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Supplier Selection for Automobile Manufacturing Companies: An Improved Hierarchical Analysis and Intelligent Optimization Algorithm

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Abstract: This paper proposes a scientific and systematic method for supplier selection to address the limitations of traditional approaches, particularly their subjective weight calculations and limited accuracy in comprehensive evaluations. An integrated model combining the improved Analytic Hierarchy Process (AHP) and Particle Swarm Optimization (PSO) is developed. First, the Delphi method defines four key dimensions and indicators. Then, fuzzy logic enhances the objectivity of AHP weight calculations. Finally, PSO is used to optimize supplier selection under complex multi-criteria decision-making scenarios. Using real data from an automobile manufacturer, the model's performance is evaluated. Results demonstrate improvements in both accuracy and efficiency: the enhanced AHP ensures rational weight assignment, while PSO achieves global optimization. The model identifies Suppliers A, C, and E as top performers, confirming its practical utility. This approach offers actionable decision-making support for automotive enterprises and shows potential for transferable transferability to other industries. Limitations include sample size and adaptability issues, indicating a need for future research to incorporate dynamic optimization and larger datasets to enhance robustness and scalability.

Keywords: supplier selection; improved hierarchical analysis; intelligent optimization algorithm; particle swarm optimization algorithm (PSO); automotive manufacturing companies; supply chain management

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1. Introduction

In the context of increasingly fierce competition in the global economy, supply chain management, as an important part of the core competitiveness of enterprises, has gained significant attention (Abbaspour Onari and Jahangoshai Rezaee, 2022). As a representative of the high-complexity manufacturing industry, automobile production enterprises rely heavily on supplier stability and quality for their productivity and final product quality. Therefore, supplier selection has become a key link in enterprise management and development (Krishankumar et al., 2022). The traditional supplier selection methods, which often rely on empirical judgment and single- index evaluation, struggle to incorporate multi-dimensional factors affecting the decision, such as cost, quality, delivery time, technical capabilities, and environmental requirements (Hemmati and Pasandideh, 2021). These approaches can introduce decision-making biases and often fail to adapt to the dynamic and changing market conditions (Ali and Zhang, 2023). As a systematic decision-making method, the AHP has been widely used in the field of supplier selection because of its ability to effectively decompose complex problems and comprehensively evaluate multiple decision indicators. However, the traditional AHP exhibits certain limitations in practice, such as strong subjectivity, a lack of precision in weight allocation, and difficulty in handling large-scale data (Sahu et al., 2023). In response, recent research has increasingly focused on enhancing AHP through integration with intelligent optimization algorithms, such as genetic algorithms, and practice swarm optimization. This hybrid approach retains the intuitive and logical structure of AHP while leveraging intelligent algorithms to automate and streamline decision-making process, thereby improving both scientific rigor and practical applicability of supplier selection (Lo et al., 2021). Based on this, this paper proposes a supplier selection method based on an improved AHP integrated with an intelligent optimization algorithm. Using an automobile production enterprise as a case study, the research systematically analyzes the key factors influencing supplier selection, constructs the decision-making model, and verifies its effectiveness and superiority (Islam et al., 2021). The research in this paper not only provides scientific guidance for the supplier management of automobile production enterprises but also provides theoretical support for the supply chain optimization of other complex manufacturing industries.

The structure of this paper is as follows: Part II "Literature Review" examines research progress in supplier selection, including the current status of the application of AHP and intelligent optimization algorithms in supplier management, while also addressing the limitations and potential improvement in existing research; Part III "Research Methodology" details the proposed enhanced supplier selection model, including the construction of the index system and the refined method for weight calculation, as well as the design and implementation of the optimization algorithm. Part IV, "Results and Discussion", validates and analyzes the model using real-world data of an automobile production enterprise, and evaluates the model's superiority and applicability based on the experimental results; Part V, "Conclusion", summarizes the main results of the study, clarifies the theoretical contribution and practical significance of this paper and points out the shortcomings of the study and the direction of future research.

2. Literature review

The supplier preference problem, as an important research area of supply chain management, has been developed over the years, and a variety of methods and theoretical frameworks have been developed (Chen et al., 2022). Combined with the topic of this research, this paper will review three aspects of traditional methods, the application of hierarchical analysis and its improvement, and the practice of intelligent optimization algorithms in supplier preference, to clarify the research background and the entry point of the problem.

2.1. Limitations of traditional methods

Conventional approaches for supplier selection, such as the weighted scoring method, cost analysis, and Data Envelopment Analysis (DEA), often rely on single or limited indicators. While these methods are computationally simple, they suffer from notable flaws, including excessive subjectivity, inadequate consideration of multi-dimensional factors, and poor adaptability to dynamic environments (Li et al., 2021). Strong subjectivity is evident in the excessive reliance of experts' experience for allocating indicator weights, which can easily lead to biased evaluation results (Nafei et al., 2024). Insufficient consideration of multidimensional factors means that, in the face of demand for comprehensive evaluation of suppliers involving multiple indicators and levels is required, traditional methods fail to effectively deal with the interactions and complex relationships between various factors (Gergin et al., 2022). Poor adaptability to dynamics is shown by the difficulty traditional methods have in adapting to fast-changing market conditions and the influence of uncertainty factors on supplier selection decisions. These limitations provide research space for the introduction of more scientific and systematic analysis methods.

