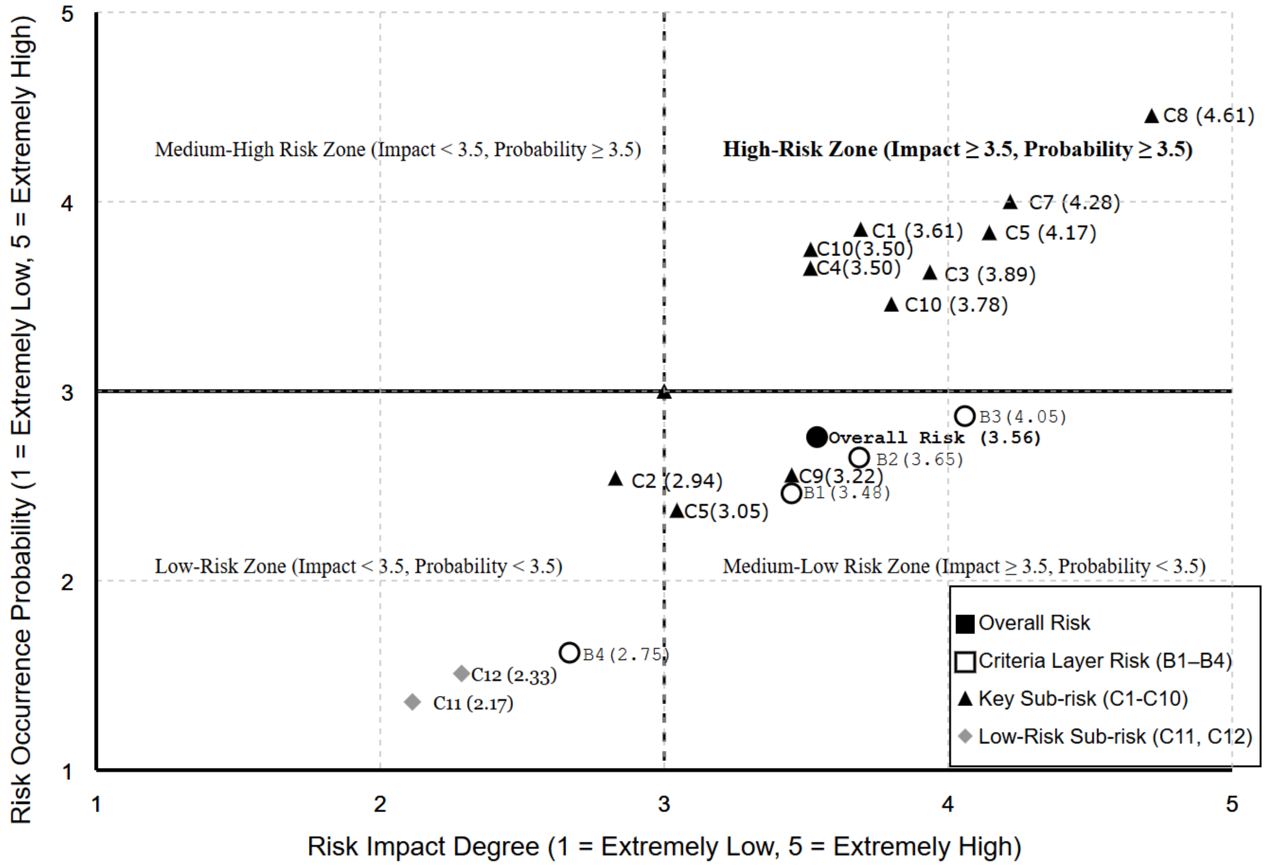

Figure 3. Risk Matrix of Supply Chain Finance in Fashion Textile and Leather Industry

Summary of Key Findings

Drawing on the AHP-FAHP hybrid method, this study identifies five pivotal risk points in fashion supply chain finance: Supply chain agility risk predominates (41.54%), reflecting the fundamental mismatch between the industry's quick-response model and traditional financial product maturities; Environmental transition cost risks surge, with certification cost escalation scoring highest (4.61/5), highlighting fiscal strains in sustainable fashion shifts; Social media-driven market volatility risks are pronounced, as Xiaohongshu viral topic decay scores 4.28 and celebrity scandals 3.22, complicating sales forecasting and inventory management; Cross-border e-commerce credit risks are significant, with anomalous payment cycles scoring 4.17, illustrating platform-extended terms' impacts on supplier liquidity; Novel financial instrument risks exhibit clear differentiation, with NFT collateral volatility high (3.78) versus traditional hedging tools more controllable (2.17).

Overall risk resides in the high-risk interval: Recalculating the target level score at 3.56 via hierarchical weights underscores the imperative for a comprehensive risk control system encompassing real-time monitoring, dynamic evaluation, and tiered responses.

