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Location Decision of E-commerce Enterprise Logistics Distribution Center Based on AHP-Entropy Weight Method and TOPSIS

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ABSTRACT

With the rapid development of e-commerce, logistics distribution speed has become a key competitive factor for e-commerce enterprises. This paper addresses the location decision problem of regional logistics distribution centers for a large e-commerce platform in East China. Four candidate cities—Nanjing, Hangzhou, Suzhou, and Wuxi—are evaluated using a combined AHP-Entropy Weight-TOPSIS model. The Analytic Hierarchy Process (AHP) determines subjective weights reflecting expert experience, while the Entropy Weight Method (EWM) calculates objective weights based on data information content. A multiplicative synthesis method integrates both weights into comprehensive weights. TOPSIS is then applied to rank alternatives by their relative closeness to the positive ideal solution. Six evaluation indicators are constructed: land cost, labor cost, transportation convenience, market radiation capacity, policy preference, and infrastructure completeness. The results show that Nanjing ranks first with a closeness coefficient of 0.7918, followed by Hangzhou (0.6301), Suzhou (0.3056), and Wuxi (0.2125). Sensitivity analysis and comparative analysis with single-weighting methods confirm the robustness and superiority of the combined weighting approach. This study provides a scientific decision-making framework for logistics distribution center location selection.

KEYWORDS

Logistics Distribution Center; Site Selection; AHP; Entropy Weight Method; TOPSIS; E-commerce

1. INTRODUCTION

With the vigorous development of the e-commerce industry, logistics distribution speed has become a major competitive factor for e-commerce enterprises. A large e-commerce platform plans to establish a new regional logistics distribution center in East China to serve customers in Jiangsu, Zhejiang, and Anhui provinces. After preliminary screening, four candidate cities are identified: Nanjing, Hangzhou, Suzhou, and Wuxi. Location decision-making involves economic, geographical, policy, and many other factors, and the trade-offs among various factors are complex. Therefore, enterprises must rely on scientific methods and systematic analysis to select the optimal location scheme.

The purpose of this decision case is to use a scientific evaluation indicator system and multi-criteria decision-making method, comprehensively considering subjective experience judgment and objective data information, to ultimately determine the most suitable city for building a regional logistics distribution center. This provides a theoretical basis and data support for enterprise investment decisions.

1.1. Construction of Evaluation Indicator System

Based on theories and practical experience related to logistics distribution center location selection, this paper establishes an evaluation system containing six specific indicators from the perspectives of economic factors, geographical factors, and environmental factors.

(1) C1 Land cost (10,000 yuan/mu): reflects the land acquisition cost of candidate cities, a cost-type indicator; the lower the value, the better.

(2) C2 Labor cost (yuan/month): reflects the average wage level of local warehouse operators, a cost-type indicator; the smaller the value, the better.

(3) C3 Transportation convenience (10-point scale): comprehensively evaluates the development level of transportation networks including highways, railways, aviation, and water transport in candidate cities, a benefit-type indicator; scored by experts based on the current status of transportation infrastructure, the higher the score, the better.

(4) C4 Market radiation capacity (population within 100 km, 10,000 persons): the total population within a radius of 100 km centered on the candidate city, reflecting the potential consumer market scale, a benefit-type indicator; the larger the value, the better.

(5) C5 Policy preference (10-point scale): evaluates the intensity of policy incentives such as tax reductions, land approval, and industrial support provided by local governments, a benefit-type indicator; scored by experts based on local policy documents.

(6) C6 Infrastructure completeness (10-point scale): reflects the support status of supporting infrastructure such as electricity, communications, water supply, and sewage disposal for logistics operations, a benefit-type indicator; scored by experts.

The original data of the four candidate cities under each indicator are shown in Table 1.

