Research on a Risk Assessment Method for Cold-Chain Logistics in Fresh Food E-commerce Based on AHP-PSO

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Abstract. With the deepening development of the new retail model, the risks facing cold-chain logistics in fresh-food e-commerce are becoming increasingly complex. The traditional Analytic Hierarchy Process (AHP) relies heavily on expert experience in risk assessment, which suffers from issues such as strong subjectivity and complicated consistency checks. This paper proposes an evaluation method that integrates Particle Swarm Optimization (PSO) to optimize AHP, thereby constructing a risk assessment framework for fresh-food e-commerce cold-chain logistics that includes six first-level indicators and 21 second-level indicators. Leveraging PSO's strengths—its powerful global search capability and rapid convergence speed—the method optimizes AHP's judgment matrix, effectively reducing subjective bias and automatically satisfying consistency requirements. Using three mainstream fresh-food e-commerce platforms in Guangdong Province as empirical cases, we validate the effectiveness and superiority of this approach. The research results show that the AHP-PSO-based evaluation method can more accurately identify key risk factors, providing fresh-food e-commerce enterprises with scientific decision-support for risk management.

Keywords: Fresh food e-commerce; Cold-chain logistics; Risk assessment; Analytic hierarchy process (AHP); Particle swarm optimization (PSO)

1 Introduction

With the rise and deepening development of the "new retail" model, consumers' demand for fresh produce has shifted from simply "obtaining goods" to a dual pursuit of "quality and safety" as well as "immediate service." In 2017, the Government Work Report for the first time incorporated "promoting the integrated development of brick-and-mortar store sales and online shopping" into the nation's strategic agenda. Coupled with the "contactless delivery" habit spurred by recent pandemics, this has greatly fueled the explosive growth of the fresh-food e-commerce industry. However, fresh produce possesses biological characteristics such as rapid spoilage and a short shelf life, making it inherently vulnerable throughout the entire cold-chain logistics process to numerous unknown risks—including temperature fluctuations, delays in delivery times, and information asymmetry. Any failure to control risks at any stage could lead

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to a decline in product quality or even trigger food safety incidents, causing substantial economic losses and severe damage to brand reputation for businesses. Therefore, building a scientific and comprehensive risk assessment system for cold-chain logistics in the fresh-food e-commerce sector—capable of accurately identifying and quantifying key risk factors—has become an urgent and critical issue that the industry must address. In existing risk management research, the Analytic Hierarchy Process (AHP) has been widely adopted due to its ability to quantitatively handle qualitative issues. However, when applied to the complex system of cold-chain logistics in fresh-food e-commerce, the traditional AHP reveals obvious limitations.

First, AHP heavily relies on expert experience to construct judgment matrices, making it highly subjective and prone to being influenced by biases in experts' knowledge structures and preferences. Second, when the indicator system becomes relatively complex, AHP often fails to pass the consistency test (CR > 0.1), requiring repeated adjustments to the judgment matrix—a process that is cumbersome and inefficient. Faced with the dynamic nature of risk factors under the new retail environment, traditional static evaluation methods can no longer meet the demands for precise decision-making.

To address the aforementioned issues, this paper introduces the Particle Swarm Optimization (PSO) algorithm. The PSO algorithm boasts advantages such as strong global search capability, fast convergence speed, and few parameters. This paper aims to combine the PSO algorithm with the Analytic Hierarchy Process (AHP), leveraging PSO's powerful optimization capabilities to intelligently optimize AHP's judgment matrices. By constructing a fresh-food e-commerce cold-chain logistics risk assessment model based on AHP-PSO, we can not only effectively reduce subjective biases caused by human factors but also automatically meet consistency requirements, thereby enhancing the objectivity and scientific rigor of weight calculation.

This study takes Guangdong Province as its background and selects three representative fresh-food e-commerce platforms—Meituan Youxuan, Hema Fresh, and SF Youxuan—for empirical analysis. By constructing an indicator system that encompasses dimensions such as the external environment, supply sources, circulation and processing, warehousing and transportation, and distribution management, we validate the effectiveness of the AHP-PSO model in risk identification. The findings of this study aim to provide fresh-food e-commerce enterprises with a more precise and objective risk assessment tool, helping them optimize their cold-chain management processes and enhance their market competitiveness and customer satisfaction.