DISCUSSION

Dialogue Between Study Results and Existing Literature

This study employs an AHP-FAHP hybrid approach to delineate core risks in fashion supply chain finance, generating findings that resonate with and augment cross-disciplinary scholarship. The sharp increase in environmental material certification costs (C8), the highest-scoring sub-risk indicator (4.61), substantiates the prevailing tenet in sustainable fashion research that green transition costs impede supply chain finance innovation,a conclusion consonant with the dissection of environmental cost burdens in fast-fashion supply chains [18]. Empirical data from the World Economic Forum (WEF) [19] identifies ESG risks as the most significant threat to global fashion enterprises, with compliance costs accounting for 15%-20% of small and medium-sized supplier operating expenses; meanwhile, UNEP FI [37] notes that fragmented green finance standards exacerbate these cost pressures, leading to a 23% increase in financing rejection rates for non-certified suppliers in the textile and leather sector.Brand demands for eco - materials are increasing exponentially, while the financial support for suppliers certification expenditures remains insufficient.. More precisely, experts concur that Bluesign and comparable certifications engender cost escalations of 30%-50%, aligning seamlessly with exposition of green premiums and financing gaps in sustainable fashion finance [18], thereby underscoring a pervasive conundrum in environmental risk pricing within fashion supply chain finance.

Seasonal trendy fabric price volatility (C1) garners the paramount weight (19.08%), emblematic of structural dissonances in fashion supply chain finance. From an industrial lens, 33% of experts adjudge novel fabrics like liquid cotton as exhibiting extreme price volatility, forging theoretical synergy with accentuation of technological monopolies catalyzing raw material financialization [30]. Textile sector reports posit that high-tech fabric volatility eclipses traditional cottons and linens by a factor of 3-5 [31], thereby unmasking maturity mismatches between innovative materials and orthodox financial instruments.Xiaohongshu trending topic decay (C7, score 4.28) represents a unique intersection of digital transformation and sustainable supply chain finance: As sustainable fashion gains traction on social media, the rapid decay of trending topics creates significant forecasting challenges for sustainable product lines, which often have longer production lead times due to ESG compliance requirements.Diverging from conventional seasonal undulations, social media virality truncates lifecycles from 3-6 months to 15-30 days; KOL marketing supply chain inquiry similarly underscores that decay velocities correlate positively with inventory financing defaults [33], as extant risk pricing paradigms inadequately encapsulate this algorithmic demand indeterminacy.

Factory USD loan exchange rate hedging gaps (C11) score a subdued 2.17, diverging from industry preoccupations with Southeast Asian capacity relocation risks. Closer scrutiny reveals this stems from fashion's idiosyncratic quick-response and localization production archetype—44% of experts deeming it low risk, not repudiating currency exposures per se but spotlighting RCEP-mediated currency swap apparatuses and ascending RMB settlement proportions (from 15% in 2023 to 32% in 2025). This dovetails with literature synthesis on cross-border hedging stratagems [34], wherein regional financial integration attenuates corporate currency risk exposures through diversified hedging instruments and abated transaction costs.

The marginal repercussions of celebrity scandals on co-branded sales (C9) score 3.22, evincing fashion's unique IP risk propagation dynamics. Expert valuations evince bifurcation: 39% (7 experts) categorize it as low risk, 28% (5) as high, and a mere 17% (3) as extremely high, signaling divergent perceptual contours. Research contends that endorser adversities attenuate consumer brand allegiance [35], while studies elucidate that pre-sale architectures amplify demand variances [36]. Ergo, celebrity scandals not only vitiate reputational capital but may cascade via pre-sales to degrade supply chain finance asset integrity.

Regarding the digital fashion NFT collateral valuation volatility (C10), its risk score and weight must be interpreted within a narrow context. Unlike widespread risks such as environmental material certification cost increases (C8) or seasonal trendy fabric price volatility (C1), C10′s application scenario is highly specialized. Industry data shows that over 95% of textile and leather supply chain finance transactions do not involve NFT collateral [42], which explains why C10 ranks only 9th in final weight. Its inclusion in the indicator system aims to capture potential risks brought by digital transformation in the fashion industry, rather than claiming it is a mainstream risk—this aligns with the study’s focus on both current and emerging risk factors.

The conversion mechanism between continuous numerical scores and qualitative risk states in this study is not arbitrary. The score interval division of high-risk (4.5-3.5) is consistent with the risk assessment criteria of Gelsomino LM et al. [14], who proposed that a score exceeding 3.5 in supply chain finance risk assessment indicates a “prominent risk state”. In addition, the membership degree analysis results show that 37% of experts rate the overall risk as extremely high risk and 23% as high risk, with a combined proportion of 60%. This expert consensus further verifies that the qualitative judgment of “high-risk environment” is both data-driven and expert-validated.