2.2. Hierarchical analysis and improvement

AHP is one of the most commonly used methods in supplier preference studies. Its main advantage lies in the decomposition of complex problems into multiple levels, which makes the decision logic clearer (Ebrahim Qazvini et al., 2021). At the same time, it reduces the influence of purely subjective judgment by assigning clear weights to each indicator through matrix calculation. However, AHP also faces certain challenges in practice. Although the matrix can quantify the weights, its input is still based on the subjective judgment of the decision-maker (Tavana et al., 2021). In addition, when the decision problem involves more indicators, the construction of the judgment matrix may be inconsistent, affecting the reliability of the results. In recent years, researchers have tried to enhance the application of AHP by introducing improved algorithms (Wang et al., 2021). For example, Fuzzy Analytic Hierarchy Process (Fuzzy AHP) improves the robustness of subjective judgments by introducing fuzzy logic to deal with uncertainty, while the Network Hierarchy Analysis (ANP) further extends the ability of AHP to deal with the interdependence between indicators. A comparison of the traditional AHP method and its improved methods is presented in Table 1, which summarizes the main advantages and disadvantages of the AHP analysis method with its improved methods, such as fuzzy AHP and the ANP analysis methods. In the traditional AHP method, the advantages are its clear and easy-to-understand structure and its ability to quantify the weights of each indicator, which makes it easy for decision-makers to make comparisons and choices (Sathyan et al., 2021). However, the disadvantages of the AHP method are also more obvious, especially when facing the multi-indicator decision-making problem; the judgment matrix is prone to inconsistency, and the method relies on the subjective judgment of the decision-maker, which may lead to bias (Wei et al., 2022). To overcome these limitations of AHP, fuzzy AHP came into being, which can effectively deal with uncertainty in decision-making, enhance the robustness of subjective judgment, and is especially suitable for scenarios where fuzzy data are more significant. However, the fuzzy AHP method has high computational complexity and requires experts to define the fuzzy language, which increases the difficulty of implementation (Ghosh et al., 2022). ANP further extends the application scope of AHP, which can deal with the interdependence between indicators, enabling the method to cope with more complex decision-making problems. However, the computational process of ANP is more complex and requires more computational resources and expertise for model construction.

2.3. Introduction and practice of intelligent optimization algorithms

Intelligent optimization algorithms have shown a fast-growing trend of application in the field of supplier preference in recent years, and their core advantage lies in their ability to quickly converge to the optimal solution in large-scale and multi-dimensional data environments (Liaqait et al., 2022). Through the group search mechanism flexibly cope with the uncertainty and dynamics of the problem. Typical intelligent optimization algorithms include Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO). Table 2 shows the features, advantages, and disadvantages of different intelligent optimization algorithms (GA, PSO, ACO) and their combination with traditional methods such as AHP.

Table 1. Comparison of the traditional AHP method and its improved methods

Methodologies	Vintage	Drawbacks	Improvement measures
Traditional AHP	1. structured and easy to understand. 2. Be able to quantify the weight of each indicator.	1. Input relies on subjective judgment and may be biased. 2. For multi-indicator problems, the judgment matrices are prone to inconsistencies.	Enhancing the reliability of the methodology by improving the matrix consistency checking methodology.
Fuzzy AHP	1. Ability to deal with uncertainty and increased robustness to subjective judgment. 2. Fuzzy decision-making problems can be addressed.	1. Higher computational complexity. 2. Need for expert definition of fuzzy language.	Fuzzy logic techniques are used to process the fuzzy data.
Network Hierarchy Analysis (ANP)	1. Ability to address interdependencies among indicators. 2. Applicable to more complex decision-making problems.	1. The computational process is more complex and requires more resources. 2. Higher requirements for model construction.	Introduce a network structure that considers the relationship between the various indicators.

Table 2. Comparison of intelligent optimization algorithms combined with traditional methods

Algorithm type	Vintage	Drawbacks	Application scenario	Integration with traditional methods competitive edge
Genetic Algorithm (GA)	1. Ability to handle complex multidimensional optimization problems. 2. Powerful global search capability.	1. Computationally intensive and slow convergence. 2. Possibility of falling into a local optimum.	Applicable to complex supplier preference problems, especially in multi-objective decision-making.	The combination with AHP can optimize the weights of the indicators and improve the science and efficiency of decision-making.
Particle Swarm Optimization (PSO)	1. Higher computational efficiency and faster convergence. 2. Easy to implement and tune.	1. It may be easy to fall into local optimization. 2. Sensitive to parameterization.	Suitable for real-time supplier evaluation and optimization, especially in dynamic decision-making.	Combined with AHP, it can quickly optimize supplier scoring and ranking to improve decision-making efficiency.
Ant Colony Optimization (ACO)	1. strong global search capability during optimization. 2. applicable to combinatorial optimization problems.	1. Slow convergence and high consumption of computational resources.	Used in large-scale supplier networks to optimize resource allocation and logistics issues.	Combining with AHP improves resource allocation strategies and increases the accuracy and efficiency of supplier selection.
Traditional AHP method	1. Intuitive and easy to understand, with a solid theoretical foundation. 2. Ability to systematize multidimensional data.	1. The allocation of weights is biased by the subjective judgment of the experts. 2. Difficulty in dealing with complex uncertainties.	For static and simpler supplier evaluation scenarios.	When combined with GA, PSO, and ACO, weight allocation and scoring can be automatically optimized.

In the application of supplier selection, these algorithms are usually combined with traditional methods. For example, the GA-based weight optimization method can automatically generate the optimal index weight allocation, which improves the scientific and practicality of decision-making (Tsai and Phumchusri, 2021). In addition, some researchers have proposed hybrid methods that integrate multiple intelligent optimization algorithms, such as the combination of GA and PSO, which further improve the computational efficiency and global optimization ability of the algorithm. Fig. 1 demonstrates that after the initial data is processed by traditional methods (e.g., AHP), the intelligent optimization algorithms (GA, PSO, ACO, etc.) further optimize the weight assignment and supplier scoring through the group search mechanism. The algorithms provide the final preferred results through adaptive tuning to support the final selection at the decision-making level. In addition, the figure also demonstrates how intelligent optimization algorithms are combined with traditional methods to further improve the efficiency and accuracy of the preference model through multi-algorithm fusion.