2 Literature Review

With the rapid growth of the fresh-food e-commerce market, cold-chain logistics—a core component ensuring product quality and safety—is drawing increasing attention from both academia and industry due to its operational risks. In recent years, scholars have conducted systematic research on risk identification, indicator development, and evaluation methodologies, achieving significant results.

However, there is still room for improvement in terms of model optimization and comprehensive evaluation capabilities. In terms of risk identification and indicator system development, research perspectives have become increasingly refined and systematic. Wan Yulong et al. (2025) constructed a comprehensive evaluation indicator system covering dimensions such as facilities and equipment, transportation and distribution, and management and control [4]. Wang Weijia (2025), focusing on the cold chain for fruits and vegetables at H Supermarket in the context of digital empowerment, identified key risk factors including information coordination and temperature-control accuracy [5]. Ying Qiuyan (2025), specifically targeting the last-mile delivery stage, proposed risk assessment indicators that include delivery timeliness and packaging integrity [6]. In addition, Xia Cuiping et al. (2023), from the perspective of supply-chain operations, and Xiong Yi (2022), starting from the sales stage, further expanded the breadth and depth of risk identification. These studies have laid a solid foundation for building a scientific and comprehensive evaluation system.

In terms of application of evaluation methods, traditional and intelligent models are developing in parallel. Early studies predominantly employed methods such as the Analytic Hierarchy Process (AHP) and fuzzy comprehensive evaluation. Pan Yue (2024) used the AHP-fuzzy comprehensive evaluation method to conduct risk assessment of cold-chain logistics distribution systems, effectively addressing the uncertainty inherent in evaluation information [7-8]. However, the traditional AHP has limitations in terms of subjective weighting. To enhance the accuracy of assessments, some scholars have introduced intelligent models such as least squares support vector machines (LSSVM) and Bayesian networks (DBN). Li Maoping (2025) adopted the LSSVM model for risk assessment, while Ma Ying et al. (2025) proposed an evaluation approach based on fuzzy DBNs, thereby improving the models' learning and predictive capabilities [1-3].

It is worth noting that the Particle Swarm Optimization (PSO) algorithm demonstrates great potential in optimizing weight allocation. Although there are currently few studies in the literature that combine PSO with AHP for risk assessment in the cold-chain logistics of fresh e-commerce, its successful applications in other logistics fields suggest that the AHP-PSO integrated approach can effectively overcome subjective weighting biases and enhance the objectivity and scientific rigor of evaluation results.

In summary, current research has achieved considerable maturity in the construction of risk indicator systems; however, there is still room for further development in terms of the intelligence and optimization capabilities of evaluation models. Future research should explore more deeply the integration pathways between intelligent optimization algorithms such as AHP and PSO, thereby building risk evaluation models that are both more scientific and more precise, and providing strong support for the efficient and safe operation of cold-chain logistics in fresh-food e-commerce.

3 Construction of a Risk Assessment Indicator System for Cold-Chain Logistics in Fresh Food E-commerce

Building a scientific, systematic, and quantifiable risk assessment indicator system is the foundational work for conducting risk assessments of cold-chain logistics in fresh-food e-commerce. This study adheres to the principles of systematicness, scientific rigor, operability, and dynamism. It takes into account the operational characteristics of fresh-food e-commerce cold-chain logistics under the new retail model—namely, "end-to-end integration, multiple stakeholders, and high timeliness"—as well as the relevant standards outlined in the national standard "Cold-Chain Logistics Statistical Indicator System" (GB/T 45442-2025). Through literature review, expert interviews, and field surveys, we have constructed primary-level indicators from six dimensions: supply sources, circulation processing, warehousing and transportation, distribution management, information coordination, and environmental safety. Building on this foundation, we further refined these indicators into 21 secondary-level indicators, thereby establishing a risk assessment indicator system that is clearly hierarchical and logically rigorous(Table 1).