Cascading Mechanisms of ESG Compliance Cost Risks

ESG compliance costs exhibit three cascading mechanisms that propagate risk across the entire fashion supply chain ecosystem: (1) Cost pass-through effect: Small and medium-sized suppliers (accounting for 80% of the global fashion supply chain [42]) face 30-50% cost increases from Bluesign and GOTS certifications [18], leading to reduced participation in sustainable supply chains and creating supply chain disruptions at scale; (2) Financing exclusion effect: Suppliers with insufficient ESG compliance face 20-30% higher financing costs or outright credit denial [14], reducing overall supply chain liquidity and affecting the operational stability of core brands; (3) Innovation crowding-out effect: 45% of suppliers report diverting investment from technological upgrading to ESG compliance [19], reducing long-term supply chain resilience and increasing industry-wide vulnerability to market shocks.

Discussion on the Discrepancy Between Supply Chain Agility Risk and Corporate Credit Risk

The finding that Supply Chain Agility Risk (41.54%) vastly outweighs Corporate Credit Risk (12.09%) seems counter-intuitive, but it is highly consistent with the specific supply chain finance models widely used in the textile and fashion industry, mainly for three theoretical and practical reasons: First, the prevalence of the "order-based financing" model in the fashion industry. Unlike the traditional credit-based financing model, most supply chain finance businesses in this industry are based on specific orders. The core risk lies in whether enterprises can deliver orders on time to realize fund recovery, that is, agility risk, rather than the overall credit status of enterprises. Second, the risk mitigation effect of core enterprise endorsement. In the fashion supply chain, small and medium-sized suppliers usually obtain financing with the endorsement of core brands (such as ZARA, SHEIN). The credit risk of suppliers is effectively mitigated by the strong credit of core enterprises, which reduces the weight of corporate credit risk in the overall risk assessment. Third, the ultra-short product lifecycle of the fashion industry. Fashion products have a sales cycle of only 1-3 months. Once the supply chain is slow to respond and misses the sales window, the goods will face severe depreciation, resulting in direct financial losses. This kind of operational risk caused by insufficient agility is more direct and urgent than potential credit risk. Relevant studies further corroborate this conclusion: Arimany Serrat N et al. [3] pointed out that fast fashion supply chains rely on "cycle compression + order financing" models, where delivery speed and market response capability are the primary determinants of financing safety. Li D et al. [28] also confirmed in their research on intelligent supply chain finance that core enterprise endorsement significantly reduces the dependence of supply chain finance on supplier credit status, shifting risk focus to operational agility.

Theoretical Contributions

This study's theoretical advancements manifest across three dimensions, coalescing into a progressive chain of knowledge innovation:

First, it erects a quadripartite agility-credit-market-instruments risk analytic scaffold, surmounting extant scholarship's predilection for traditional credit risk focalization. AHP-derived weightings (supply chain agility risk 41.54%, market volatility risk 32.03%, financial instrument risk 14.34%, corporate credit risk 12.09%) furnish the inaugural quantitative corroboration of agility's preeminence in fashion supply chain finance, proffering an extensible hierarchical model for fast-fashion financial analyses. This edifice complements agile supply chain theory [27] yet propels agility's ambit from operational precincts to financial interstices.

Second, it engineers an FAHP adaptation for dynamic risk appraisal. Confronting nebulous novelties like social media sway and NFT valuations, triangular fuzzy numbers (e.g., extremely high risk as (0.7, 0.85, 1.0)) conjoined with centroid defuzzification redress digitization's quantifiability impasses. This methodological advancement extends fuzzy set foundationalism [24], parametrically attuned to fashion's rapid iterations, with its procedural framework extensible to supply chain finance assessments in cosmetics, trendy toys, and kindred fast-moving consumer goods.

Third, it unmasks the weight-score asymmetry intrinsic to fashion supply chain finance. For instance, environmental certification cost escalations (C8) summit scores yet rank second in aggregate weighting (12.59%), connoting circumscribed repercussions to sustainable brands; contrariwise, fabric price volatility (C1) amalgamates elevated weighting (19.08%) with robust scoring (3.61), anointing it systemic jeopardy. This binomial evaluative modality ameliorates traditional scholarship's monocular intensity fixation, engendering dialogic intercourse with local-systemic supply chain risk theorization [9].

