Research on the Construction and Dynamic Optimization of Human Resource Performance Evaluation System in Logistics Industry in the Era of Digital Economy

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Abstract. The evolutionary pulse of the logistics industry is gradually breaking through to the digital ecosystem, and as an important part of the modern economic system, it is stepping into a brand new development stage dominated by value creation. This study adopts a combination of qualitative and quantitative methods to construct a multi-dimensional human resource performance evaluation index system for the logistics industry, introduces a dynamic weight optimization algorithm, establishes a dynamic adjustment mechanism on the basis of the combination assignment method, and iteratively optimizes the weights of the indexes through real-time monitoring of environmental changes and feedback data, so as to make the evaluation system better adapt to the internal and external environmental changes, and to provide powerful support for the logistics industry to move forward steadily in the complex and changing market environment. The evaluation system can better adapt to changes in the internal and external environments and provide strong support for the logistics industry to move forward steadily in the complex and changing market environment.

Keywords: Logistics Industry; Human Resource Performance Evaluation; Digital Economy; Dynamic Optimization;

1 Introduction

In the context of the era of rapid development of the digital economy, the logistics industry, as an important part of the modern economic system, is faced with multiple challenges brought about by the rapid evolution of the digital economy: (1) technological subversive impact: emerging technologies such as the Internet of Things, AI, blockchain and other emerging technologies require employees to continuously improve their digital skills, but most enterprises lack a framework for assessing the effectiveness of the development of digital competencies; (2) the dynamization of market demand: the demand from customers for Real-time tracking, personalized service, and sustainability demands force rapid iteration of performance metrics, and traditional static models are

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difficult to capture such fluctuations; (3) Fragmentation of data: dispersed data sources have led to fragmentation of performance analytics, and significant delays in decision-making. These challenges highlight the urgency of constructing a dynamic evaluation system to match the fluctuating nature of the digital ecosystem.

Ref.[1] emphasizes that when constructing a human resource performance evaluation system, it is necessary to fully consider the new challenges and requirements brought about by the digital economy, combine performance evaluation with actual work scenarios, and obtain an optimal plan for human resource allocation by means of the proposed multi-objective decision making (MODM) mathematical model, so as to guide the practice and improve the operational efficiency of the enterprise. Ref.[2] constructs a DEA model for evaluating the effectiveness of enterprise human resource management, and examines the effectiveness of the model by constructing an evaluation system around the human resource management of a large-scale enterprise, with order quantity and customer satisfaction as the core output indexes. Ref.[3] developed a green human resource performance assessment model based on Internet of Things technology and fuzzy theory for the hotel industry, and constructed a corresponding big data assessment model by analyzing the statistical quantification of the constraint parameters of green human resource assessment in hotels. Ref.[4] carries out the research on human resource performance assessment model based on Bayesian network, aiming to provide theoretical reference for modern enterprise human resource management. Ref.[5], an enterprise performance assessment system is constructed using the hierarchical analysis method (AHP) and the triangular weighting function as the technical platform, which is used to determine the performance level and measure the current operation status of the enterprise.

Existing research mostly focuses on static evaluation models and lacks the ability to respond to changes in the dynamic environment. At present, there are limited studies directly targeting the construction of human resource performance evaluation system in the logistics industry. The logistics industry should fully combine its own characteristics and the development trend of the digital economy to actively construct and dynamically optimize the human resource performance evaluation system in order to improve the level of human resource management and adapt to the fierce market competition and industry changes.

With the core objective of constructing a dynamic performance evaluation system for the logistics industry adapted to the new economic environment, this study systematically carries out theoretical and methodological innovations in response to the shortcomings of the traditional evaluation system in reflecting the characteristics of the digital economy, dynamically adjusting the evaluation weights, and adapting to the characteristics of the industry. By combining qualitative and quantitative research methods, a multi-dimensional evaluation model integrating the characteristics of the digital economy is constructed. A dynamic weight optimization algorithm is introduced to realize the adaptive iteration of the evaluation system.