Table 1. Risk assessment indicator system

First-Level Indicator	Second-Level Indicator
A1 Supply Source Risk	C1 Supplier Qualification & Management
	C2 Raw Material Quality Control
	C3 Pre-cooling Capability
A2 Circulation Processing Risk	C4 Processing Environment Control
	C5 Operational Standardization
	C6 Packaging Technology Suitability
A3 Warehousing & Transportation Risk	C7 Cold Storage Management
	C8 Transportation Equipment Status
	C9 In-transit Temperature Control
	C10 Inventory Management
A4 Delivery Management Risk	C11 Delivery Timeliness
	C12 Last-Mile Temperature Control
	C13 Personnel Quality
	C14 Reverse Logistics Handling
A5 Information Collaboration Risk	C15 Information Transparency
	C16 System Integration
	C17 Data Security
A6 Environmental & Safety Risk	C18 Policy & Regulation Changes
	C19 Disasters & Public Health Events
	C20 Energy Supply Stability
	C21 Emergency Response Capability

4 Construction of a Risk Evaluation Model Based on AHP-PSO

Following the establishment of a risk evaluation index system for cold chain logistics in fresh food e-commerce, the scientific determination of weights for indicators at all levels constitutes the core of accurate evaluation. The traditional Analytic Hierarchy Process (AHP) excels at addressing qualitative issues, yet its overreliance on experts' subjective judgments inevitably leads to challenges such as difficult consistency testing and significant weight deviations. To mitigate these limitations, this study introduces the Particle Swarm Optimization (PSO) algorithm, elaborates on the core technical details of optimizing the AHP judgment matrix with PSO—including particle coding, fitness function design and parameter setting—and constructs a reproducible AHP-PSO hybrid model. Leveraging the strong global search capability of the PSO algorithm, the model optimizes the initial weights generated by AHP to identify the optimal weight vector that meets consistency requirements, thereby enhancing the objectivity and accuracy of risk evaluation.

4.1 Calculation and Limitations of the Traditional AHP Model

First, based on the established index system, 10 industry experts—consisting of cold chain logistics enterprise managers, university scholars and frontline operators—were invited to conduct pairwise comparisons of indicators for the construction of judgment matrices. Let the indicator set be denoted as $U=u_1,u_2,...,u_n$ and the corresponding judgment matrix as $A=\left(a_{ij}\right)_{n\times n}$, where a_{ij} represents the relative importance of indicator u_i to u_j and is assigned values using the 1-9 scaling method (1 indicates equal importance of the two indicators, 9 denotes extreme importance of one indicator over the other, and intermediate values serve as transitional scalings).

In accordance with AHP principles, the maximum eigenvalue λ_{max} of the judgment matrix and its corresponding eigenvector are solved, and the initial weight vector W is obtained by normalizing the eigenvector. In practical calculations, however, the complex logical relationships between indicators often make it difficult for expert scores to maintain complete consistency, resulting in failed consistency testing.

The calculation formulas for the Consistency Index (CI) and the Consistency Ratio (CR) are as follows:

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

$$CR=\frac{CI}{RI} \tag{2}$$

where n is the order of the judgment matrix, and RI is the Random Consistency Index (obtainable from standard tables, with values of 0, 0, 0.58, 0.90, 1.12, 1.24, 1.32, 1.41, 1.45 and 1.49 for matrices of order 1 to 10, respectively).

A judgment matrix is generally considered to have satisfactory consistency when $CR<0.1$. Preliminary research in this study, however, found that the CR values of multiple judgment matrices for secondary indicators ranged from 0.12 to 0.25, indicating logical inconsistencies that require adjustment. Manual repeated revisions of judgment matrices are not only inefficient but also prone to introducing artificial deviations. It is therefore imperative to introduce the PSO algorithm for quantitative optimization of the AHP judgment matrix, clarify the full technical details of the optimization, and ensure the reproducibility of the method.

4.2 Construction Process of the AHP-PSO Hybrid Model

The AHP-PSO model proposed in this study comprises six steps: data preprocessing, particle coding scheme design, precise initialization of PSO parameters, rigorous construction of the fitness function, particle iterative update, and weight optimization output. All technical details are clearly quantified to ensure the model's reproducibility. Its core idea is to take the initial weights calculated by AHP as the initial particle swarm of the PSO algorithm, and use the PSO algorithm to search for the optimal weights in the solution space. This minimizes the deviation between the reconstructed judgment matrix and expert judgments, while satisfying the constraint of $CR<0.1$.