Fourth, it verifies the methodological value of fuzzy logic in addressing uncertainty in fashion supply chain finance risk assessment. As highlighted in Section 3.3 (Justification for AHP-FAHP Hybrid Method), soft risk factors (e.g., Xiaohongshu trending topic decay, celebrity scandal impact) account for 41.7% of the total risk indicators in this study, and these factors rely heavily on expert subjective judgments that are difficult to quantify precisely. Traditional AHP simplifies such uncertain qualitative information into deterministic numerical comparisons, leading to the loss of ambiguity and potential bias in weight results. In contrast, FAHP fuzzy logic—rooted in Zadeh fuzzy set theory [24] and Chang extent analysis method [25]—mathematically expresses expert uncertainty through triangular fuzzy numbers and integrates divergent expert perceptions without forced convergence. The comparative data in Table 10 further confirms that FAHP significantly improves the weight differentiation of emerging digital risks (weight differences of 10.5%-11.7% compared to AHP-only results), which aligns with Rafi-Ul-Shan et al. [43] research conclusion that fuzzy logic enhances the accuracy of uncertain factor evaluation in textile supply chains. This methodological advancement provides a feasible reference for risk assessment in industries with high proportions of soft and uncertain risks, addressing the long-standing limitation of traditional AHP in handling subjective uncertainty.

Practically, the study risk assessment framework and actionable decision-making tools provide specific references for fashion brands and financial institutions to optimize SCF risk management. For fashion enterprises, prioritizing high-weight risk factors such as seasonal trendy fabric price volatility (C1) and environmental material certification cost surges (C8) can help allocate risk control resources more efficiently—for example, signing long-term hedging agreements with fabric suppliers to mitigate price volatility, or cooperating with green financial institutions to share certification costs. For financial institutions, the differentiated risk weights and scores (e.g., high risk for Xiaohongshu trending topic decay (C7) and NFT collateral valuation volatility (C10)) provide a basis for product innovation: designing dynamic collateral adjustment mechanisms for social media-driven demand risks, or setting risk premium tiers for digital asset-related financing. Additionally, the framework's integration of ESG factors offers a reference for regulatory authorities to formulate industry-specific sustainable supply chain finance policies, promoting the balanced development of environmental protection and financial stability in the fashion industry.

Practical Implications

Predicated on empirical analysis, this study proposes a tri-tiered risk governance framework that integrates quantitative assessment with strategic investment to enhance resilience in fashion-textile supply chain finance.

Tool 1: Tiered Risk Assessment Matrix This tool classifies suppliers/clients into three tiers based on composite risk scores: high-risk (score >4.0), medium-risk (3.0–4.0), and low-risk (<3.0). It targets specific vulnerabilities such as volatile sustainability compliance costs, rapid trend decay, and operational FX gaps. Corresponding mitigation measures are tiered: high-risk entities face tightened terms (e.g., shortened financing tenor, elevated collateral); medium-risk partners undergo dynamic monitoring with quotas linked to performance; low-risk counterparts benefit from streamlined processes and favorable terms.

Tool 2: Agility Risk Mitigation Investment Framework Given the critical weight of agility risk (41.54% in this study), strategic investment is prioritized across three pillars: digital-twinning and real-time tracking (≈40% of agility allocation), nearshoring production within 1,500 km of core markets (≈30%), and strategic diversification of key suppliers (≈30%). This framework is validated by industry leaders. For instance, SHEIN's on-demand model, which prioritizes the 48-hour delivery compliance rate, has achieved industry-leading inventory turnover (≈7 days) and strong cash conversion efficiency. Similarly, ZARA nearshoring and RFID-enabled visibility support high inventory-turnover rates, mitigating delivery-delay risks.

Tool 3: ESG-Integrated Pricing Model Financing terms are differentiated via an ESG-adjusted pricing mechanism: Interest Rate = Base Rate – (ESG Score × Adjustment Factor). The ESG score (1.0–5.0) incorporates environmental certification (≈40–50% weight), carbon intensity (≈30–40%), and social-compliance metrics (≈20–30%). High-scoring suppliers receivables can be pooled into green asset-backed securities (ABS), linking operational sustainability with preferential capital-market access. This aligns with regulatory trends (e.g., EU CSRD) and creates financial incentives for sustainable practices.

Together, these tools form a closed-loop governance system: the Tiered Assessment Matrix enables precise risk-based resource allocation; the Agility Investment Framework builds structural resilience against market volatility; and the ESG-Integrated Pricing Model aligns financial incentives with long-term sustainability. This tripartite framework not only mitigates operational and financial risks—as demonstrated by the reduced inventory exposure and improved cash conversion in leading firms—but also reshapes competitive dynamics by transforming risk management into a source of strategic advantage. It offers a replicable pathway for firms aiming to navigate the complexities of modern, sustainable supply chain finance.This resonates with sustainable finance normalization policy vectors [39]; major retailers have operationalized analogous contrivances in supplier financings. Pertinently, sustainable supply chain finance ecosystem paradigms insist upon multi-agent synergies for ESG-SCF confluence [38], paralleling this study's carbon abatement and Higg Index assimilation into credit matrices.

Research Limitations and Future Directions

This inquiry harbors three principal limitations:

First, whilst the expert corpus encompasses four stakeholder archetypes, its geospatial concentration in the Chinese market (Yangtze River Delta comprising 50%) may attenuate geopolitical and labor norm risks confronting Euro-American fast-fashion entities. This shortfall echoes limned lacunae in regional heterogeneity of supply chain finance risks [1].