Table 1. Original decision matrix

Indicator	Nanjing (A1)	Hangzhou (A2)	Suzhou (A3)	Wuxi (A4)	Type
C1 Land cost (10k yuan/mu)	80	95	70	65	Cost
C2 Labor cost (yuan/month)	6500	7000	6000	5800	Cost
C3 Transportation convenience	9	8	7	7	Benefit
C4 Market radiation (10k persons)	3500	3200	2800	2500	Benefit
C5 Policy preference	8	9	7	6	Benefit
C6 Infrastructure completeness	9	8	8	7	Benefit

2. DECISION MODEL ESTABLISHMENT AND SOLUTION

This case uses a combined AHP-Entropy Weight-TOPSIS decision model. AHP (Analytic Hierarchy Process) is used to determine the subjective weights of indicators, reflecting the decision-maker's empirical judgment on the importance of each indicator. EWM (Entropy Weight Method) is used to determine the objective weights, reflecting the information content and discrimination ability of each indicator in the original data. The multiplicative synthesis method combines subjective and objective weights to obtain comprehensive weights. Finally, TOPSIS is used to calculate the closeness of each alternative to the positive ideal solution for ranking.

2.1. AHP for Determining Subjective Weights

2.1.1. Construction of Judgment Matrix

Three experts in the logistics field (one university professor, one enterprise executive, and one industry association researcher) were invited to conduct pairwise comparisons of the importance of each indicator using the 1-9 scale method. The geometric mean was taken to obtain the comprehensive judgment matrix A, as shown in Table 2.

Table 2. AHP judgment matrix A

Indicator	C1	C2	C3	C4	C5	C6
C1	1	1/2	1/4	1/3	1/2	1/3
C2	2	1	1/3	1/2	1	1/2
C3	4	3	1	2	3	2
C4	3	2	1/2	1	2	1
C5	2	1	1/3	1/2	1	1/2
C6	3	2	1/2	1	2	1

2.1.2. Calculation of Weight Vector

The geometric mean method is used to obtain the weights of each indicator. First, calculate the geometric mean of each row of elements in the judgment matrix:

$$M_1=(1\times1/2\times1/4\times1/3\times1/2\times1/3)^\wedge(1/6)=0.4368$$

$$M_2=(2\times1\times1/3\times1/2\times1\times1/2)^\wedge(1/6)=0.7418$$

$$M_3=(4\times3\times1\times2\times3\times2)^\wedge(1/6)=2.2894$$

$$M_4=(3\times2\times1/2\times1\times2\times1)^\wedge(1/6)=1.3480$$

$$M_5=(2\times1\times1/3\times1/2\times1\times1/2)^\wedge(1/6)=0.7418$$

$$M_6=(3\times2\times1/2\times1\times2\times1)^\wedge(1/6)=1.3480$$

Normalize to obtain the weight vector W:

$$W_1=0.4368/6.9059=0.0632$$

$$W_2=0.7418/6.9059=0.1074$$

$$W_3=2.2894/6.9059=0.3315$$

$$W_4=1.3480/6.9059=0.1952$$

$$W_5=0.7418/6.9059=0.1074$$

$$W_6=1.3480/6.9059=0.1952$$

The subjective weight vector is W = (0.0632, 0.1074, 0.3315, 0.1952, 0.1074, 0.1952).

2.1.3. Consistency Test

Calculate the maximum eigenvalue λmax of the judgment matrix:

$$AW=A\times W=(0.3837,0.6470,2.0098,1.1756,0.6470,1.1756)^T$$

$$\lambda_{max}=\frac{1}{6}\sum_{i=1}^{6}\frac{(AW)_i}{W_i}=6.0368$$

$$CI=\frac{\lambda_{max}-n}{n-1}=\frac{6.0368-6}{5}=0.0074$$

The random consistency index RI = 1.24 when n = 6.

Consistency ratio:

$$CR=\frac{CI}{RI}=\frac{0.0074}{1.24}=0.0059$$

Since CR = 0.0059 < 0.1, the expert scoring is consistent and the obtained weights are credible.

According to the AHP weights, experts believe that "transportation convenience" most determines the value of logistics distribution center location, with a weight of 0.3315, followed by market radiation capacity and infrastructure completeness at 0.1952 each, while land cost has the smallest weight of 0.0632. This is consistent with the industry consensus that "accessibility takes priority over land cost."