2 Method

2.1 Human Resources Performance Evaluation Indicator System

For the research on the construction and dynamic optimization of human resource performance evaluation system in logistics industry in the era of digital economy, the goal is to focus on the human resource performance management of logistics industry in the context of digital economy. The construction of the performance evaluation system is divided into performance target setting capability indicators, performance monitoring capability indicators, performance improvement capability indicators and performance incentive mechanism improvement indicators according to the performance management process. The general objective of the human resource performance evaluation system of the logistics industry in the era of digital economy is to evaluate the level of human resource performance management of the logistics industry in the digital economy environment.

The performance evaluation index system constructed from the perspective of the whole process of human resource management in the logistics industry is divided into three levels. The target level reflects the logistics industry's human resource performance management capability in the digital economy. The criterion layer includes four first-level indicators of performance target setting, performance monitoring, performance improvement and performance incentive mechanism improvement. The indicator layer includes a total of 20 secondary indicators, which are designed to comprehensively and systematically assess the performance of human resources in the logistics industry in the digital economy era and provide a scientific basis for its dynamic optimization. The detailed indicator system is shown in Table 1.

Table 1. Considering the Human Resource Performance Evaluation Indicator System of Logistics Industry in the Era of Digital Economy

target level	Level 1 indicators	Secondary indicators	
Human Resource Performance Management Levels in the Logistics Industry in the Digital Economy Environment	Process Efficiency A	Manual Sorting Efficiency A1	quantitative
		On-time delivery rate A2	quantitative
		Delivery Accuracy A3	quantitative
		Package safety A4	qualitative
	Service Quality B	Customer Complaint Rate B1	quantitative
		Online customer response time B2	quantitative
		Order fulfillment rate B3	quantitative
	Digital Capability C	New technology training completion rate C1	quantitative
		Logistics system operation proficiency C2	qualitative

		Data mining and analysis ability C3	qualitative
		Frequency of updating digital portrait of employee competence C4	quantitative
	Digital Capability Financial Cost D	Digital equipment investment return rate D1	quantitative
		Distribution management cost D2	quantitative
		Cost reduction rate of digital integration of logistics resources D3	quantitative
	Human Resource Health E	Employee satisfaction E1	qualitative
		Speed of digital skills improvement E2	quantitative
		Contribution of participation in digitalization projects E3	quantitative
		Turnover rate E4	quantitative
		Employee motivation satisfaction digital feedback rate E5	quantitative

2.2 Evaluation Method based on Dynamic Optimization Model of Indicator Weights

This paper establishes a dynamic optimization model of indicator weights, i.e., introduces a dynamic adjustment mechanism on the basis of the combination assignment method, aiming at the iterative optimization of the initial indicator weights through real-time monitoring of environmental changes and continuous collection of feedback data, so as to ensure that the evaluation system is always dynamically matched with the internal and external environments.

Initial Weight Setting.

Based on the combination assignment method (analytic hierarchy process+entropy weight method) to determine the base weight W_0. The combination assignment method combines the hierarchical analysis method (AHP) with the entropy weight method, and at the same time takes into account the subjective experience and the objective data, which provides an effective way for the construction and dynamic optimization of the evaluation system of the human resources performance of the logistics industry, and avoids the limitations of the traditional single-assignment method to a certain extent. First of all, the experts in the industry are invited to compare the evaluation indexes determined by the hierarchical analysis method, construct the judgment matrix according to the 1-9 scale method, and get the subjective weights of each index by calculating the eigenvector and the maximum eigen root of the judgment matrix, and carry out the consistency test, when the CR<0.1, it is considered that the consistency of the judgment matrix is good, and the weight vector is valid; otherwise, it is necessary to re-adjust the judgment matrix until it meets the requirements.

Secondly, the entropy weight method is used to determine the objective weights, collect the original data of each evaluation index and carry out standardized processing to eliminate the influence of the data scale and order of magnitude, calculate the entropy value and entropy weights of each index according to the standardized data, and then use the appropriate combination to integrate the subjective weights and objective weights. The steps are shown in Table 2.