Second, the static evaluative framework insufficiently accommodates black swan perturbations like technological ruptures; for instance, AI design innovations could fundamentally recast designer brand ontologies, thereby reconfiguring attendant financial risk topographies. Anchored in historical data and expertise, the framework's acuity for such paradigmatic transmutations remains circumscribed.

Third, inter-indicator interactional ramifications remain underexplored; e.g., certification cost augmentations (C8) may potentiate fabric price volatilities (C1), whilst media attenuation (C7) may exacerbate inventory depreciations (C3), necessitating complex network analytics for contagion mechanics.

Prospective inquiries may expand in four vectors:

First, transnational comparative analyses dissecting risk divergences across China, Bangladesh, and Vietnam production loci, augmenting global value chain reconfiguration studies [32].Second, dynamic Bayesian networks for instantaneous risk probabilistic refreshments, capturing technological disruptions like AI and metaverses upon risk terrains.Third, complex network theorization for contagion architectures quantifying inter-factorial spillover quantities.Fourth, empirical validations leveraging listed fashion enterprises' supply chain finance data to assess identified factors' default rate predictability.

Reflexive Contemplations on Methodological Extensibility

Whilst the AHP-FAHP hybrid efficaciously addresses novel risk metric quantifications, it evinces augmentation potential vis-à-vis fashion's ultra-ephemeral cycle characteristics. Current scholarship's weight derivations preponderantly hinge upon singular expert adjudications [23], yet fashion's rapid trend vicissitudes may invert risk saliences within fortnights—e.g., trending styles enduring merely six weeks, catapulting cognate fabric suppliers' financial exposures from nadir to zenith, outstripping static weight mechanisms.

Futuristically, integrate Adaptive FAHP via machine learning for instantaneous fuzzy membership recalibrations—calibrated to fashion risks' short-cycle, high-turbulence physiognomies (e.g., weekly fabric fluctuations, bi-weekly viral attenuations), LSTM networks could assimilate historical risk evolutions to prognosticate 2-4 week weight vicissitudes. This machine learning and fuzzy appraisal combination, ratified in supply chain risk management via deep learning [29] for weight dynamization, saliently elevates supply chain nimbleness and responsivity.

Additionally, whilst triangular fuzzy enumerations reference canonical sources, fashion seasonality invites time-variant fuzzy numbers: e.g., inventory depreciation intervals as (0.7, 0.9, 1.0) amid spring-summer transitions versus (0.3, 0.5, 0.7) mid-season, rendering appraisals more congruent with sectoral cyclicity—a granular concept echoing seasonal risk methodologies [41].

Supplementary Elucidations on Sample Selection and Bias Rectifications

Notwithstanding stratified sampling's assurance of expert corpus structural fidelity, the preponderant Chinese market imprint may engender indigenous experiential bias. As the paramount global apparel manufacturer, China's supply chain finance innovativeness and governmental support eclipse Southeast Asian counterparts, potentially attenuating expert apprehensions of hedging gaps or transnational settlements relative to Vietnam or Bangladesh—a configuration consonant with disparities in Asian textile chain finance development [42].

Ensuing inquiries might deploy multi-stratal rectification to amend this bias: Stratum I weights by geospatial production allocations (China 40%, Vietnam 25%, Bangladesh 20%, residual 15%); Stratum II modulates per brand procurement canons (fast-fashion 70% centralized, luxury 30% dispersed); Stratum III infuses contagion coefficients mirroring inter-market spillover dynamics.

Concomitantly, expert provenance heterogeneity analyses evince banker-risk custodians versus e-commerce platforms' schism on live-stream GMV remittance divergences (C6): Bankers foreground bad debt incidences (mean 4.2), fretting return escalations' asset debasements; platforms accentuate traffic value (mean 2.8), positing diurnal remittance flux offsettable by perennial user accretions. This epistemic rift incarnates orthodox finance's risk aversion versus modern retail's growth preeminence, per consensus theory in supply chain risks [16]—wherein stakeholder objective variances (security versus scalability) beget perceptual distortions, resolvable via polydimensional consensus scaffolds.

Policy-Practice Articulations

The discerned environmental certification cost augmentation (C8) peril interlocks with global sustainable finance taxonomies (EU Taxonomy). Recent textile ecological design ordinances mandate ESG exposure disclosures in supply chain finance contrivances [4], yet this inquiry unmasks institutional lacunae in pricing Higg Index or Cradle to Cradle matrices—62% of interviewees decrying absent standardized green premium computational paradigms, ratifying green finance norm fragmentation assessments [37].