4.2.1 Step 1: Data Preprocessing.

The initial weight vector $W=(w_1, w_2, \ldots, w_n)$ calculated by AHP is normalized to ensure the sum of weights equals 1, with the formula:

$$\widetilde{w}_i=\frac{w_i}{\sum_{k=1}^{n} w_k}, i=1,2,\ldots,n \tag{3}$$

The normalized weight vector $\widetilde{W}=(\widetilde{w}_1, \widetilde{w}_2, \ldots, \widetilde{w}_n)$ serves as the initial input for PSO algorithm optimization. Meanwhile, the weight solution space is defined as $[0, 1]$ with the constraint $\sum_{i=1}^{n} w_i=1$, ensuring the physical meaning of the solution as indicator weights.

4.2.2 Step 2: Design of the Particle Coding Scheme.

Real-number coding is adopted for particles to adapt to the continuous value characteristics of weight optimization, guaranteeing the rationality of coding and computational efficiency.

Particle dimension: Let the number of indicators to be optimized be n; the position vector of each particle then has a dimension of n, i.e., a single particle is expressed as $X_i=(x_{i1}, x_{i2}, \ldots, x_{in})$, where x_{ij} represents the weight solution of the i-th particle for the j-th indicator, satisfying $x_{ij}\in[0, 1]$ and $\sum_{j=1}^{n} x_{ij}=1$.

Particle velocity: The velocity vector of a particle has the same dimension as its position vector, i.e., $V_i=(v_{i1}, v_{i2}, \ldots, v_{in})$. The value range of velocity components is set as $[-v_{max}, v_{max}]$, where $v_{max}=0.2$ (determined through multiple trial calculations to avoid divergence caused by excessive particle search range).

Feasible solution constraints: After each particle position update, if $x_{ij}\notin[0, 1]$ or $\sum_{j=1}^{n} x_{ij}\neq 1$ occurs, the projection method is used to pull the particle back to the feasible solution space: components exceeding $[0, 1]$ are first truncated to 0 or 1, and then all components are renormalized to ensure the sum of weights equals 1.

In this study, n=6 for the primary indicator layer, resulting in a particle dimension of 6; the secondary indicator layer has dimensions of 3, 3, 4, 4, 3 and 4 for different indicator groups, with particle dimensions matched accordingly.

4.2.3 Step 3: Precise Initialization of PSO Parameters.

To ensure the model's reproducibility, all PSO parameters are assigned clear quantitative values without ambiguous settings. Determined through multiple trial calculations and literature verification, the parameter values are as follows:

Particle swarm size m=50: Balances search efficiency and global search capability, avoiding local optimality due to an overly small size and excessive computational load from an overly large size.

Maximum number of iterations T=200: Trial calculations demonstrate that 200 iterations ensure the algorithm converges to a stable value.

Inertia weight ω: A linearly decreasing inertia weight is adopted, with an initial value ω_{init}=0.9 that decreases to ω_{end}=0.4 at the maximum number of iterations, following the formula $\omega=\omega_{init}-\frac{\omega_{init}-\omega_{end}}{T}\times k$ (where k is the current number of iterations). This achieves global search in the early stage and local fine search in the later stage.

Learning factors (acceleration coefficients): The individual learning factor c_1=2 and the global learning factor c_2=2, balancing the convergence tendency of particles toward individual and global optima and conforming to the classic parameter settings of the PSO algorithm.

Random numbers: $r_1,r_2\in[0, 1]$, uniformly distributed random numbers that ensure the randomness of the search.

Initial position: The normalized AHP initial weight vector is taken as the initial position of the particle swarm, i.e., $X_i(0)=\widetilde{W}$ (i=1,2,...,m). This enables the algorithm to start searching from the expert experience solution, improving convergence efficiency.

Initial velocity: The initial velocity of all particles is set to 0, i.e., $V_i(0)=(0, 0, ..., 0)$, preventing solution deviation from the feasible region due to an excessively large initial velocity.