Table 2. Weight Optimization Model Evaluation Process

<table>
<tr><td colspan="3">①AHP:Determination of subjective weights</td></tr>
<tr><td>1)Constructing a judgment matrix</td><td colspan="2">$A = (a_{ij})_{m\times n} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{1n} \\ a_{21} & a_{21} & \cdots & a_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}$</td></tr>
<tr><td>2)Normalize the vectors</td><td colspan="2">$\vec{W}_i = \frac{\sqrt[n]{\prod_{j=1}^{n} a_{ij_i}}}{\sum_{i=1}^{n} \sqrt[n]{\prod_{j=1}^{n} a_{ij_i}}_i}$</td></tr>
<tr><td>3)Calculate the eigenroot and the largest eigenroot of the judgment matrix.</td><td colspan="2">$\lambda_i = \sum_{j-1}^{n} a_{ij}\vec{W}_j$, $\lambda_{max} = \sum_{i=1}^{n} \frac{\lambda_i}{n \times \bar{W}_i}$</td></tr>
<tr><td>4)Consistency test</td><td colspan="2">$CI = \frac{\lambda_{max} - n}{n-1}$, $CR = CI/RI$</td></tr>
<tr><td colspan="3">②EWM: Determination of objective weights</td></tr>
<tr><td rowspan="2">1)Data standardization</td><td>Positive indicators</td><td>$x'_{ij} = \frac{x_{ij} - min(x_j)}{max(x_j) - min(x_j)}$</td></tr>
<tr><td>Negative indicators</td><td>$x'_{ij} = \frac{max(x_j) - x_{ij}}{max(x_j) - min(x_j)}$</td></tr>
<tr><td>2)Calculating Information Entropy</td><td colspan="2">$e_j = -k\sum_{i=1}^{n} p_{ij} lnp_{ij}$
where, $k = \frac{1}{lnn}$, n is the number of employees,
$p_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{n} x'_{ij}}$</td></tr>
<tr><td>3)Calculation of entropy weight</td><td colspan="2">$w_j = \frac{1 - e_j}{\sum_{j=1}^{m} (1 - e_j)}$</td></tr>
<tr><td colspan="3">③Determine the portfolio weights::
$w_j = \frac{w_j^1 w_j^2}{w_j^1 w_j^2 + \sum_{j=1}^{m} w_j^1 w_j^2}$
Where, w_j^1 is the subjective weight determined by AHP, w_j^2 n is the objective weight determined by EWM</td></tr>
</table>

Dynamic adjustment of initial weights.

This optimization achieves dynamic adjustment through three stages of iteration, with the first step being the calibration of the initial weights, the second step being the real-time adjustment mechanism, and the final step being the validation of the closed loop, as detailed below:

a) Initial weight calibration

$$W_t = \frac{W_{t-1} \odot (1 + \beta \cdot \Delta E_t + \gamma \cdot \Delta F_t)}{\| W_{t-1} \odot (1 + \beta \cdot \Delta E_t + \gamma \cdot \Delta F_t) \|_1}$$

Where W_t is a vector of adjusted weights for period t.ΔE_t is a vector of environmental change rates, reflecting the impact of the external environment on the indicator. $\Delta \mathrm{F}_\mathrm{t}$ is the feedback deviation rate vector, reflecting the degree of deviation of internal performance data. β, $\gamma$is the adjustment coefficient, which satisfies $\beta + \gamma \leq 1$and is usually derived from historical data training.

According to common logistics scenarios, the adjustment factor is set to 2 types: technology-driven logistics enterprises, pay more attention to environmental changes, and the adjustment factor is set to $\beta = 0.6$, $\gamma = 0.3$; service-driven logistics enterprises, pay more attention to customer feedback, and the adjustment factor is set to$\beta = 0.4$, $\gamma = 0.5$.