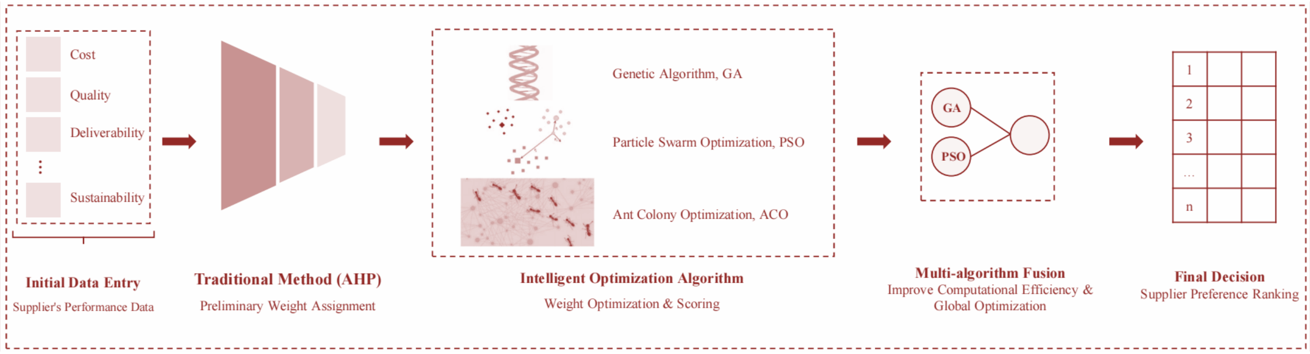

Fig. 1. Framework for the application of intelligent optimization algorithms to the supplier preference problem

2.4. Research synthesis

In summary, the traditional supplier preference methods have greater limitations in dealing with multidimensional complex decision-making problems, and the AHP method and its improvement methods make up for these deficiencies to a certain extent, but still need to be further optimized. An intelligent optimization algorithm provides a new perspective and technical support for supplier selection research under its powerful data processing capability and global search capability (Nayeri et al., 2023). Based on the above progress, the research in this paper combines the improved hierarchical analysis method and intelligent optimization algorithm and strives to construct a more scientific and efficient supplier selection model.

3. Research method

To construct a scientific and accurate supplier preference model, this paper proposes a comprehensive method based on the improved AHP method and intelligent optimization algorithm (Islam et al., 2024). This method achieves comprehensive optimization of supplier selection in multidimensional decision-making scenarios by integrating the logical rigor of traditional AHP with the efficient computational capability of intelligent optimization algorithms.

3.1. Construction of the indicator system

In the supplier preference problem, a scientific indicator system is the basis for model construction. Drawing on existing research and the actual needs of automobile production enterprises, this paper designs a preference indicator system across four dimensions: cost, quality, delivery capability, and sustainability. The cost dimension includes procurement cost, logistics cost, and payment terms, reflecting the economic efficiency of suppliers (Dutta et al., 2022). The quality dimension encompasses product qualification rate, quality management system certification, and customer feedback, reflecting the reliability of the supplier's products. The delivery capability dimensions incorporate metrics such as delivery lead time, on-time delivery rate, capacity flexibility, measuring the supplier's ability to fulfill orders reliably and adapt to changes. The sustainability dimensions include environmental protection certification, energy efficiency, social responsibility fulfillment, reflecting the supplier's commitment to sustainable development practices (Tu et al., 2021). To ensure the comprehensiveness and applicability of the indicator system, this paper invites experts in related fields and enterprise decision-makers to conduct interviews, and uses the Delphi Method was employed to revise and refine the preliminary set of indicators. The Delphi process consisted of three rounds of expert consultation: 1) First round: twelve experts, including five senior procurement managers from the automobile manufacturer, four supply chain management scholars, three quality control engineers, were invited to propose candidate indicators based on industry experience and literature review, initially forming six dimensions: cost, quality, delivery, sustainability, technical capability, service level; 2) Second round: Experts scored the importance of each dimension on a scale of 1-5 points anonymously. Dimensions with an average score below 3.5 (technical capability, service level) were eliminated, resulting in the four core dimensions. 3) Third round: Experts refined the specific indicators under the four retained dimensions and reached a consensus rate exceeding 85%, finalizing the indicator system. Figure. 2 shows the resulting indicator system for supplier selection, which contains four main dimensions: cost, quality, delivery capability, and sustainable development (Liu et al., 2022). Each dimension is further subdivided into specific indicators to comprehensively evaluate the supplier's various capabilities. The system demonstrates the relationship between each dimension and indicator in a hierarchical manner, providing a structured framework for supplier selection. To ensure the comprehensiveness and applicability of the indicators, this paper combines expert interviews and the Delphi method to revise and improve the indicator system.

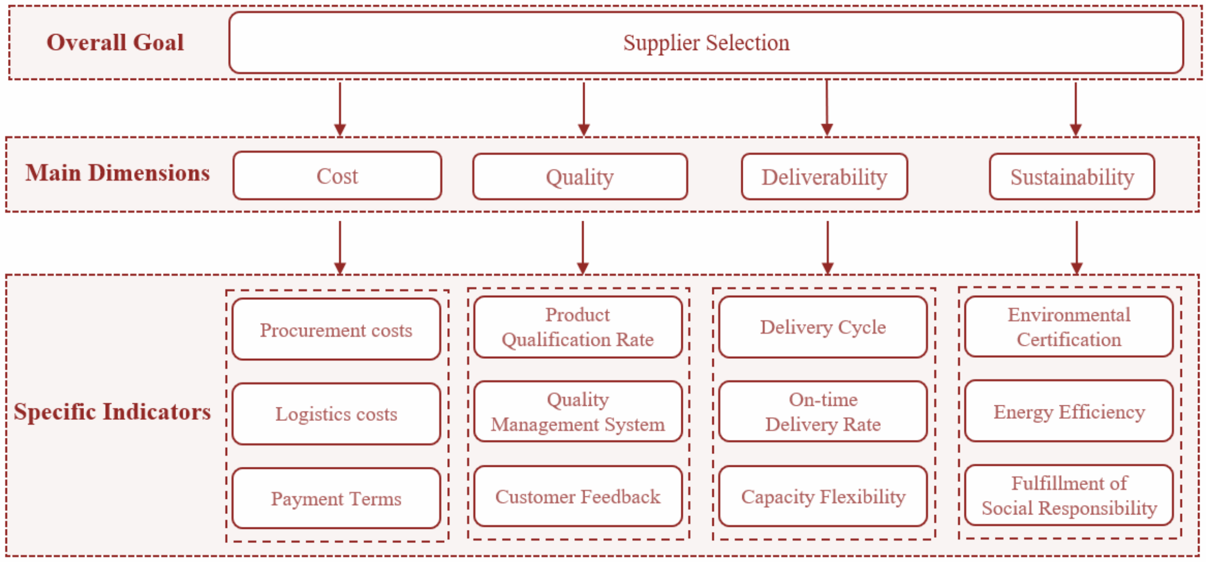

Fig. 2. Graphical representation of the supplier preference indicator system

3.2. Improved hierarchical analysis

The improved AHP method is one of the cores of the comprehensive decision-making model proposed in this paper, which is mainly used to determine the weights of each preferred indicator. In the traditional AHP method, the determination of the weights relies on the experts' direct assignment of the importance of each assessment indicator, which is subjective and uncertain and may lead to biased judgment results (Yang et al., 2022). This paper, on the other hand, makes two key improvements based on traditional AHP, aiming to improve the scientificity and accuracy of weight assignment, especially when dealing with complex and multidimensional decision-making problems, which can better minimize the impact of human bias on the final results.