2.2. Entropy Weight Method for Determining Objective Weights

2.2.1. Data Standardization

Since the dimensions and magnitudes of each indicator differ, vector normalization is first performed on the original decision matrix. For cost-type indicators (C1, C2), take the reciprocal first to convert them into benefit-type indicators, then normalize; for benefit-type indicators (C3-C6), normalize directly. The standardization formula is:

$$z_{ij}=\frac{x_{ij}}{\sqrt{\Sigma_{j=1}^{4}x_{ij}^{2}}} \tag{1}$$

The standardized matrix Z is shown in Table 3.

Table 3. Standardized matrix Z

Indicator	Nanjing (A1)	Hangzhou (A2)	Suzhou (A3)	Wuxi (A4)
C1 Land cost	0.4698	0.3957	0.5370	0.5783
C2 Labor cost	0.4827	0.4482	0.5229	0.5410
C3 Transportation	0.5774	0.5132	0.4491	0.4491
C4 Market radiation	0.5787	0.5291	0.4630	0.4134
C5 Policy preference	0.5275	0.5934	0.4616	0.3956
C6 Infrastructure	0.5603	0.4981	0.4981	0.4358

2.2.2. Calculation of Proportion Matrix

Calculate the proportion of the j-th alternative under the i-th indicator: $p_{ij}=\frac{z_{ij}}{\sum_{j=1}^{4} z_{ij}}$, obtaining the proportion matrix P.

2.2.3. Calculation of Information Entropy and Difference Coefficient

The information entropy of the i-th indicator is calculated as: $e_i=-k\sum_{j=1}^{4} p_{ij}\ln(p_{ij})$, where $k=\frac{1}{\ln m}=\frac{1}{\ln 4}=0.7213$ and m is the number of alternatives.

The calculated information entropy of each indicator:

$e_1=0.9928$, $e_2=0.9981$, $e_3=0.9959$, $e_4=0.9942$, $e_5=0.9919$, $e_6=0.9972$

Difference coefficient: $d_i=1-e_i$

$d_1=0.0072$, $d_2=0.0019$, $d_3=0.0041$, $d_4=0.0058$, $d_5=0.0081$, $d_6=0.0028$

2.2.4. Calculation of Objective Weights

The objective weight is: $w_i=d_i/\mathrm{sum}(d_i)$

The entropy weight method objective weights are calculated as:

$$w'=(0.2406,0.0633,0.1362,0.1954,0.2700,0.0946)$$

From the entropy weight results, "policy preference" (0.2700) and "land cost" (0.2406) have the highest objective weights, meaning these two indicators have the largest differences and strongest discrimination ability among the four cities in the original data. "Labor cost" (0.0633) and "infrastructure completeness" (0.0946) have the lowest objective weights, indicating small differences among the four cities for these indicators.

2.3. Combined Weighting

To ensure the organic combination of subjective experience and objective information, the multiplicative synthesis method is used to calculate combined weights:

$$w_i^*=\frac{w_i^{AHP}\cdot w_i^E}{\sum_{i=1}^{6}(w_i^{AHP}\cdot w_i^E)}$$

The calculation results are shown in Table 4.

Table 4. Combined weight calculation results

Indicator	AHP Weight	Entropy Weight	Product	Combined Weight
C1 Land cost	0.0632	0.2406	0.0152	0.0996
C2 Labor cost	0.1074	0.0633	0.0068	0.0445
C3 Transportation	0.3315	0.1362	0.0452	0.2956
C4 Market radiation	0.1952	0.1954	0.0381	0.2496
C5 Policy preference	0.1074	0.2700	0.0290	0.1899
C6 Infrastructure	0.1952	0.0946	0.0185	0.1209
Total	1.0000	1.0000	0.1528	1.0000

Transportation convenience and market radiation capacity have influence coefficients of 0.2956 and 0.2496 respectively, together exceeding 54%, making them the two most influential indicators. Policy preference is the third most influential factor. This result shows that experts attach great importance to accessibility, while also being sensitive to policy differences reflected in the data.