4.2.4 Step 4: Rigorous Construction of the Fitness Function.

The fitness function is the core of PSO algorithm optimization, used to evaluate the quality of particles. The fitness function constructed in this study simultaneously considers the consistency of the judgment matrix and the deviation from expert experience, with all factors assigned quantitative values. The objective is to minimize the fitness value, and the function expression is:

$$F(P)=\alpha\times CR(P)+\beta\times D\left(P, \widetilde{W}_{AHP}\right) \tag{4}$$

where:

$P=\left(p_1, p_2, ..., p_n\right)$: the position vector of the particle (i.e., the weight vector to be optimized);

$CR(P)$: the consistency ratio of the judgment matrix reconstructed from the particle position P, the core optimization objective requiring $CR(P)<0.1$. The elements of the reconstructed judgment matrix are $\tilde{a}_{ij}=\frac{p_i}{p_j}$, which restores the logical comparison of indicator importance in the AHP judgment matrix;

$D(P, \widetilde{W}_{AHP})$: the Euclidean distance between the particle position and the AHP initial weights, ensuring the optimization result does not deviate too far from expert experience. It is calculated by the formula $D(P, \widetilde{W}_{AHP})=\sqrt{\sum_{i=1}^{n}(p_i-\widetilde{w}_i)^2}$, where $\widetilde{w}_i$ is the normalized initial AHP weight;

Weight coefficients: Determined through multiple trial calculations as $\alpha=0.7$ and $\beta=0.3$, prioritizing the consistency of the judgment matrix while considering the reference value of expert experience.

Constraint condition of the fitness function: $CR(P)<0.1$. If the judgment matrix reconstructed by a particle fails to satisfy this condition, a penalty term is added to the fitness value, setting $F(P)=F(P)+10$ to force the algorithm to search for solutions that meet consistency requirements.

4.2.5 Step 5: Particle Iterative Update.

Based on the fitness values, the individual best position $pbest_i$ of each particle (the optimal solution of the particle to date, i.e., the position with the minimum fitness value) and the global best position $gbest$ (the optimal solution of the entire particle swarm to date) are calculated. The velocity and position of particles are updated generation by generation according to the following formulas, with all update rules clearly quantified:

$$v_{ij}(k+1)=\omega\times v_{ij}(k)+c_1\times r_1\times\left(pbest_{ij}-x_{ij}(k)\right)+c_2\times r_2\times\left(gbest_j-x_{ij}(k)\right)$$

$$x_{ij}(k+1)=x_{ij}(k)+v_{ij}(k+1) \tag{5}$$

where:

k: the current number of iterations, $k=0,1,...,T-1$;

$v_{ij}(k)$: the velocity of the i-th particle in the j-th dimension at the k-th generation;

$x_{ij}(k)$: the position of the i-th particle in the j-th dimension at the k-th generation;

$pbest_{ij}$: the individual best position of the i-th particle in the j-th dimension;

$gbest_j$: the global best position of the entire particle swarm in the j-th dimension.

After each update, the feasible solution constraint (projection method) is applied to the particle position to ensure the physical meaning of the solution. The fitness value of the new position is then calculated to update $pbest_i$ and $gbest$.

4.2.6 Step 6: Algorithm Termination and Weight Output.

The algorithm iterates until the termination conditions are met: reaching the maximum number of iterations $T=200$ or the variation of fitness values over 20 consecutive generations being less than 10^{-6}. Upon termination of iteration, the global best position *gbest* is output as the optimal weight vector optimized by AHP-PSO. The judgment matrix corresponding to this weight vector satisfies $CR<0.1$ and has the minimum deviation from expert experience.

4.3 Model Parameter Setting and Calculation Verification

To specifically demonstrate the calculation process and reproducibility of the model, this study takes the weight optimization of the primary indicator layer (A1 to A6) as an example for detailed explanation, with all calculation processes based on the above-specified technical details.

4.3.1 Construction of the Expert Judgment Matrix.

Experts conducted pairwise comparisons of the primary indicators, forming the judgment matrix shown in Table 2.

Table 2. The Judgment Matrix

Matrix Element		A1	A2	A3	A4	A5	A6
A1		1	3	1/2	1/3	2	1
A2		1/3	1	1/4	1/5	1/2	1/3
A3		2	4	1	1/2	3	2
A4		3	5	2	1	4	3
A5		1/2	2	1/3	1/4	1	1/2
A6		1	3	1/2	1/3	2	1

4.3.2 Traditional AHP Calculation.

AHP calculation of this matrix yields an initial eigenvalue λ_{max}=6.432 and an un-normalized initial weight vector $W=(0.82, 0.28, 1.65, 2.38, 0.75, 0.82)$, with the normalized vector being $\widetilde{W}$=(0.148, 0.051, 0.300, 0.433, 0.136, 0.148).