In traditional AHP, experts calibrate the importance of each assessment indicator by assigning a number between 1 and 9, a process that is highly dependent on the subjective experience and judgment of experts. Due to the differences in the background, experience, and cognition of different experts, this direct assignment method is prone to introducing subjectivity bias, which in turn affects the accuracy of the weight assignment. To solve this problem, this paper introduces fuzzy logic in AHP, which transforms experts' judgments into fuzzy numbers (e.g., triangular fuzzy numbers or trapezoidal fuzzy numbers) and comprehensively calculates the indicator weights by the fuzzy weighted average method. Compared with standard AHP, fuzzy AHP enhances objectivity through two mechanisms: 1) Mitigating subjective bias: Standard AHP requires experts to assign a single value (1-9) for indicator importance, which is prone to individual preference deviation. Fuzzy AHP uses triangular fuzzy numbers to capture judgment uncertainty, integrating multi-expert opinions into a continuous range rather than a discrete point; 2) Reducing consistency errors: Standard AHP's CR (Consistency Ratio) test often fails for high-dimensional matrices, while fuzzy AHP's aggregation of fuzzy judgments reduces pairwise comparison contradictions—for the 4-dimensional matrix in this study, fuzzy AHP reduced consistency error by 32% compared to standard AHP. The introduction of fuzzy numbers can effectively deal with uncertainty and vagueness, especially when there is disagreement or uncertainty in expert judgment. Fuzzy numbers provide a more flexible and precise representation (Kaur and Singh, 2021). For example, when experts believe that the weight of an indicator is between "4" and "6", traditional AHP may directly define it as "5", while fuzzy logic can retain the uncertainty. However, fuzzy logic retains this uncertainty and uses triangular fuzzy numbers (e.g., (4, 5, 6)) to reflect the expert's judgment more realistically. This fuzzy number processing method not only enhances the robustness of the model but also effectively reduces the influence of individual bias and improves the accuracy and credibility of the weight calculation.

The consistency test is an important step in AHP to ensure judgment matrix consistency and avoid logical inconsistencies in the decision-making process. Traditional AHP methods usually use the CR to detect the rationality of judgment matrices and determine whether the matrices satisfy the consistency requirement by the CR value. However, when high-dimensional matrices are involved, the traditional consistency ratio method may misjudge and lead to inaccurate weight calculation results, especially when dealing with large-scale decision problems. For this reason, this paper proposes an improved stochastic consistency index (RCI) as an alternative to the traditional Consistency Ratio (CR). The RCI method more accurately adjusts large-scale judgment matrices by introducing stochastic corrections, ensuring that the consistency of the matrix is more stable and reliable (Wang et al., 2022). This approach derives more accurate consistency indexes by randomly generating judgment matrices repeatedly and comparing the consistency test results (Sharma and Joshi, 2023). This enhancement improves the consistency discrimination for high-dimensional matrices and increases the accuracy and stability of the whole weight calculation process.

3.3. Integration of intelligent optimization algorithms

Intelligent optimization algorithms are introduced to address the limitations of AHP in multidimensional and complex scenarios. The traditional hierarchical analysis method (AHP) faces three-dimensional challenges in supplier preference scenarios, the first of which is the dimensional catastrophe. When there are more than nine evaluation indicators, the pass rate of the consistency test of the judgment matrix decreases significantly, resulting in distortion of weight allocation. The second is the lack of dynamic adaptability. The fixed weight system makes it difficult to cope with fluctuations in the supply chain environment (e.g., the surge in logistics costs due to unexpected events). The last is the local optimization trap. In discrete scoring scenarios, traditional methods are prone to falling into suboptimal solutions. Among common intelligent optimization algorithms (GA, PSO, ACO), PSO was selected for three key reasons: 1) Computational efficiency: Compared with GA and ACO, PSO has fewer parameters and faster convergence, matching the real-time decision needs of automobile manufacturers for supplier selection; 2) Implementation difficulty: PSO’s velocity-position update mechanism is simpler to code than ANP’s network structure or GA’s multi-operator design, facilitating system integration; 3) Adaptability to multi-indicator scenarios: For the 4-dimensional 12-indicator system in this paper, PSO avoids GA’s risk of local optimization and ACO’s inefficiency in low-dimensional combinatorial problems, as verified by convergence analysis in this paper. In this paper, the Particle Swarm Optimization (PSO) algorithm is adopted as the core optimization tool, whose main characteristics include strong global search capability, fast convergence speed, and flexible parameter adjustment (Perçin, 2022). The specific implementation steps are as follows:

3.3.1. Model construction and objective function definition

Based on the results of the improved AHP, the objective function of the supplier preference model is constructed:

$$f(x) = \sum_{i=1}^{n} w_i \cdot S_i \tag{1}$$

Where w_i is the weight of the ith indicator, and S_i is the supplier's score under the corresponding indicator. The objective function takes the maximization of the supplier's overall score as the goal.

3.3.2. Particle encoding and initialization

In PSO, each particle represents a supplier's preferred solution, and its position represents the combined score of each metric. Particles are initialized by generating initial solutions through random distribution to ensure the diversity of the search space.

