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How to Evaluate New Quality Productive Forces for Chinese Express Delivery Enterprises: A Hybrid DEMATEL-BBWM-CoCoSo Method

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ABSTRACT

The integration of New Quality Productive Forces (NQPF), characterised by innovation, advanced technology, operational efficiency, and high-quality outputs, is transforming express delivery enterprises in China. Conventional performance evaluation systems are increasingly inadequate for assessing the evolving requirements associated with NQPF. To address this gap, this study proposes a comprehensive evaluation framework encompassing three principal dimensions: strategic leadership, technological innovation, and development support. A hybrid Multi-Criteria Decision Making (MCDM) approach, incorporating DEMATEL, Best–Worst Method (BBWM), and Combined Compromise Solution (CoCoSo), is employed to account for interdependencies among evaluation indicators, improve the precision of weighting, and maintain consistency in group decision-making, thereby enhancing the reliability of performance assessments. A case study of five major A-share listed Chinese express delivery firms illustrates the practical application of the proposed framework. The methodology provides a rigorous decision-support tool for evaluating NQPF and yields strategic insights to facilitate sustainable development within the express delivery sector. By aligning the advancement of NQPF with broader industry quality improvements, the study delivers actionable recommendations for modernising China's logistics industry through innovation-driven productivity transformation.

1. Introduction

The information age and globalisation have fostered the emergence of NQPF, characterised by advanced technology, high efficiency, and superior quality. Its development must align with technological innovation and reflect substantial improvements in total factor productivity, achieved through the optimal integration of labour, means of production, and objects of labour. In 2024, China's express delivery industry recorded an annual business volume of 175.08 billion parcels and revenue of 1.4 trillion yuan, representing year-on-year growth of 21.5% and 13.8%, respectively, with multiple listed firms reporting significant increases in parcel volume [1]. Concurrently, express delivery enterprises increasingly recognise NQPF as a pivotal driver for achieving high-quality and

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sustainable growth. To address gaps in NQPF evaluation and propose effective development strategies, this study focuses on two primary research questions:

- How can NQPF be defined in express delivery enterprises, and what index system can be constructed for its evaluation?
- Which evaluation method can effectively mitigate the influence of indicator interdependencies and subjective bias when assessing NQPF?

Current academic research exhibits notable limitations. First, existing studies predominantly employ qualitative methods, with quantitative analyses remaining insufficient, thus limiting comprehensive understanding of NQPF development dynamics. Second, research largely targets regional or city-level contexts, with relatively few enterprise-level investigations, resulting in inadequate insight into firm-level NQPF progression. Finally, conventional evaluation frameworks in logistics enterprises are outdated and fail to capture the multidimensional and innovation-driven nature of NQPF. To address these research questions, this study constructs an evaluation index system reflecting NQPF development in express delivery enterprises from three dimensions: technological innovation, strategic leadership, and development support. A hybrid DEMATEL-BBWM-CoCoSo methodology is applied to account for interdependence among indicators, enhance weighting precision, and reduce subjective bias in evaluations. The study aims to quantify the development level of NQPF in China's express delivery enterprises and provide managerial guidance for improving enterprise-level NQPF implementation. It seeks to offer a scientifically grounded index system and methodology to support rigorous evaluation and strategic development of NQPF across the sector.

The structure of this paper is as follows: Section 2 presents a literature review on NQPF, associated index systems, and MCDM methods; Section 3 develops the enterprise-level NQPF evaluation index system across the three dimensions; Section 4 details the research design and application of the hybrid DEMATEL-BBWM-CoCoSo approach; Section 5 presents a case study assessing NQPF for selected listed Chinese express firms; Section 6 examines the relationship between NQPF development and financial performance; and Section 7 summarises the study's conclusions, limitations, and managerial recommendations.