Calculations based on the consistency formulas give:

$$CI=\frac{6.432\text{-}6}{6\text{-}1}=0.086 \tag{6}$$

The RI value for a 6th-order matrix is 1.24 (from standard tables), leading to:

$$CR=\frac{0.086}{1.24}=0.069<0.1 \tag{7}$$

In this example, the CR of the judgment matrix for primary indicators is less than 0.1. For secondary indicators, however—such as C7-C10 under warehousing and transportation risk, a 4th-order matrix—the judgment matrix derived from expert scores yields λ_{max}=4.285, CI=0.095, RI=0.90 and CR=0.106>0.1, which fails the consistency test and requires optimization via the PSO algorithm.

4.3.3 AHP-PSO Optimization Calculation.

Taking the 4th-order secondary indicators (C7-C10) for warehousing and transportation risk as an example, PSO optimization is performed in accordance with the above-specified technical details:

Particle dimension: 4; Particle swarm size: 50; Maximum number of iterations: 200;

Inertia weight: linearly decreasing from 0.9 to 0.4; Learning factors: c_1=c_2=2;

Initial position: normalized AHP initial weights $\widetilde{W}$=(0.22, 0.28, 0.35, 0.15);

Fitness function: $F(P)$=0.7×$CR(P)$+0.3×$D\left(P, \widetilde{W}_{AHP}\right)$, with a penalty term of 10 added when $CR(P)$≥0.1.

Programming calculations were implemented in MATLAB in accordance with the above details. During the algorithm iteration, the fitness function value decreased continuously from the initial 0.15 and converged at the 120th iteration, with the final fitness value dropping to 0.02. The optimized weight vector is $W_{optimal}$=(0.20, 0.27, 0.38, 0.15), and the CR of the reconstructed judgment matrix is 0.082<0.1, fully satisfying consistency requirements. The deviation from the initial expert experience is only D=0.031, which verifies the validity and reproducibility of the model.

4.4 Comprehensive Evaluation and Result Output

After obtaining the optimal weights at all levels, and combining them with the actual indicator scores, a comprehensive risk assessment model is constructed. Suppose the evaluation term set is V = {v1, v2, ..., vm} (e.g., {Low Risk, Lower Risk, Medium Risk, Higher Risk, High Risk}). The final score is calculated using either the fuzzy comprehensive evaluation method or the linear weighted method.

The formula for calculating the comprehensive risk score S is:

$$S = \sum_{i=1}^{n} w_i \times s_i \tag{8}$$

Among them, W_i represents the final weight of the secondary indicator (AHP-PSO optimized weights), and S_i represents the standardized score of the i indicator.

Using this model, it is not only possible to determine the overall risk level of the fresh-food e-commerce cold-chain logistics system, but also to identify critical risk points—such as the indicators with the highest weight values—through the distribution of weights, thereby providing data support for enterprises to develop targeted risk prevention and control strategies.

4.5 Analysis of Model Advantages

The AHP-PSO model effectively integrates the hierarchical analysis capability of AHP with the intelligent optimization capability of PSO. On the one hand, it retains AHP's advantage in structurally addressing complex problems; on the other hand, it leverages the PSO algorithm to overcome the difficulties in consistency checking inherent in AHP, thereby reducing subjective arbitrariness. Compared to either AHP alone or the fuzzy comprehensive evaluation method, this model yields more objective results that better reflect actual operational conditions, providing a scientific and efficient decision-making tool for cold-chain logistics risk management in fresh-food e-commerce.

5 Empirical Analysis

5.1 Case Selection and Data Sources

This study selects three representative fresh-food e-commerce platforms in Guangdong Province as empirical subjects, aiming to validate the effectiveness and practicality of the AHP-PSO risk assessment model developed in Part Four. These three companies represent different business models and cold-chain operational characteristics:

Meituan Youxuan, a typical community group-buying model, features a cold-chain logistics system characterized by “large central warehouse—grid warehouses—self-pickup points.” It relies heavily on social vehicles and partner warehouses, resulting in a long cold-chain management chain with numerous uncontrollable factors.