2.4. TOPSIS for Alternative Ranking

2.4.1. Construction of Weighted Standardized Matrix

Multiply the standardized matrix Z by the combined weights to obtain the weighted standardized matrix V:$V_{ij}=z_{ij}\cdot w_i^*$. The weighted standardized matrix V is shown in Table 5.

Table 5. Weighted standardized matrix V

Indicator	Nanjing (A1)	Hangzhou (A2)	Suzhou (A3)	Wuxi (A4)
C1 Land cost	0.0468	0.0394	0.0535	0.0576
C2 Labor cost	0.0215	0.0199	0.0233	0.0241
C3 Transportation	0.1706	0.1517	0.1327	0.1327
C4 Market radiation	0.1445	0.1321	0.1156	0.1032
C5 Policy preference	0.1002	0.1127	0.0877	0.0751
C6 Infrastructure	0.0677	0.0602	0.0602	0.0527

2.4.2. Determination of Positive and Negative Ideal Solutions

The positive ideal solution V+ takes the maximum value of each indicator in the weighted matrix:

$$V^{+}=(0.0576, 0.0241, 0.1706, 0.1445, 0.1127, 0.0677)$$

The negative ideal solution V- takes the minimum value of each indicator in the weighted matrix:

$$V^{-}=(0.0394, 0.0199, 0.1327, 0.1032, 0.0751, 0.0527)$$

2.4.3. Calculation of Euclidean Distance and Closeness

The distances of each alternative from the positive ideal solution D+ and negative ideal solution D-:

$$D_j^{+}=\sqrt{\sum_{i=1}^{6}(V_{ij}-V_i^{+})^2}$$

$$D_j^{-}=\sqrt{\sum_{i=1}^{6}(V_{ij}-V_i^{-})^2}$$

Closeness coefficient: $C_j=\frac{D_j^{-}}{D_j^{+}+D_j^{-}}$

The calculation results are shown in Table 6.

Table 6. Calculation results and alternative ranking

Alternative	D^+	D^-	Closeness C	Rank
Nanjing (A1)	0.0167	0.0637	0.7918	1
Hangzhou (A2)	0.0303	0.0516	0.6301	2
Suzhou (A3)	0.0545	0.0240	0.3056	3
Wuxi (A4)	0.0691	0.0187	0.2125	4

3. RESULT ANALYSIS AND DECISION CONCLUSION

3.1. Ranking Result Analysis

According to the TOPSIS closeness calculation results, the ranking of the four candidate cities is: Nanjing > Hangzhou > Suzhou > Wuxi. Nanjing's closeness is significantly higher than other cities, making it the optimal location scheme.

From the weighted standardized matrix, Nanjing's advantages come from "transportation convenience" (0.1706) and "infrastructure completeness" (0.0677), both of which Nanjing performs best among cities in East China as a comprehensive transportation hub. Nanjing has Lukou International Airport, Nanjing Port (the largest inland river port in Asia), and dense railway and highway networks, performing excellently on the high-weight indicators C3 and C6. Additionally, Nanjing's market radiation indicator (0.1445) ranks first due to its geographical advantage of being located at the center of Jiangsu Province, radiating both Jiangsu and Anhui provinces.

Hangzhou ranks second (0.6301), mainly because its policy preference score is the highest (0.1127), consistent with the Hangzhou municipal government's strong support for e-commerce logistics industry policies in recent years. However, Hangzhou's disadvantages in "land cost" (0.0394) and "market radiation" (0.1321) reduce its overall score.

Suzhou and Wuxi have lower closeness mainly because their "transportation convenience" and "market radiation" scores are lower, lacking competitiveness on high-weight indicators.

3.2. Result Reliability Analysis

(1) At the model level, the AHP-Entropy Weight-TOPSIS combined model used in this paper is the most widely used multi-criteria decision model in logistics distribution center location selection. AHP incorporates expert experience, the entropy weight method overcomes errors caused by human subjectivity, and TOPSIS fully utilizes the original data. The combination of the three makes decision results both scientific and practical.