2. Literature Review

2.1 New Quality Productive Forces

In September 2023, Chinese President Xi Jinping referenced NQPF for the first time during his visit to Heilongjiang. Research on NQPF has progressively evolved, showing simultaneous theoretical development and empirical analysis. Studies indicate that digital economic development enhances green innovation efficiency, thereby strengthening NQPF, with industrial structure upgrading acting as a moderating factor [21]. Frameworks linking innovation across the digital economy, industry, academia, and research institutions have identified synergy thresholds that determine their combined effect on NQPF, highlighting the necessity of coordinated advancement to achieve multiplier outcomes [28]. The "Energy Triangle" framework has been proposed to measure the balance among energy security, economic growth, and sustainability during transitional periods [2].

In the study of regional disparities, entropy-based analyses have been applied to compute the average annual growth rate for marine NQPF, revealing the substantial influence of regional resource endowments and policy orientations [7]. Further analyses demonstrate that a 1% increase in education is associated with a 0.7-hour reduction in weekly leisure time, suggesting potential welfare trade-offs accompanying productivity gains [19]. Research on institutional-technological interactions has identified nonlinear moderating effects of fiscal decentralization, underscoring the importance of policy adaptability [25]. Additionally, pilot zones for big data development have been shown to compel significant portions of the workforce to reskill due to talent agglomeration and industrial innovation pressures, highlighting social costs during transitional processes [29].

Despite the growing body of macro-level NQPF research, industry-specific applications remain underdeveloped. In express delivery enterprises, key aspects such as intelligence integration and green transformation lack standardized evaluation criteria, and quantitative studies often rely on static indicators that inadequately capture dynamic technological evolution. To address these gaps, this study integrates three dimensions—scientific and technological innovation, strategic leadership, and developmental support—to construct a comprehensive and applicable evaluation system.

2.2 Performance Evaluation Index System of Express Delivery Enterprises

The evolution of logistics enterprise performance evaluation has progressively shifted from a predominant focus on financial metrics to comprehensive, multidimensional frameworks. Initial studies concentrated on financial efficiency, demonstrating the direct influence of indicators such as return on assets and cost control rate on operational performance through data envelopment analysis, yet these approaches exhibited limitations that highlighted the need for more holistic evaluation [3]. Subsequent research introduced non-financial indicators, including delivery accuracy, underscoring their pivotal role in enhancing market competitiveness [27]. Integrated evaluation systems further matured with models encompassing multiple dimensions, such as cold chain logistics frameworks combining economic efficiency, informatization level, and equipment investment rate, thereby reflecting the evolution from single-factor to multidimensional assessment [17].

Recent investigations emphasise dynamic efficiency analysis. Fuzzy AHP-based models for port resource integration revealed that technological innovation contributes substantially to overall performance, quantifying the synergy between technological input and capital returns [4]. Structural equation modelling further demonstrated strong correlations between financial competitiveness and latent development potential, providing methodological support for dynamic, data-driven evaluation [22]. Innovations in supply chain management have additionally expanded evaluation perspectives. SERVQUAL-FAHP-TOPSIS frameworks incorporating service indicators have empirically quantified the impact of operational delays on customer retention [10]. The integration of supply chain compliance into reverse logistics evaluation, weighted through DEMATEL-ANP, exemplifies the systematic incorporation of regulatory adherence into performance measurement [16].

Advanced approaches increasingly integrate technological innovation and sustainability. Fuzzy frameworks prioritising factors such as temperature-control stability in pharmaceutical cold chains reflect the shift towards technology-driven assessment, surpassing conventional financial metrics [15]. ESG indicators, including carbon intensity and labour rights compliance, have emerged as critical determinants of long-term competitiveness, often assigned weights exceeding 40% in logistics evaluation [6]. Despite these advances, conventional performance systems inadequately capture green innovation and digital empowerment. Traditional metrics such as transportation costs or warehouse efficiency do not reflect emerging practices including unmanned delivery systems and blockchain traceability. The present study addresses these gaps by incorporating NQPF dimensions, exemplified by green innovation metrics (e.g., carbon reduction in intensity) and intelligent inputs (e.g., unmanned development capabilities). Furthermore, "logistics NQPF orientation depth" is quantified using keyword frequency analyses in annual reports, enabling dynamic tracking of strategic priorities and technological trends. This approach bridges deficiencies in traditional evaluation systems and provides a robust framework for quantifying green and smart logistics performance.