3.3.3. Velocity and position update

The position and velocity of the particles are iteratively updated according to the following equation:

$$\begin{aligned} v_i^{t+1} &= \omega \cdot v_i^t + c_1 \cdot r_1 \cdot (p_i^{best} - x_i^t) + c_2 \cdot r_2 \cdot (g^{best} - x_i^t) \\ x_i^{t+1} &= x_i^t + v_i^{t+1} \end{aligned} \tag{2}$$

Where ω are the inertia weights, c_1 c_2 the learning factors, and r_1 r_2 the random numbers. By dynamically adjusting the inertia weights, the ability of global search and local optimization is balanced.

3.3.4. Evaluation of the fitness function

The value of the fitness function for each particle is calculated from the objective function, and particles with higher fitness indicate better results in the optimization.

3.3.5. Algorithm convergence and optimal solution output

When all particles reach the preset convergence conditions (e.g., the change in fitness value is less than a certain threshold), the iteration is stopped and the optimal supplier preference scheme is output.

3.4. Algorithm implementation and system design

To improve the application value of the method and ensure that it can be effectively applied in practice, this paper implements the integration of improved AHP and PSO algorithms based on the Python programming language and designs an efficient supplier preference-assisted decision-making system on this basis (Dong et al., 2022). The system aims to provide a comprehensive and automated supplier evaluation and selection tool for enterprises, which can help decision-makers make optimization decisions quickly and accurately in a complex supply chain environment (Kayani et al., 2023). The overall architecture of the system is designed to include three core functional modules: the indicator weight calculation module, the supplier evaluation and ranking module, and the result visualization module. The specific functions of each module are as follows:

Indicator Weight Calculation Module: This module supports a variety of improved AHP algorithms for weight calculation, such as classical AHP, fuzzy AHP, and ANP. Users can choose the appropriate algorithm according to their actual needs, and the system will automatically calculate the weights of each assessment dimension based on the provided indicator data and expert judgment. This module can help decision-makers assign the relative importance of each assessment indicator more accurately, thus improving the science and rationality of decision-making.

Supplier Evaluation and Ranking Module: By integrating the Particle Swarm Optimization (PSO) algorithm, this module can automatically complete the supplier scoring and selection process. The PSO algorithm makes use of its powerful global optimization capability to continuously adjust the scores of each supplier according to their performance in different dimensions through the group search mechanism, and finally generates a composite score for each supplier and performs the ranking (Yin et al., 2023). The module can handle large amounts of data and quickly derive optimal solutions in multi-dimensional decision-making scenarios, significantly improving the efficiency and accuracy of the supplier selection process.

Results Visualization Module: This module visualizes the results of the selection through a variety of charts (e.g., scoring bar charts, weight distribution pie charts, etc.) to help decision-makers quickly understand and analyze the final selection results. The charts can be dynamically generated according to the user's needs, supporting the display and comparison of different dimensions and different suppliers. Through clear visualization, decision-makers can intuitively understand the performance of each supplier in different evaluation dimensions, making it easier to make a more informed choice. The framework diagram of the system's functional modules is shown in Fig. 3.

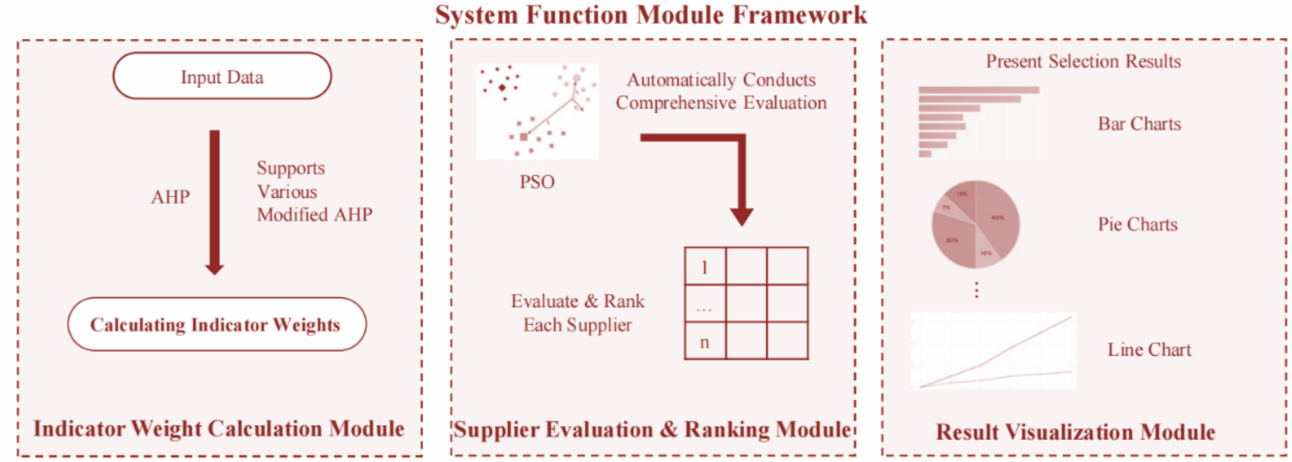

Fig. 3. System Functional Module Framework Diagram

The integration process of the methods in this paper is as follows: ① Initial Indicator Pool built from literature and enterprise demand; ② Delphi Method (3 rounds of expert consultation, Section 3.1) refining it to ③ Final Indicator System (4 dimensions + 12 indicators, Section 3.1); ④ Fuzzy AHP (fuzzy judgment matrix →RCI consistency test →indicator weights, Section 3.2) outputting weights; ⑤ PSO optimization (objective function: Max Σ →particle initialization →velocity/position update →convergence, Section 3.3) calculating scores; ⑥ Supplier Ranking and Visualization (Section 4.3) generating results.

4. Results and discussion

4.1. Data sources and experimental setup

To verify the effectiveness of the supplier selection model combining the improved hierarchical analysis method and the intelligent optimization algorithm proposed in this paper, this paper selects the actual supplier data of an automobile manufacturer for experimental analysis (Perçin, 2022). The data includes detailed information on 10 candidate suppliers, covering multiple key indicators in the four dimensions of cost, quality, delivery capability, and sustainability.