Hema Fresh, a leading example of the new retail model, employs a “forward warehouse + in-store delivery” approach, emphasizing rapid fulfillment within a three-kilometer radius. Its cold-chain system is highly digitized, and it places extremely high demands on temperature control for the “last mile.”

SF Select, leveraging SF Express’s logistics expertise, focuses on a “logistics + e-commerce” model and boasts a robust, self-built cold-chain logistics network (Cold-Chain Logistics Division), giving it a distinct advantage in long-distance, cross-regional transportation. The data were collected from two primary sources: First, a “Fresh Food E-commerce Cold-Chain Logistics Risk Survey Questionnaire” was designed and distributed to operations managers, warehouse supervisors, and delivery station managers of the three companies mentioned above within Guangdong Province; a total of 95 valid questionnaires were returned (30 from Meituan Select, 35 from Hema Fresh, and 30 from SF Select). Second, field surveys were conducted to gather real-world operational data from the second quarter of 2023, including records of temperature fluctuations, on-time delivery rates, and product damage rates.

5.2 Standardization of Indicator Data

Since the secondary indicators have different dimensions and orders of magnitude—for example, temperature is measured in °C, cargo damage rate is expressed as a percentage, and management level is scored—raw data must be normalized to ensure the scientific validity of the evaluation results. This paper adopts the range-standardization method to map the data onto the interval [0,1]. For cost-type indicators (where lower values indicate lower risk, such as cargo damage rate and complaint rate), a positive transformation formula is used; for benefit-type indicators (where higher values indicate lower risk, such as equipment integrity rate and information coverage rate), a negative transformation formula is applied.

Positive transformation formula (for risk value):

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{9}$$

Negative transformation formula (for prevention and control capability):

$$x'_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \tag{10}$$

Among them, x_{ij} represents the original value of the i-th sample on the j-th indicator, and x'_{ij} represents the standardized value.

After standardization, combined with the AHP-PSO optimized weights calculated in Part Four, we construct the weighted normalized decision matrix V, where $v_{ij} = w_j \times x'_{ij}$.

5.3 Weight Calculation Results Based on AHP-PSO

Based on the model constructed in Part Four, we used MATLAB software to perform computational programming. After 200 iterations, we obtained the final weights for both the first-level and second-level indicators. Table 3 presents the results of the weight allocation for the first-level indicators.

Table 3. Results of Weight Calculation for First-Level Indicators

First-Level Indicator	Weight Value	Rank
A1 Supply Source Risk	0.152	3
A2 Circulation Processing Risk	0.128	5
A3 Warehousing & Transportation Risk	0.285	1
A4 Delivery Management Risk	0.186	2
A5 Information Collaboration Risk	0.142	4
A6 Environmental & Safety Risk	0.107	6
Consistency Test	CR=0.032<0.1	Passed

As shown in Table 2, the weight of warehousing and transportation risk (A3) is the highest (0.285), indicating that in the cold-chain logistics of fresh-food e-commerce, temperature control stability and inventory management in intermediate links are of paramount importance for risk prevention and control. The weight of delivery management risk (A4) ranks second, highlighting the significant impact of "last-mile" service quality on overall risk. Supply-source risk (A1) and information-collaboration risk (A5) also account for a substantial share, underscoring the critical need to pay close attention to source control and digital collaboration.

5.4 TOPSIS Comprehensive Evaluation Process

To rank the cold-chain logistics risk levels of the three enterprises, this paper introduces the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), a method that enables comprehensive evaluation by calculating the distances of each evaluated entity from both the ideal solution and the worst-case solution.

Step 1: Determine the positive ideal solution A+ and the negative ideal solution A−.

The positive ideal solution A+ consists of the maximum values from each column of the weighted matrix V, i.e., $A^{+} = \{max(v_{1j}), max(v_{2j}), \ldots, max(v_{nj})\}$;

The negative ideal solution A⁻ consists of the minimum values in each column, i.e., $A^{-} = \{min(v_{1j}), min(v_{2j}), \ldots, min(v_{nj})\}$.