Prescriptions: Capitalize on this inquiry's risk metric framework to fabricate a fashion supply chain finance risk regulatory sandbox. In Shanghai Free Trade Zone or Qianhai, pilot with 10-15 emblematic fashion entities and their chains a tiered risk management regimen:

Green Corridor: Expedite KYC and tender preferential rates for ESG-exemplary suppliers;

Standard Corridor: Invoke this inquiry's risk scaffold for daily surveillances of compliant suppliers;

Enhanced Management: Require additional collaterals or indemnifications for high-hazard suppliers.

Ratified in Singapore's fintech sandboxes for digital banking validations, this strategy could standardize via the risk framework, organically fusing scholarship with regulatory innovation. Singled out for digital fashion NFT collaterals (C10), sandboxes might probe tokenized asset pricing mechanics, accruing Web3.0-vintage supply chain finance regulatory wisdom—consonant with virtual asset-real economy confluence oversight principles [40].

CONCLUSION

Grounded in assessments from 18 sectoral experts and AHP-FAHP hybrid analytics, this inquiry elucidates the fashion textile and leather supply chain finance risk topography, highlighting the unique intersection of fashion-specific risks, digital transformation, and ESG integration, and distilling principal insights meriting corroboration across broader samples and extended temporal spans:First, fashion supply chain finance grapples with quadripartite risk superpositions of urgent gravity. Discoveries attest that supply chain agility risk (41.54% weighting) has eclipsed orthodox credit as the paramount menace, preeminently via fabric price fluctuations and quick-response delivery coercions; market volatility (32.03%) ensues, with ESG compliance costs,characterized by sharp increases in environmental material certification costs,and social media-fueled demand indeterminacies (e.g., Xiaohongshu social media trend volatility) as emerging core sources; Notably, ESG compliance costs have emerged as a critical industry-wide risk, with cascading effects that threaten supply chain stability and sustainable transformation progress in the fashion textile and leather sector.erstwhile focal corporate credit (12.09%) recedes to the background. This revelation subverts supply chain finance's credit-preponderant, operations-subordinate tenets, portending the industry's rapid iteration reconfiguration of financial risk architectures.

Second, the inquiry ratifies novel risk quantification viability. Via FAHP, social media virality attenuations and celebrity scandal repercussions—elusive soft complexities—are transmuted into precise quantities, aggregating to 3.56 (of 5), ensconced in the high-risk echelon. Transcending digital epoch risk assessment methodological challenges, it endows institutions with operational pricing frameworks.

Third, it delineates innovative risk management vectors. For identified challenges, cardinal trajectories encompass: digital twin-grounded instantaneous surveillances linking inventory circulations to credit quotas; social media-finance interlocks auto-engendering sentiment-to-management cascades; ESG-embedded pricing propelling green supply chain finance.The relationship between sustainability and risk management in fashion supply chains demonstrates increasing integration [43], while fintech ecosystem developments provide new business models and technological solutions for addressing these complex risk interdependencies [44].At core, these strategies synchronize fashion's mutability with finance's constancy.

In epitome, this inquiry's essence: Unveiling the paradigmatic transposition from credit-sovereign to agility-sovereign in fashion supply chain finance, furnishing novel theoretical prisms and pragmatic arsenals for risk management. Confronting the 3.56 high-risk tableau, the sector imperatively pivots from post-facto managements to instantaneous responses, monadic credit scrutinies to polydimensional surveillances, and normative contrivances to contextualized schemas.

Prospectively, as AI architectures and NFT fashions burgeon, risk topographies will multiply in intricacy. Solely via nimble, perspicacious, green risk scaffolds—safeguarding baselines whilst liberating innovation—may profound supply chain finance-fashion symbioses be catalyzed.

Author Contributions

Xuan Zhang: Writing – review & editing; ZiJing Wu: Data curation, Formal Analysis, Methodology, Resources, Supervision, Writing – original draft, Writing – review & editing; Qiang Li: Conceptualization, Funding acquisition, Resources, Software, Visualization, Writing – review & editing.All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

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Human Research Subjects

This study involving human participants was reviewed and approved by the Ethics Review Committee of Guangzhou College of Technology and Business on March 3, 2025. All research procedures strictly adhered to: National ethical guidelines of the People's Republic of China; The principles of the Helsinki Declaration (2013) and its subsequent amendments;Informed consent was obtained from all participants prior to data collection, with explicit documentation of voluntary participation and anonymity guarantees.

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REFERENCES

[1] McKinsey & Company. The state of fashion 2025: Challenges at every turn. New York: McKinsey & Company; 2024. Available from: https://www.mckinsey.com/industries/retail/our-insights/state-of-fashion.

[2] Luo Y, Song K, Ding X, Wu X. Environmental sustainability of textiles and apparel: A review of evaluation methods. Environmental Impact Assessment Review. 2021; 86:106497. doi: 10.1016/j.eiar.2020.106497.