2.3 Application of MCDM in Performance Evaluation

MCDM methods have become essential in logistics enterprise performance evaluation, providing structured solutions for complex decision-making problems through multidimensional frameworks that integrate quantitative and qualitative considerations. Initial investigations predominantly applied conventional models. For instance, applications of AHP and TOPSIS in infrastructure management were systematized to ensure transparent and consistent criterion weighting [8]. More recent research has focused on hybrid frameworks to enhance robustness. Bayesian BWM-TOPSIS models, which probabilistically aggregate expert preferences, have improved ranking stability by approximately 15%, offering methodological guidance for cost-efficiency evaluation [5]. Similarly, the combination of DEMATEL and BBWM has demonstrated effectiveness in resolving interdependencies among multiple criteria in inland port assessments [11].

Weight allocation remains a critical challenge in MCDM. Early studies largely relied on expert judgment, whereas entropy-based weighting revealed the informatization level as considerably more significant than traditional warehousing capacity [26]. Fuzzy enhancements to DEMATEL, such as q-ROF sets, reduced model error rates below 5% under high-uncertainty conditions [15]. To further address data ambiguity, the integration of BBWM with Pythagorean fuzzy TOPSIS incorporated a weighted sinusoidal similarity algorithm, improving decision accuracy [23]. The fusion of multiple MCDM methods through statistical averaging and semi-quadratic programming has mitigated the limitations of single-model approaches in dynamic logistics systems [24].

Under the "dual-carbon" agenda, MCDM increasingly emphasises low-carbon and green dimensions. Analyses indicate that 63% of low-carbon transportation studies employ TOPSIS or VIKOR, often enhanced with fuzzy sets to handle carbon data uncertainty [18]. Spherical fuzzy AHP combined with CoCoSo has been applied to optimize agricultural distribution centers, validating the potential of fuzzy MCDM for sustainable supply chain management [9]. For dynamic weight adjustments, modifications to BWM have enabled consideration of multiple optimal criteria Pamučar et al. [13], while Bayesian aggregation has been employed to reduce subjective bias in green innovation weights [12]. Despite these advances, MCDM methods for evaluating NQPF face two major challenges: (1) interdependencies among primary indicators violate traditional independence assumptions, and (2) secondary indicators necessitate the integration of both group preferences and objective data to ensure comprehensive evaluation.

3. Evaluation Index System

NQPF represents the evolutionary trajectory of advanced productive forces, emerging from technological breakthroughs, innovative allocation of production factors, and the deep transformation and upgrading of industries. In the logistics sector, NQPF contribute significantly to cost reduction and efficiency enhancement. The "new" aspect of NQPF is reflected in novel logistics development patterns, application of advanced technologies, and innovative operational models, including comprehensive logistics services. The "quality" dimension denotes superior service standards, advanced logistics capabilities, and high levels of innovation. The integration of digital economy tools, such as big data and artificial intelligence, with traditional production factors has driven substantial changes in the logistics industry's economic development models. Compared with conventional productivity, NQPF facilitate the integration of digital and real economies, support green transformation, optimise the allocation of logistics production factors, and reduce overall societal logistics costs. Based on these theoretical and empirical insights [1; 2; 7; 19; 21; 28], the evaluation of NQPF in express delivery enterprises should emphasise three primary dimensions:

- Technology Innovation Capacity
- Strategy Leading Orientation
- Development Support

Building on the preceding analysis, this study develops a framework to evaluate the development of NQPF in express delivery enterprises. Drawing on prior literature on NQPF evaluation and considering the distinctive characteristics of express delivery operations, the study identifies specific indicators and calculation methodologies to comprehensively measure NQPF performance. The evaluation index system is designed to capture multiple dimensions of enterprise performance, including technological innovation, operational efficiency, service quality, and sustainable development. As presented in Table 1, all indicators are positively oriented, except for the degree and intensity of unmanned development within NQPF logistics, which are treated as negative indicators to reflect their inverse relationship with desired performance outcomes.