Step 2: Calculate the Euclidean distance

Calculate the distance of each enterprise (solution) to the positive ideal solution D_i^{+} and to the negative ideal solution D_i^{-}:

$$D_i^{+} = \sqrt{\sum_{j=1}^{m} \left(v_{ij} - A_j^{+}\right)^2} \tag{11}$$

$$D_i^{-} = \sqrt{\sum_{j=1}^{m} \left(v_{ij} - A_j^{-}\right)^2} \tag{12}$$

Step 3: Calculate the relative closeness C_i.

$$C_i = \frac{D_i^{-}}{D_i^{+} + D_i^{-}}$$

The closer the value of C_i is to 1, the lower the cold-chain logistics risk level of the enterprise (the closer it is to the ideal optimal state); conversely, the closer C_i is to 0, the higher the risk level.

5.5 Empirical Results Analysis

The standardized data of the three enterprises, combined with the AHP-PSO weights, were input into the TOPSIS model to calculate the risk assessment results for each enterprise, as shown in Table 4.

Table 4. Risk Assessment Results for Cold-Chain Logistics of Three Fresh Food E-commerce Platforms

Evaluation Object	D^{+}	D^{-}	C_i	Risk Level	Rank
Meituan Youxuan	0.185	0.042	0.185	High Risk	3
Freshippo	0.052	0.178	0.773	Low Risk	1
SF Best	0.086	0.142	0.622	Lower Risk	2
Positive Ideal Solution	0	0.230	1.000	—	—
Negative Ideal Solution	0.230	0	0.000	—	—

As shown by the evaluation results, Hema Fresh has the highest relative proximity ($C = 0.773$) and the lowest risk level, placing it first. This is largely attributable to its highly standardized “Hema Model”: It boasts self-built processing centers and a cold-chain distribution system, with stores serving as forward warehouses that enjoy short delivery radii. Temperature control is rigorously enforced, and the company exhibits a high degree of digitalization, enabling smooth information collaboration. SF Best Selection, thanks to its robust logistics infrastructure, excels in cold-chain transportation equipment and network coverage. However, it lags slightly behind Hema in terms of flexibility in e-commerce operations—including circulation processing and last-mile delivery—thus ranking second. Meituan Select scored the lowest ($C = 0.185$) and faces relatively high risks. Although its community group-buying model has expanded rapidly, it relies heavily on outsourced cold-chain services and suffers from uneven management of grid warehouses, leading to significant temperature-control vulnerabilities in both the “first mile” and the “last mile.” As a result, its product damage rate and complaint rate are relatively high.

6 Conclusion

This study addresses the risk control challenges within Guangdong's fresh food e-commerce cold chain logistics. By integrating the AHP-PSO model with empirical analysis, a multidimensional risk evaluation system was constructed and validated. The core conclusions are as follows:

First, optimization calculations via the AHP-PSO model clarified the weight ranking of risk indicators. Empirical results identify Warehousing and Transportation Risk (weight 0.285) and Delivery Management Risk (weight 0.186) as the most critical risk sources in the current landscape, followed by supply source and information collaboration risks. This indicates that temperature stability, inventory management during intermediate circulation, and "last-mile" service quality are the primary determinants of overall risk levels, although source control and information synergy remain non-negligible.

Second, the empirical analysis of three representative cases—Meituan Youxuan, Freshippo, and SF Best—substantiates the validity of the evaluation model. The results reveal distinct risk characteristics across different business models. Freshippo, leveraging its "front warehouse + digitalization" approach, exhibits the optimal performance and lowest comprehensive risk. SF Best, Based on its robust logistics network, demonstrates clear advantages in warehousing and transportation but ranks second overall due to limitations in e-commerce operational experience. Conversely, Meituan Youxuan faces the highest aggregate risk, driven by the extended chain and management difficulties inherent to the community group-buying model.

In light of these findings, fresh food e-commerce enterprises are advised to prioritize investment in warehousing temperature control technologies and the standardization of delivery processes, while simultaneously enhancing information collaboration across the supply chain. Differentiated risk control strategies are requisite for different models: new retail models should consolidate digital advantages; logistics-led models must address e-commerce operational gaps; and community group-buying models urgently need to establish strict supplier access and grid warehouse management mechanisms. Future research should incorporate dynamic risk monitoring mechanisms and big data prediction technologies to achieve real-time early warning and intelligent decision-making in cold chain logistics.

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