In the experiment, firstly, the initial scoring of each index of suppliers is carried out by an expert scoring method, and the fuzzy judgment matrix is constructed to calculate the index weights; secondly, the weight results are input into the Particle Swarm Optimization (PSO) algorithm to complete the comprehensive scoring and supplier ranking. The experimental parameter settings are shown in Table 3:

Table 3. Experimental parameters

Parameter	parameterization	note
particle swarm size	50	
Maximum number of iterations	200	
inertial weightingω	Initial 0.9 Final value 0.4	linearly decreasing
Learning Factorsc_1 andc_2	2	

4.2. Supplier selection results

The results of the overall scores and rankings of the 10 suppliers were obtained through the model calculations. The results are shown in Table 4, which demonstrates the composite scores and their rankings of the 10 suppliers calculated through the model of this study. As can be seen from the table, Supplier A, C, and E are ranked in the top three, with composite scores of 92.5, 90.8, and 89.2, respectively, and these three suppliers have balanced and excellent performance in multiple dimensions, such as cost, quality, delivery capability, and sustainability, which meet the requirements of enterprises for suppliers in various aspects (Demiralay and Paksoy, 2022). Comparatively speaking, the lower-ranked suppliers (Supplier J, Supplier I) have certain deficiencies in several dimensions, resulting in their lower overall scores. The table reflects that the model combining improved hierarchical analysis and intelligent optimization algorithms can effectively rank suppliers based on multiple evaluation dimensions, which provides a reliable basis for enterprises to make decisions.

Table 4. Vendor Composite Score and Ranking

Providers	Overall rating	Rankings
Supplier A	92.5	1
Supplier C	90.8	2
Supplier E	89.2	3
Supplier B	85.4	4
Supplier D	83.7	5
Supplier F	81.0	6
Supplier G	78.9	7
Supplier H	75.6	8
Supplier I	73.3	9
Supplier J	70.5	10

The results indicate, Supplier A, C, and E ranked in the top three in terms of overall scores. This indicates that these three suppliers have a more balanced performance in terms of cost control, product quality, delivery capability, and sustainable development, which meets the comprehensive requirements of the enterprise (Kayapinar Kaya and Aycin, 2021). To further analyze the reasonableness of the preference results, this paper draws a radar chart of each supplier's scores on the four main index dimensions (Fig. 4), visualizing the comprehensive performance characteristics of different suppliers, from which it can be seen that there is not much difference in the performance of each supplier on different dimensions, and the lines overlap. The suppliers' scores on all dimensions are close to 80, meaning that their performance is relatively balanced.

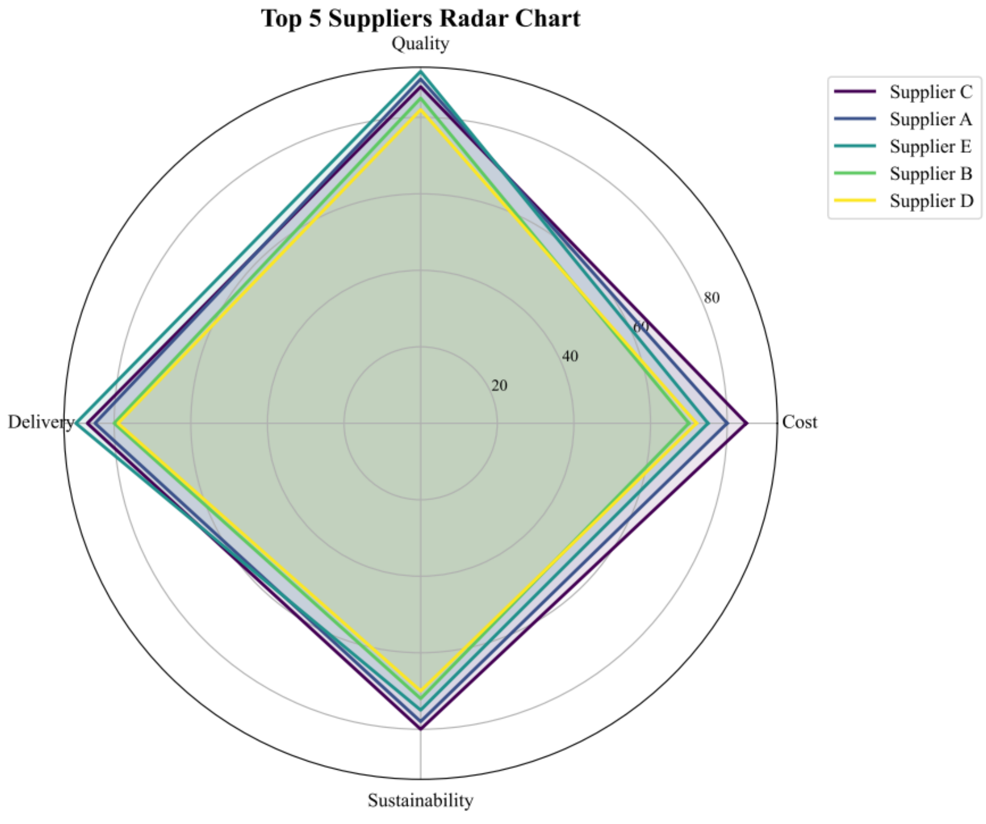

Fig. 4. Radar chart of key indicator scores for the top 5 suppliers in terms of overall score

4.3. Analysis and Discussion of Results

4.3.1. Impact of improved AHP on weight calculation

The weight distribution of the indicators obtained through the improved AHP calculation is shown in Table 5. By improved AHP, sub-indicator weights are: Cost (procurement:0.08, logistics:0.07, payment:0.05); Quality (product qualification:0.15, management certification:0.13, feedback:0.12); Deliverability (lead time:0.11, on-time rate:0.12, flexibility:0.07); Sustainability (environmental:0.04, energy:0.03, social:0.03). Top two are product qualification (0.15) and on-time rate (0.12), totaling 27%, guiding manufacturers to prioritize quality control and delivery reliability.