Table 1
NQPF Evaluation Index System of Express Delivery Enterprises

First-Level Indicators	Second-Level Indicators	Unit	Concept
Technological Innovation	Enterprise Technological Innovation Capacity	Item	Number of patent applications granted
	Enterprise Research Capacity	Paper	Number of high-level publications
	Enterprise Software Innovation Capacity	Item	Number of software copyrights authorized
	Enterprise Talent Capability	%	Percentage of employee with bachelor's degree or above
Strategy Leading	Logistics NQPF Oriented Breadth	Section	Types of characteristic terms related to logistics new quality productive forces
	Logistics NQPF Oriented Depth	Word	Total number of words in the characterization related to logistics new quality productive forces
	Enterprises' Emphasis on Green Development	Word	Total number of words in the characterization related to green development
	Degree of Carbon Reduction in Logistics NQPF	Word	Total number of words in corporate annual reports describing ESG
Development Support	Logistics NQPF Capital Investment Efforts	Yuan	Total R&D investment in logistics new quality productive forces
	Logistics NQPF Capital Investment Degree	%	Percentage of total R&D investment in logistics new quality productive forces of operating income
	Logistics NQPF Unmanned Development Efforts	Yuan	Amount of labour costs
	Logistics NQPF Unmanned Development Degree	%	Labour costs as a percentage of total costs

4. Evaluation Method

4.1 Research Framework

The research design is illustrated in Figure 1. A hybrid multi-criteria decision-making approach is adopted, integrating DEMATEL, BBWM, and CoCoSo to systematically determine the relative weights of each evaluation indicator and to generate the comprehensive rankings of the express delivery enterprises. This integrated methodology facilitates the handling of interdependencies among criteria, enhances the precision of weight allocation, and ensures consistency in the overall decision-making process. The input and output parameters corresponding to each component of the hybrid methodology are summarised in Table 2, providing a structured overview of the data flow and analytical processes for DEMATEL, BBWM, and CoCoSo.

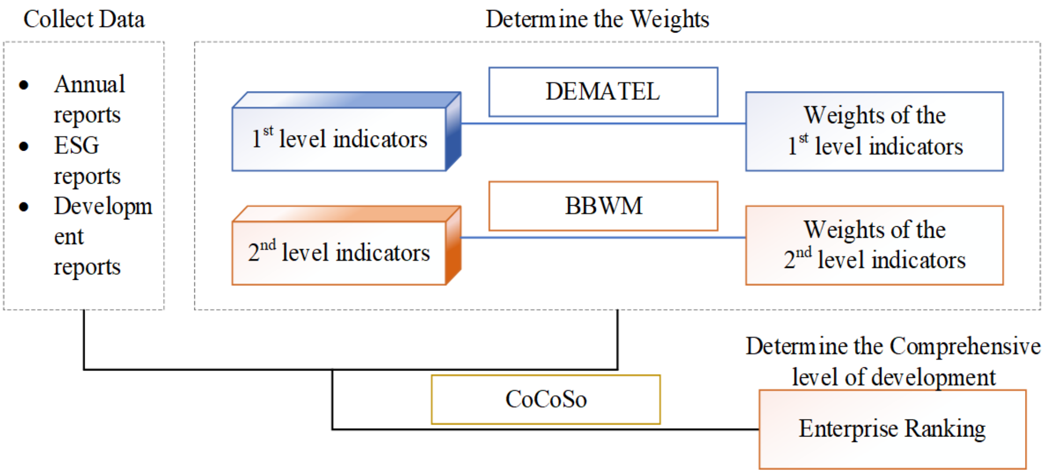

Fig.1: Framework of the Research Methodology

Table 2
Functions of Each Method

Method	DEMATEL	BBWM	CoCoSo
Input	Experts Opinions on First Level Indicators	Experts Opinions on Second Level Indicators	Weights of Second Level Indicators to NQPF Performance of Second Level Indicators for Each Company
Output	Weights of First Level Indicators to NQPF	Weights of Second Level Indicators to First Level Indicators	Rankings of Companies

4.2 DEMATEL

The DEMATEL method is employed to mitigate the distortions arising from interdependencies among evaluation metrics [11]. In this study, DEMATEL is applied to account for the interrelationships among the first-level indicators, namely technological innovation capacity, strategic leadership orientation, and development financial support.