(2) In terms of data, the original data comes from local statistical yearbooks, government public reports, and expert assessments. Land cost and labor cost are objective statistical data, while indicators such as transportation convenience and policy preference are scored independently by multiple experts and averaged to reduce subjective bias caused by a single evaluator.

(3) In terms of sensitivity, changing any element in the AHP judgment matrix (except scale values) and recalculating still maintains the order Nanjing > Hangzhou > Suzhou > Wuxi, indicating that the model has strong robustness to parameter changes.

3.3. Comparative Analysis of Three Weighting Methods

To verify the superiority of the combined weighting method, this study also conducted a comparative analysis of the ranking results of pure AHP-TOPSIS and pure entropy-TOPSIS.

The ranking result of pure AHP-TOPSIS is: Nanjing (0.8385) > Hangzhou (0.5648) > Suzhou (0.2875) > Wuxi (0.1964). Since AHP assigns a high weight (0.3315) to "transportation convenience," Nanjing achieves a clear leading position through its transportation advantages, but the gap between Hangzhou and Nanjing widens, and the scores of Suzhou and Wuxi become lower.

The ranking result of pure entropy-TOPSIS is: Nanjing (0.6356) > Hangzhou (0.5586) > Suzhou (0.4612) > Wuxi (0.4022). Since the entropy weight method assigns higher weights to land cost and policy preference, Suzhou and Wuxi, which have greater advantages in these two aspects, see their scores significantly increase. The gaps among the four cities narrow, and Suzhou even approaches Hangzhou.

The ranking result of combined weighting TOPSIS is: Nanjing (0.7918) > Hangzhou (0.6301) > Suzhou (0.3056) > Wuxi (0.2125). This result lies between the two, maintaining Nanjing's leading advantage (since both AHP and entropy weight recognize Nanjing's advantages in transportation and market radiation) while appropriately widening the gaps between Hangzhou and Suzhou/Wuxi (since combined weights reduce the influence of land cost and highlight the importance of transportation convenience and market radiation), making the ranking result closer to the practical decision logic of logistics distribution center location.

Thus, using only subjective weighting overstates expert preferences while ignoring data differences; using only objective weighting overemphasizes data randomness while negating professional experience. Combined weighting uses multiplicative synthesis to integrate subjective and objective aspects, making decision results reflect industry consensus (transportation convenience first) while acknowledging data facts (significant policy differences), and is more scientific and robust.

3.4. Sensitivity Analysis

To test the stability of the model to weight perturbations, ±20% perturbations were applied to each indicator's combined weight to observe changes in ranking results. The specific method is to multiply the combined weight of the i-th indicator by (1+δ), where δ varies between -20% and +20%, normalize the weights of other indicators proportionally, and re-solve the TOPSIS closeness and ranking.

The sensitivity analysis results show that:

(1) When the weight of C1 (land cost) changes within ±20%, the ranking of the four cities remains Nanjing > Hangzhou > Suzhou > Wuxi. Nanjing's closeness fluctuates slightly between 0.78 and 0.81, Hangzhou's between 0.62 and 0.64, while Suzhou and Wuxi show minimal changes. This indicates that changes in land cost weight have little impact on the overall ranking.

(2) When the weight of C3 (transportation convenience) fluctuates within ±20%, the ranking remains stable. Nanjing's closeness fluctuates between 0.75 and 0.84, and Hangzhou's between 0.59 and 0.66. Since transportation convenience is the indicator with the largest weight, its fluctuation has the greatest impact on each city's score. However, Nanjing always ranks first and Hangzhou second.

(3) When the weight of C5 (policy preference) changes within ±20%, Hangzhou's closeness fluctuates most dramatically (0.58 to 0.67), as Hangzhou has the greatest advantage in this indicator. Even if the policy preference weight increases by 20%, Hangzhou's closeness remains at 0.67, less than Nanjing's 0.79, and the ranking does not change.

(4) Under all perturbation scenarios, the ranking order of each city remains unchanged: Nanjing > Hangzhou > Suzhou > Wuxi. This well demonstrates that the results obtained in this study are stable and reliable.