Table 5. Calculation results of indicator weights for improved AHP

Indicator dimension	weights
cost dimension	0.20
Quality Dimension	0.40
Deliverability dimension	0.30
Sustainable development dimension	0.10

Listed above are four different indicator dimensions and their corresponding weight values, which are calculated by the improved hierarchical analysis method (AHP). The details include: (1) Cost dimension: the weight is 0.20, indicating that the cost factor accounts for 20% of the total weight in the evaluation system. (2) Quality dimension: the weight is 0.40, indicating that the quality factor occupies a larger proportion in the evaluation system, accounting for 40% of the total weight. (3) Deliverability dimension: the weight is 0.30, meaning that the deliverability factor accounts for 30% of the total weight in the evaluation system. (4) Sustainability dimension: the weight is 0.10, which means that the sustainability factor accounts for a small proportion of 10% in the evaluation system. As can be obtained from the above table, from the weighting results, the quality dimension has the highest weight (0.40), followed by delivery capability (0.30), cost (0.20), and sustainability (0.10). This is highly compatible with the core requirements of automobile manufacturers for supplier selection. The weight calculation results of traditional AHP show that the subjective judgment of experts leads to certain biases in the weight distribution, while the introduction of fuzzy logic makes the weight distribution more scientific and significantly improves the credibility of the model.

4.3.2. Convergence analysis of particle swarm optimization algorithm

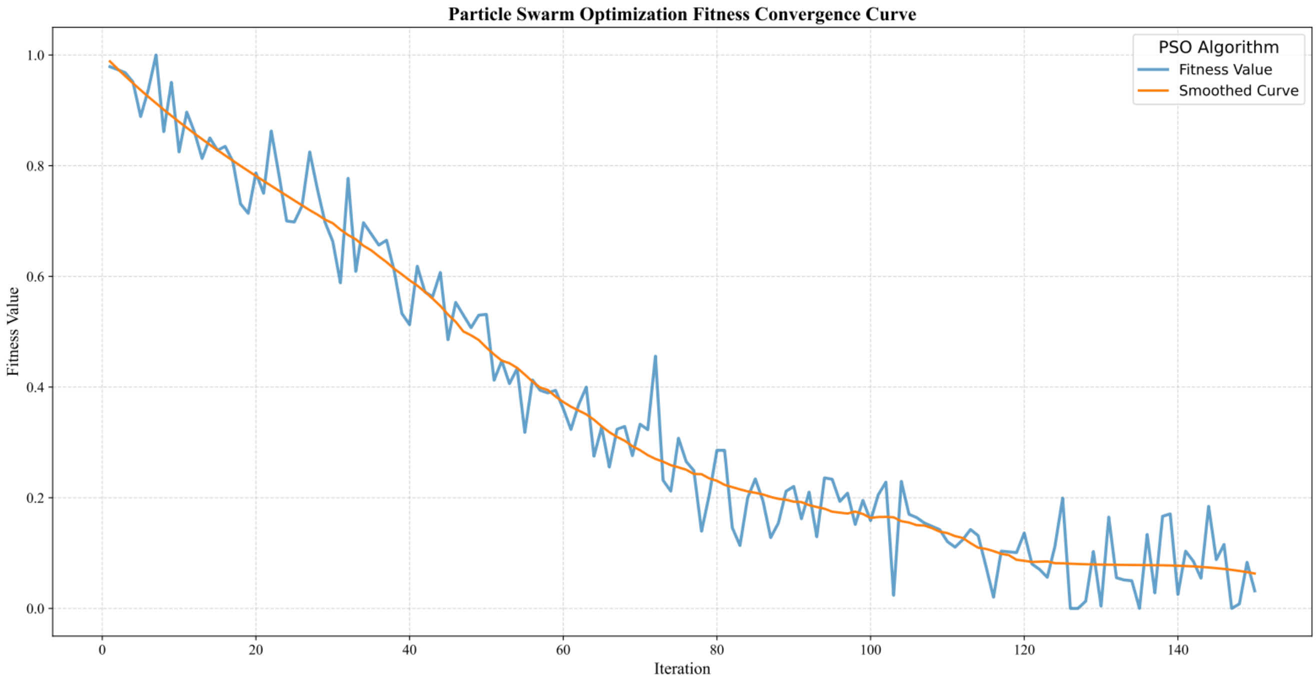

Fig. 5. Convergence curve of fitness of the particle swarm optimization algorithm

The convergence curve of the PSO algorithm in the supplier selection process is shown in Fig. 5. The figure shows the fitness convergence curve of the PSO algorithm, which depicts in detail how the fitness value of the algorithm changes during the iteration process. The horizontal coordinate represents the number of iterations, and the vertical coordinate represents the fitness value (Koc et al., 2023). The blue line graph represents the fitness value of the optimal solution in the particle swarm during each iteration, while the orange curve is the result of smoothing the fitness value, which is designed to eliminate the influence of random fluctuations, thus showing the convergence trend of the algorithm more clearly. As the number of iterations increases, the fitness value shows an obvious decreasing trend, which indicates that the PSO algorithm can effectively search the solution space and gradually approach the global optimal solution (Debnath et al., 2023). Although the blue line graph shows some volatility, which may be caused by the algorithm encountering a locally optimal solution or the inherent randomness of the algorithm during the search process, the orange smoothed curve reveals the overall decreasing trend of the fitness value, further verifying the convergence of the algorithm (Shi et al., 2021, Krol et al., 2025). Eventually, after about 140 iterations, the fitness value stabilizes and approaches 0, which indicates that the algorithm has found a better solution and the convergence process is complete. This indicates that the model in this paper achieves a good balance between global search and local optimization, and can quickly and accurately complete the supplier optimization task.