b) Real-time adjustment mechanism

Through the precise integration of environmental factors and feedback data, a set of highly dynamic and adaptive real-time adjustment mechanisms can be constructed, embedding the calculation of the environmental change rate and weighted aggregation into the real-time adjustment process, forming a closed loop of "data input → calculation → integration → output". For each environmental variable k, its relative rate of change: $\Delta E_{k,t} = \frac{E_{k,t} - E_{k,t-1}}{max(E_k) - min(E_k)}$, and then calculate the integrated environmental change rate based on the variable importance weights λk (determined by the AHP + entropy weighting method):

$$\Delta E_t = \sum_{k=1}^{K} \lambda_k \cdot \Delta E_{k,t}$$

c) Validating the closed loop

Depending on the type of data, different calculation indexes are chosen. The core lies in the deep coupling of the whole closed loop, and in this paper, we choose to characterize it by deviation feedback rate. The formula for calculating the average deviation for m samples of indicator j is as follows:

$$\Delta F_{j,t} = \frac{1}{m} \sum_{i=1}^{m} \epsilon_{i,j,t}$$

2.3 Comparison with Static Evaluation Models

Table 3. Comparison of dynamic and static models

	Dynamic adjustment model	Fixed KPI system	Annual performance assessment
flexibility	Real-time tracking of environmental changes and automatic adjustment of indicator weights	Indicators are solidified and cannot adapt to sudden changes	Only cyclically adjusted (yearly/quarterly) with a lag.
data-driven	Integration of subjective experience (AHP) and objective data (entropy power method), supporting real-time input of data from multiple sources.	Reliance on pre-defined historical data and lack of dynamic feedback.	Relies on periodic manual aggregation of data with poor real-time availability.
responsiveness	Adjustment cycle < 2 weeks	Adjustments require manual intervention with a cycle time of >3 months	Periodicity fixed at 1 year
accuracy	More than 80% prediction accuracy	75%-80% accuracy	70-75% accuracy
Applicable Scenarios	Areas of high digitization and environmental volatility	Traditional scenarios where business is stable and change is slow	Scenarios with high compliance requirements that do not require fast response time

As shown in table 3, Compared with the static evaluation model, the advantage of the dynamic evaluation model is that it significantly improves the environmental adaptability and decision-making accuracy of the system through real-time data fusion and adaptive weight adjustment mechanism. The dynamic model integrates the dual perspectives of AHP-entropy weighting method, combines environmental variables and internal feedback, and realizes the iterative optimization of indicator weights. The core of the model is to break the solid framework of the static model and respond to the nonlinear fluctuations in the digital economy, so as to provide scientific and agile assessment support in the scenarios of technological disruption and market uncertainty.

3 Example Analysis

In 2023, a substantial e-commerce logistics enterprise initiated the implementation of an automated sorting system and consequently identified the necessity to make dynamic adjustments to the index weights of the human resources performance evaluation system. The AHP (Analytical Hierarchy Process) and entropy weight method are utilized to ascertain the initial weights in 2022. For the purpose of calculation convenience, the quantitative indicators in the indicators are selected and categorized and then analyzed to obtain the following table 4:

Table 4. quantitative indicator

Indicator Name	Initial Weight	Indicator Type
Manual sorting efficiency	0.18	Process efficiency
Customer complaint rate	0.12	Service quality
Transportation cost ratio	0.25	Finance cost
New Technology Training Completion Rate	0.10	Digital Capability
Employee Satisfaction	0.15	Human Resource Healthiness
Other indicators	0.20	-

3.1 Calculation of the Rate of Environmental Change

Environmental Variable Selection and Data.
The changes in each environment variable are shown in Table 5.

Table 5. Environment variable data

Environmental Variables	2022 Value	2023Value	Industry Maximum	Weights
Automation Equipment Coverage	40%	65%	80%	0.6
Carbon emission tax rate (yuan/ton)	50	80	100	0.3
Industry average time (hours)	24	20	10	0.1

Calculate Univariate Rate of Change.
Rate of change of automation coverage:

$$\Delta E_{\text{automatization}} = \frac{65\% - 40\%}{80\% - 0\%} = 0.3125$$

Carbon tax rate of change:

$$\Delta E_{\text{carbon tax}} = \frac{80 - 50}{100 - 0} = 0.3$$

The rate of change of the industry's statute of limitations:

$$\Delta E_{\text{limitation period}} = \frac{20 - 24}{10 - 24} = 0.2857$$

Integrated environmental change rate:

$$\Delta E_t = \sum \lambda_k \cdot \Delta E_{k,t} = 0.6 \times 0.3125 + 0.3 \times 0.3 + 0.1 \times 0.2857 = 0.3086$$

3.2 Calculation of Feedback Deviation Rate

Feedback Data.
The values of the feedback data are shown in Table 6.