4. LITERATURE REVIEW

The analytic hierarchy process (AHP) and entropy weight method (EWM) have emerged as powerful multi-criteria decision-making (MCDM) tools across diverse disciplines, ranging from geohazard assessment to energy system optimization. This section reviews recent advancements in the application of these methodologies, following the sequential order of contributions that illustrate their evolving scope and integration with complementary techniques.

Okegbola et al. [1] demonstrated the integration of multi-temporal LiDAR data with AHP for landslide detection and susceptibility mapping in Prince George's County, Maryland, highlighting the value of combining remote sensing technologies with hierarchical decision frameworks for geospatial risk assessment. Extending the application of AHP into energy systems, Chen and Kang [2] proposed an AHP-aware forecasting and economic management framework for fuel cell-enabled renewable-rich energy clusters, incorporating shared hydrogen storage and financial–social welfare considerations to address complex energy management challenges. In the domain of software security, Shameem et al. [3] employed an integrated approach of systematic literature review and fuzzy AHP (F-AHP) to develop a taxonomy of challenges influencing secure code generation using large language models (LLMs), showcasing AHP's adaptability to emerging digital threats.

The intersection of machine learning, geographic information systems (GIS), and MCDM was explored by Chaoui et al. [4], who developed a hierarchical indicator-based spatial decision-support framework for evaluating trade-offs between urban sustainability and resilience. In pharmaceutical research, Ziteng et al. [5] integrated high-performance liquid chromatography (HPLC) amino acid profiling with AHP-CRITIC (Criteria Importance Through Intercriteria Correlation) to guide freeze-drying process optimization, chemical-pharmacodynamic equivalence evaluation, and acute toxicity assessment of Scorpio, demonstrating the potential of combined weighting methods in traditional medicine standardization. Bingran and Hong [6] applied an integrated visual grammar-AHP-entropy weight method (EWM) approach to construct a visual discourse system for cultural and creative brands in Xizang, illustrating how MCDM can support cultural heritage communication and brand development.

Risk assessment methodologies incorporating entropy-based approaches have gained significant traction in material and infrastructure safety. Zhang et al. [7] investigated the fire risk of expanded polystyrene under ultraviolet aging using fuzzy cluster analysis combined with the entropy method, providing a data-driven foundation for construction material safety evaluation. Kumar et al. [8] addressed circular resource management in the healthcare sector through an integrated fuzzy AHP and fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) approach, emphasizing the role of MCDM in promoting sustainable healthcare practices.

Returning to geohazard assessment, Dwivedi et al. [9] introduced a data-driven hybrid approach integrating frequency ratio, AHP, and random forest with entropy-based information gain-derived weights for landslide susceptibility assessment, representing a convergence of statistical, machine learning, and MCDM techniques. Afolabi et al. [10] conducted a morphometric-based flood hazard assessment of the Anambra–Imo Sedimentary Basin using fuzzy-AHP and sensitivity analysis, while Landry et al. [11] integrated the relative active tectonic index with AHP for assessing active deformation in the Bafoussam–Mamfe region of West Cameroon.

In manufacturing and operations research, Raman et al. [12] presented a critical review revealing the benefits of the entropy weights method for multi-objective optimization in machining operations, establishing the theoretical foundations for entropy-based weighting in industrial applications. Huang et al. [13] compared the entropy weight method with the scatter degree method for historical data-driven risk assessment of railway dangerous goods transportation systems, contributing to the methodological discourse on objective weighting techniques in transport safety. Han et al. [14] evaluated intelligent swarm efficiency based on the AHP-entropy weight method, while Wang et al. [15] applied the same hybrid methodology to safety evaluation of bolt support systems, collectively demonstrating the synergy between subjective AHP judgments and objective entropy-derived weights in engineering safety and performance assessment.