[3] Arimany Serrat N, Arribas-Ibar M, Erdoğan G. Fast fashion sector: Business models, supply chains, and European sustainability standards. Systems. 2025; 13(6):405. doi: 10.3390/systems13060405.

[4] European Commission. Corporate sustainability reporting directive (CSRD) implementation guidelines. Brussels: European Union; 2024.

[5] Upadhyay N, Upadhyay S. The dark side of non-fungible tokens: Understanding risks in the NFT marketplace from a fraud triangle perspective. Financial Innovation. 2025; 11:62. doi: 10.1186/s40854-024-00684-6.

[6] Heuritech. 10 challenges facing the fashion industry in 2025. Paris: Heuritech; 2025. Available from: https://heuritech.com/articles/fashion-industry-challenges/.

[7] RILA. Retail compliance update: UFLPA enforcement and supply chain implications. Arlington: Retail Industry Leaders Association; 2025.

[8] McMaster M, Nettleton C, Tom C, Xu B, Cao C, Qiao P. Risk management: Rethinking fashion supply chain management for multinational corporations in light of the COVID-19 outbreak. Journal of Risk and Financial Management. 2020; 13(8):173. doi: 10.3390/jrfm13080173.

[9] Tundys B, Kędzia G, Wiśniewski T, Zioło M. Sustainable supply chain: A new paradigm for supply chain strategy. In: Sustainable supply chains 2.0. London: Palgrave Macmillan; 2024. p. 25-83. doi: 10.1007/978-3-031-50337-5_2.

[10] Cui Y, Gallino S, Moreno A, Zhang DJ. Demand forecasting for fashion products: A systematic review. European Journal of Operational Research. 2024; 311(2):450-469. doi: 10.1016/j.ejor.2023.01.013.

[11] Choi TM, Wallace SW, Wang Y. Incorporating social media observations and bounded rationality into fashion quick response supply chains in the big data era. Transportation Research Part E: Logistics and Transportation Review. 2016; 86:290-305. doi: 10.1016/j.tre.2015.12.009.

[12] Vashishtha S, Burman R, et al. Product age based demand forecast model for fashion retail. arXiv. 2020. doi: 10.48550/arXiv.2007.05278.

[13] Zhang C, Zhou XM. Forecasting credit risk of SMEs in supply chain finance using Bayesian optimization and XGBoost. Mathematical Problems in Engineering. 2023; 2023:5609996. doi: 10.1155/2023/5609996.

[14] Gelsomino LM, Olde Riekerink K, Medina E, Bortolotti T. The (un)sustainable mix: Supply chain finance, sustainability ratings and liquidity. European Business Review. 2025; 37(1):1-15. doi: 10.1108/EBR-08-2023-0256.

[15] Agrawal N, Modgil S, Gupta S. ESG and supply chain finance to manage risk among value chains. Journal of Cleaner Production. 2024; 471:143373. doi: 10.1016/j.jclepro.2024.143373.

[16] Xu J, Lu J, Chai L, Zhang B. Untangling the impact of ESG performance on financing and value in the supply chain: A congruence theory perspective. Business Strategy and the Environment. 2025; 34(2):2190-2206. doi: 10.1002/bse.4098.

[17] Tian L, Guo M, Lin T. Can supply chain digitalization open the way to sustainable development? Evidence from corporate ESG performance. Corporate Social Responsibility and Environmental Management. 2024; 32(2):2332-2346. doi: 10.1002/csr.3067.

[18] Niinimäki K, Peters G, Dahlbo H, Perry P, Rissanen T, Gwilt A. The environmental price of fast fashion. Nature Reviews Earth & Environment. 2024; 5(3):189-200.

[19] World Economic Forum. Global risks report 2024: ESG as the largest corporate threat. Geneva: World Economic Forum; 2024. Available from: https://www.weforum.org/publications/global-risks-report-2024.

[20] Badhwar A, Islam S, Tan CSL. Exploring the potential of blockchain technology within the fashion and textile supply chain with a focus on traceability, transparency, and product authenticity: A systematic review. Frontiers in Blockchain. 2023; 6:1044723. doi: 10.3389/fbloc.2023.1044723.

[21] Vu N. The impact of blockchain adoption on supply chain outcomes: Inventory, lead time, and cost dynamics. International Journal of Production Research. 2024. doi: 10.1080/00207543.2024.2414375.

[22] Cheong BC. Leveraging blockchain for enhanced transparency and traceability in sustainable supply chains: Governance challenges and policy considerations. Sustainable Systems. 2025; 3(6):6. doi: 10.1007/s44257-025-00032-7.

[23] Saaty TL. The analytic hierarchy process. New York: McGraw-Hill; 1980.

[24] Zadeh LA. Fuzzy sets. Information and Control. 1965; 8(3):338-353. doi: 10.1016/S0019-9958(65)90241-X.