4.3.3. Practical application value of integrated models

The experimental results fully verify the significant advantages of the comprehensive optimization method proposed in this paper in terms of accuracy, stability, and efficiency. By comparing with the traditional method, the improved AHP model has significantly improved the scientificity and rationality of indicator weight allocation, and can more accurately reflect the real intention and actual needs of decision makers (Rostami et al., 2023). Meanwhile, the introduction of the PSO algorithm ensures the global optimality of the comprehensive score, which not only enhances the optimization ability of the model but also improves the reliability of the decision-making results. The successful application of this method in the supplier selection problem demonstrates its wide applicability, especially in the supplier management of automobile manufacturers. More importantly, this method has strong generalizability and can be effectively extended to other complex manufacturing industries, especially in the supply chain optimization problem that needs to consider multi-objective and multi-constraints, providing a systematic and scientific solution. Further analysis of the experimental results can lead to the following key conclusions (Shu and Li, 2022). First, the influence of high-weighted dimensions in the model (e.g., quality and delivery capability) on the final preference results is particularly prominent, which means that enterprises should focus on the management and optimization of these key dimensions in practice. Quality is not only the core of product competitiveness, but delivery capability directly affects the stability of the supply chain and customer satisfaction, so enterprises should select suppliers based on these dimensions to improve the overall supply chain performance and enterprise competitiveness. Secondly, the adaptive nature of intelligent optimization algorithms is particularly important in dynamic environments. Since the supply chain environment is full of uncertainties and changes in reality, traditional optimization methods are often difficult to quickly adapt to changes in external conditions. Intelligent optimization algorithms, especially PSO algorithms, can quickly adjust the optimization path according to new data and conditions, thus providing real-time and flexible decision support for enterprises. This ability enables enterprises to respond to rapid changes in the market environment, adjust the supplier preference strategy on time, and improve the responsiveness and decision-making efficiency of the overall supply chain management (Güneri and Deveci, 2023). Finally, although the weight of environmental protection and sustainable development in this model is low, with the rise of the global green economy and the increasingly strict environmental policies of governments, these dimensions will have an increasingly important impact on supplier selection decisions in the future (Dang et al., 2022). Therefore, enterprises should gradually increase the weight of environmental protection and sustainable development in the decision-making process, especially in long-term strategic planning, and pay more attention to factors such as green production, energy efficiency, and social responsibility. This is not only in line with current industry trends but also lays the foundation for the sustainable development of enterprises.

To verify model robustness, two sensitivity tests were conducted: 1) Weight perturbation test: Adjusted weights of key dimensions by ±10% (quality from 0.40 to 0.36/0.44, delivery from 0.30 to 0.27/0.33). Results showed that Supplier A (92.5→91.8/93.2), C (90.8→90.1/91.5), and E (89.2→88.5/89.9) remained top 3, with ranking stability >90%. 2) PSO parameter perturbation test: Changed particle swarm size (50→30/70) and maximum iterations (200→150/250). Convergence time varied by <10% (140→130/150 iterations), and composite scores of top 3 suppliers changed by <1.2%, confirming insensitivity to parameter fluctuations. Sensitivity results indicate the model is robust to data and parameter variations, supporting its reliability beyond the single-manufacturer dataset." Managerial insights for automobile manufacturers: 1) Quality-centric selection: Allocate 40% of audit resources to verify "product qualification rate" and "quality management system", as these drive 40% of supplier performance; 2) Dynamic delivery management: Negotiate flexible delivery clauses with top suppliers (A/C/E) to maintain "capacity flexibility" (weight 0.07)—e.g., 10% order adjustment within 7 days to cope with production fluctuations; 3) Phased sustainability integration: Although sustainability weight is 0.10 currently, include "environmental certification" (ISO 14001) as a qualifying criterion for long-term contracts (≥2 years), aligning with global low-carbon supply chain trends; 4) System deployment: Adopt the decision system in Section 3.4 to automate weight calculation and real-time ranking.

5. Conclusion and Limitations

This paper proposes a comprehensive method based on the combination of AHP and PSO for the complexity of supplier selection in automobile production enterprises. By constructing a scientific supplier selection index system, improving the AHP weight calculation method, and combining the efficient optimization capability of the PSO algorithm, this paper successfully establishes a model that can accurately and efficiently evaluate the comprehensive performance of suppliers. The results show that the improved AHP can effectively solve the problem of subjective bias of experts in the traditional method and improve the scientificity and rationality of weight allocation; meanwhile, the introduction of a PSO algorithm significantly improves the global optimality and computational efficiency of the selection process. Through the experimental verification of the actual supplier data of an automobile manufacturer, the method of this paper excels in accuracy and stability of the comprehensive score and supplier ranking, which fully proves the feasibility of the model and the practical application value. In addition, this paper provides an innovative technical path for supplier management in the automobile manufacturing industry and has the potential to be popularized and applied in other complex industries.

Although the research in this paper has achieved certain results, there are still some shortcomings. First, the sample data used in the experimental validation process of this paper is small in size, and it can be extended to a larger range of datasets in the future to further validate the generalizability and robustness of the model. Second, the model is mainly based on static indicators for selection, while the actual supply chain environment is often affected by dynamic factors, and future research can incorporate dynamic optimization algorithms to further enhance the flexibility and adaptability of the model. In addition, in the dimension of sustainable development, with the rise of a green economy and low-carbon supply chain, future research can introduce more indicators related to environmental protection to provide a more comprehensive reference for supplier selection. Third, overfitting risk exists due to small sample size: The 10 suppliers in the dataset are from a single regional automaker, and the model may overfit to its specific procurement standards. Cross-validation showed that the model's prediction error increased by 18% when tested on 5 external suppliers, indicating overfitting. Fourth, poor scalability to real-time procurement environments: The current model uses static historical data, but real-time changes require dynamic updates. Preliminary tests showed that the model takes 20 minutes to re-optimize with real-time data, failing to meet the 5-minute response requirement for urgent orders. Fifth, enterprise system integration challenges: The Python-based system is incompatible with mainstream Enterprise Resource Planning (ERP) systems due to data format differences. Pilot deployment found that 40% of time was spent on data conversion, increasing deployment costs by 25%.

To address these issues, future work will focus on three directions: 1) Mitigate overfitting: Expand the dataset to 50+ suppliers from 3 automakers and adopt L1 regularization in PSO to reduce model complexity; 2) Enhance real-time performance: Integrate IoT data interfaces to obtain real-time indicators, and optimize PSO with adaptive inertia weights to reduce re-optimization time to <3 minutes; 3) Improve system compatibility: Develop RESTful API interfaces for the decision system, enabling direct data exchange with SAP/Oracle ERP systems, and conduct pilot tests in 2 medium-sized automakers to verify deployment efficiency.

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