Medical and diagnostic applications of entropy methods have also shown promising results. Shiying et al. [16] analyzed and processed depression misdiagnosis data based on a modified entropy weight method, addressing the critical need for objective diagnostic support tools in mental health. In urban environmental management, researchers from Tianjin University [17] developed an urban flooding risk assessment framework based on an integrated k-means cluster algorithm and improved entropy weight method in Haikou, China, while subsequent work [18] applied set pair analysis combined with an improved entropy weight method for water resources carrying capacity evaluation and diagnosis.

Finally, in the renewable energy sector, researchers from the Department of Electrical Engineering [19] presented a multi-objective optimal design of stand-alone hybrid energy systems using the entropy weight method based on HOMER (Hybrid Optimization of Multiple Energy Resources), reinforcing the method's applicability in sustainable energy planning and system configuration.

In summary, the reviewed literature collectively demonstrates that AHP, entropy weight methods, and their hybrid variants have transcended traditional decision-making boundaries to address contemporary challenges in geohazard management, urban planning, energy optimization, healthcare sustainability, and emerging technological domains. The progressive integration of these MCDM tools with GIS, machine learning, remote sensing, and statistical techniques signifies a maturing field where subjective expert knowledge and objective data-driven weights are increasingly combined to produce robust, context-sensitive assessment frameworks.

5. RESEARCH LIMITATIONS AND FUTURE WORK

5.1. Research Limitations

Although the method application and data analysis in this case are rigorous, there are still the following limitations:

(1) The indicator system is incomplete. This case only selected six indicators and did not consider emerging factors such as supply chain resilience, carbon emission intensity, and labor supply stability. With the advancement of the "dual carbon" strategy and the promotion of ESG concepts, logistics distribution center location will increasingly consider environmental impacts as evaluation criteria.

(2) Short timeliness and small data volume. The data used in this case are mainly from the 2024 statistical yearbook and expert assessments, without considering future 5-10 year transportation planning of each city (such as the construction of Nanjing North Station, Hangzhou West Station hub, etc.) and industrial policy adjustments. Logistics distribution centers generally have a service life of about 20 years, so location selection should have forward-looking considerations.

(3) Model assumptions are overly simplified. This model assumes that each indicator is independent of each other and does not consider interaction effects between indicators. Improved transportation convenience will enhance market radiation capacity; the two are not completely independent. In addition, the model does not consider the optimization problem of multi-distribution center collaborative layout, only evaluating the location of a single distribution center.

(4) Too few experts. The AHP judgment matrix uses the scoring results of three experts. Although consistency testing ensures logical self-consistency, the small sample size may cause randomness in subjective weights. Future research can increase the expert sample size or use the Delphi method for multiple rounds of consultation to improve weight stability.

5.2. Future Outlook

Addressing the above limitations, future research can be expanded from the following directions:

(1) Construct dynamic evaluation models. Using multi-period decision-making or rolling planning methods, incorporating future transportation infrastructure, industrial policies, population mobility and other factors of each city into location decision-making, making location decisions more forward-looking.

(2) Incorporate environmental and social responsibility into evaluation indicators. Under the "dual carbon" goal, adding environmental indicators such as carbon emission intensity, green energy usage rate, and packaging waste recycling rate to the evaluation system, constructing a green logistics distribution center location model.

(3) Use multiple methods comprehensively. Integrating AHP-entropy-TOPSIS with grey relational analysis, fuzzy comprehensive evaluation, and Bayesian networks for verification, or incorporating machine learning techniques (random forest, neural network) to achieve intelligent identification of automatic indicator importance generation.

(4) Implement collaborative optimization of distribution centers. Extending from single distribution center location to multi-distribution center network layout optimization, using operations research methods such as mixed integer programming and genetic algorithms to obtain the optimal structure of the logistics network.

REFERENCES

[1] Okegbola, O. M., Owolabi, O., Sheng, Z., et al. (2026). Integrating multi-temporal LiDAR and AHP for landslide detection and susceptibility mapping in Prince George's County, Maryland. Journal of Safety Science and Resilience, 7(4), 100311.

[2] Chen, Y., & Kang, D. (2026). Analytic hierarchy process-aware forecasting and economic management in fuel cell-enabled renewable-rich energy clusters with shared hydrogen storage and financial-social welfare considerations. Fuel Processing Technology, 291, 108557.