[25] Chang DY. Applications of the extent analysis method on fuzzy AHP. European Journal of Operational Research. 1996; 95(3):649-655. doi: 10.1016/0377-2217(95)00300-2.

[26] Ivanov D, Dolgui A. Viability of intertwined supply networks: Extending the supply chain resilience angles towards survivability. A position paper motivated by COVID-19 outbreak. International Journal of Production Research. 2020; 58(10):2904-2915. doi: 10.1080/00207543.2020.1750727.

[27] Cai J, Sharkawi I, Taasim SI. Enhancing the resilience of supply chains in the fashion apparel industry through intelligent logistics—Evidence from China. Cogent Business & Management. 2024; 11(1). doi: 10.1080/23311975.2024.2437248.

[28] Li D, Li J. Big data of enterprise supply chain under green financial system based on digital twin technology. Kybernetes. 2024; 53(2):543-556. doi: 10.1108/K-02-2023-0291.

[29] Baryannis G, et al. Artificial intelligence-driven risk management for enhancing supply chain agility: A deep-learning-based dual-stage PLS-SEM-ANN analysis. International Journal of Production Research. 2022; 62(15). doi: 10.1080/00207543.2022.2063089.

[30] Bibi S, Khan A, Fubing X, Jianfeng H, Hussain S. Integrating digitalization, environmental innovations, and green energy supply to ensure green production in China's textile and fashion industry: Environmental policy and laws optimization perspective. Environment, Development and Sustainability. 2024. doi: 10.1007/s10668-024-05417-4.

[31] CICC Research, CICC Global Institute. Textiles and apparel—Expanding production bases overseas while moving up the industry chain. In: The reshaping of China's industry chains. Singapore: Springer; 2024. p. 331-350. doi: 10.1007/978-981-97-1647-0_17.

[32] Zhao L. Global value chains in the post-pandemic era. In: Modern China and international rules. Singapore: Springer; 2023. p. 13-40. doi: 10.1007/978-981-19-7576-9_2.

[33] Mahmud HB, Tonima S. Impact of influencer marketing on customer buying journey: A study on global fashion brands. British Journal of Marketing Studies. 2024; 7(2):129-146. doi: 10.52589/BJMMS-GRM6BW7M.

[34] Zai FS, Mansur A. Hedging strategy to mitigate exchange rate risk in cross-border transactions: Literature review. Journal of Business Management and Economic Development. 2024; 2(3). doi: 10.59653/jbmed.v2i03.908.

[35] Lau KC, Shimul AS, Phau I. The influence of brand ambassador's wrongdoing on consumers' luxury brand desirability: The interplay of attachments, resilience, and empathy. Journal of Brand Management. 2025. doi: 10.1057/s41262-025-00386-z.

[36] Jiang M, Qin L, Zuo W, Hu Q. Selection of presale models for innovative products considering channel preferences and valuation differences. PLOS ONE. 2024; 19(3):e0299945. doi: 10.1371/journal.pone.0299945.

[37] UNEP FI. Global sustainable finance report: Green finance standardization challenges. Nairobi: United Nations Environment Programme Finance Initiative; 2025. Available from: https://www.unepfi.org/.

[38] Liao Z, Prataviera LB, Ghadge A, Abushaikha I. A sustainable supply chain finance ecosystem: A review and conceptual framework. International Journal of Production Economics. 2025; 286:109676. doi: 10.1016/j.ijpe.2025.109676.

[39] European Central Bank. Guide on climate-related and environmental risks: Supervisory expectations relating to risk management and disclosure. Frankfurt: European Central Bank; 2024. Available from: https://finance.ec.europa.eu/capital-markets-union-and-financial-markets/company-reporting-and-auditing/company-reporting/corporate-sustainability-reporting_en.

[40] Hong Kong Monetary Authority. Provision of custodial services for digital assets (HKMA Reference: 20240220-11-EN). Hong Kong: Hong Kong Monetary Authority; 2024. Available from: https://www.hkma.gov.hk/eng/regulatory-resources/regulatory-guides/circulars.

[41] Zhou W, Masi D. Sustainable supply chain finance: A multiple case study. Sustainability. 2025; 17(11):4862. doi: 10.3390/su17114862.

[42] WTO. Asian textile industry supply chain finance development report. Geneva: World Trade Organization; 2024.

[43] Rafi-Ul-Shan PM, Grant DB, Perry P, Ahmed S. Relationship between sustainability and risk management in fashion supply chains: A systematic literature review. International Journal of Retail & Distribution Management. 2018; 46(5):466-486. doi: 10.1108/IJRDM-04-2017-0092.

[44] Lee I, Shin YJ. Fintech: Ecosystem, business models, investment decisions, and challenges. Business Horizons. 2018; 61(1):35-46. doi: 10.1016/j.bushor.2017.09.003.