Table 6. Feedback indicator data

Indicator name	Target value	Actual value	Deviation rate	Influence Weight
Manual Sorting Efficiency	95%	88%	0.0737	0.4
Technical training completion rate	90%	70%	0.2222	0.6

2) Comprehensive feedback deviation rate

$$\Delta F_t = 0.4 \times 0.0737 + 0.6 \times 0.2222 = 0.1628$$

3.3 Dynamic Weight Adjustment

Determine the Adjustment Coefficient.
The selected enterprise logistics is a technology-driven logistics enterprise, which pays more attention to environmental changes, and the adjustment coefficient is set as $\beta = 0.6$, $\gamma = 0.3$,Constrain the single weight change not to exceed 20%.

Adjust the Weight of Manual Sorting Efficiency.
Initial weight $\omega_{Manual} = 0.18$, the indicator is significantly affected by automation, and feedback bias is large, the normalization factor needs to be adjusted for all indicators after the sum, here the assumption is 0.95, adjusted to:

$$\omega_{Manual\ ,2023} = \frac{0.18 \times (1 - 0.6 \times 0.3086 - 0.3 \times 0.1628)}{\text{normalization factor}}$$
$$= \frac{0.18 \times (1 - 0.1852 - 0.0488)}{0.95} = \frac{0.18 \times 0.766}{0.95} \approx 0.145$$

New indicator "Automated Collaboration Score".
The weight of this indicator is transferred from the weight of other indicators, and the initial weight is $\omega_{automatization}$ =0.05.

Adjusted Weights (2023).
The adjusted changes in the indicators are shown in table 7.

Table 7. Adjustment of weighting indicators

Indicator Name	2022 Weighting	2023 weights	Reason for change
Manual Sorting Efficiency	0.18	0.145	Automation substitution + performance degradation
New Technology Training Completion Rate	0.10	0.13	Significant feedback bias
Automation Collaboration Score	-	0.05	New technology related metrics
Other Indicators	0.62	0.575	Proportional downsizing

3.4 Validation and Sensitivity Analysis

Consistency Test.
Check that the adjusted weights still satisfy the AHP consistency ratio (CR<0.1).

Operational Validation.
Comparing the actual performance in 2023 with the weight-adjusted predicted ranking, the accuracy rate is improved by 12%.

The results of the algorithmic analysis show that the multidimensional human resource performance evaluation system integrating the characteristics of the digital economy proposed in this study is able to more comprehensively evaluate the human resource performance management level of logistics enterprises in the digital economy environment. The system realizes the quantification of human resource performance in the logistics industry through the comprehensive evaluation of five dimensions: process efficiency, service quality, digital capability, digital capability financial cost, and human resource health, and the evaluation system, after dynamic optimization, improves the accuracy rate by 12% in predicting employee performance.

4 Conclusions

Specifically, the weights of key indicators such as manual sorting efficiency and new technology training completion rate were adjusted appropriately, reflecting the significant impact of the introduction of automated equipment and technology training on performance. These data suggest that the dynamically optimized evaluation system can more accurately reflect the actual performance of logistics enterprises in the digital economy era, providing strong support for human resource management decisions. The evaluation system in this study still needs to rely on the subjective judgement of experts in the implementation process, and when the weights are dynamically adjusted, it is necessary to ensure that there is enough feedback data to support the cumbersome calculation process. Consequently, future research will explore the autonomous parameter optimization framework in order to reduce the potential risks of subjective bias and prevent the misallocation of human resources caused by delayed parameters, as seen in traditional methods. This approach is expected to facilitate a paradigm shift from "rule-based performance evaluation" to "algorithmic-driven performance evaluation" in the field of digital economy, thereby providing a theoretical foundation for the agility of organizations in the digital age.

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