[3] Shameem, M., Anwer, S., Mahmood, S., et al. (2026). Taxonomy of challenges influencing secure code generation using LLMs: An integrated approach of systematic literature review and F-AHP. Applied Soft Computing, 203, 116127.

[4] Chaoui, G., Mastere, M., Yaagoubi, R., et al. (2026). A hierarchical indicator-based spatial decision-support framework for evaluating trade-offs between urban sustainability and resilience using machine learning and GIS. Environmental and Sustainability Indicators, 31, 101458.

[5] Ziteng, W., Xiao, X., Zhen, Y., et al. (2026). Integration of HPLC amino acid profiling with AHP-CRITIC guided freeze-drying process optimization, chemical-pharmacodynamic equivalence, and acute toxicity evaluation of Scorpio. Biomedical Chromatography, 40(9), e70562.

[6] Bingran, Z., & Hong, Z. (2026). Constructing a visual discourse system for cultural and creative brands in Xizang: An integrated visual grammar-AHP-EWM approach. Global Vision Research, 3(3).

[7] Zhang, W., Zhao, M., Xie, X., et al. (2026). Study on the fire risk of expanded polystyrene under ultraviolet aging based on fuzzy cluster analysis and entropy method. Journal of Thermal Analysis and Calorimetry, 1–16.

[8] Kumar, R., Sharma, S., & Sharma, A. (2026). Circular resource management in healthcare sector integrated with fuzzy AHP and fuzzy TOPSIS approach. Circular Economy and Sustainability, 6(4), 390.

[9] Dwivedi, M., Sivasubramanian, S., & Jain, K. (2026). A data-driven hybrid approach integrating frequency ratio, analytic hierarchy process, and random forest with entropy-based information gain-derived weights for landslide susceptibility assessment. Journal of the Indian Society of Remote Sensing, 1–23.

[10] Afolabi, E. K., Ajibade, O. F., Idowu, E. T., et al. (2026). Morphometric-based flood hazard assessment of the Anambra-Imo Sedimentary Basin using fuzzy-AHP and sensitivity analysis. Spatial Information Research, 34(5), 51.

[11] Landry, P. D. W., Moussa, N. N., Christian, M. A. B., et al. (2026). Integration of the relative active tectonic index and analytic hierarchy process for assessing active deformation in the Bafoussam-Mamfe region (West Cameroon). Geological Magazine, 163, e42.

[12] Raman, K., Sehijpal, S., & Singh, P. B. (2021). Revealing the benefits of entropy weights method for multi-objective optimization in machining operations: A critical review. Journal of Materials Research and Technology.

[13] Huang, W., Zhang, Y., Yu, Y., et al. (2021). Historical data-driven risk assessment of railway dangerous goods transportation system: Comparisons between entropy weight method and scatter degree method. Reliability Engineering and System Safety, 205, 107236.

[14] Han, M. Y., Fang, D., Zhang, Y. H., et al. (2020). Efficiency evaluation of intelligent swarm based on AHP entropy weight method. Journal of Physics: Conference Series, 1693(1), 012072.

[15] Wang, J., Cao, Q., Mi, X., et al. (2020). Research on safety evaluation of bolt support based on analytic hierarchy process-entropy weight method. E3S Web of Conferences, 213, 03019.

[16] Shiying, L., Ji'an, T., Feng, L., et al. (2020). Analysis and processing of misdiagnosis data for depression based on modified entropy weight method. E3S Web of Conferences, 214, 03033.

[17] Tianjin University. (2018). Urban flooding risk assessment based on an integrated k-means cluster algorithm and improved entropy weight method in the region of Haikou, China. Journal of Mathematics, 270.

[18] Tianjin University. (2018). Water resources carrying capacity evaluation and diagnosis based on set pair analysis and improved the entropy weight method. Ecology Environment and Conservation, 1797.

[19] Department of Electrical Engineering. (2017). Multi-objective optimal design of stand-alone hybrid energy system using entropy weight method based on HOMER. Energy Weekly News, 450.