Step 1: Construct indicators for evaluating express delivery enterprises' NQPF.

Matrix D represents the direct influence among the first-level indicators, as defined in Equation (1).

$$D = \begin{pmatrix} 0 & a_{12} & a_{13} \\ a_{21} & 0 & a_{23} \\ a_{31} & a_{32} & 0 \end{pmatrix} \tag{1}$$

Where a_{ij} represents the degree of influence of indicator i to indicator j.

Step 2: Normalize matrix D and calculate the integrated impact matrix using Equation (2).

$$T \square \lim_{m\to\infty}(K^1 + K^2 + \ldots + K^m) = K(I-K)^{-1} \tag{2}$$

Step 3: Compute the indicator values using Equations (3) and (4).

The degree of influence r_i is the sum of the elements of the rows of matrix T, indicating the degree of influence of indicator i to other indicators, as in Equation (3):

$$r_i = \sum_{j=1}^{n} t_{ij} \tag{3}$$

Similarly, c_j is calculated by Equation (4):

$$c_j = \sum_{i=1}^{n} t_{ij} \tag{4}$$

The sum of r_i and c_i is the centrality M_i, $M_i = r_i + c_i$, and the causality R_i can be calculated by $r_i - c_i$.

Step 4: Determine the weights of 1st level evaluation indicators using the distance $d = \sqrt{M^2 + R^2}$

4.3 BBWM

The BBWM method has been extensively applied in group decision-making in recent years [26-27].

Step 1: Based on the second-level indicators, conduct indicator set $M = \{m_1, m_2, \ldots m_n\}$, and determine the best (m_B) and the worst (m_W) criteria from M.

Step 2: Conduct pairwise comparisons between the best/worst indicator, and the remaining indicators.

$A_B = (a_{B1}, a_{B2}, \ldots a_{Bn})$, where a_{Bj} denotes the preference of the best criterion m_B over other criteria $m_j \in M$. Similarly, $A_W = (a_{1W}, a_{2W}, \ldots a_{nW})^T$.

Step 3: Estimating the probability distribution of each individual optimal weight $w^{1:K}$ and the overall optimal weight w^{BBWM} given $A_B^{1:K}$ and $A_W^{1:K}$, where k represents the decision makers and k = 1,…, K.

The joint probability distribution can be computed using Equation (5):

$$P\left(w^{BBWM}, w^{1:K} \mid A_B^{1:K}, A_W^{1:K}\right) \quad (5)$$

The probability can subsequently be calculated using Equation (6):

$$P(x) = \sum_y P(x, y) \quad (6)$$

Where x and y are two arbitrary random variables.

According to the Bayesian model, the variable w^k is contingent upon both A_B^k and A_W^k, while w^{BBWM}, depends on w^k. We can describe the independence feature by Equation (7):

$$P\left(A_W^k \mid\mid w^{BBWM}, w^K\right) = P\left(A_W^K \mid\mid w^K\right) \quad (7)$$

By applying Bayes' theorem to Equation (1), Equation (8) can be derived as follows:

$$\begin{aligned} P\left(w^{BBWM}, w^{1:K} \mid A_B^{1:K}, A_W^{1:K}\right) &\propto P\left(A_B^{1:K}, A_W^{1:K} \mid\mid w^{BBWM}, w^{1:K}\right) P\left(w^{BBWM}, w^{1:K}\right) \\ &= P\left(w^{BBWM}\right) \prod_1^K P\left(A_W^K \mid\mid w^K\right) P\left(A_B^K \mid\mid w^K\right) P\left(w^K \mid\mid w^{BBWM}\right) \end{aligned} \quad (8)$$

Step 4: Establish the prior distribution and compute the posterior distribution to determine the weights of each indicator.

A_B^k and A_W^k serve as the inputs for BBWM and, following the Bayesian framework, can be expressed as in Equations (9) and (10):

$$A_W^k \mid w^k \sim multinomial\left(w^k\right), \forall k = 1, \ldots, K. \quad (9)$$

$$A_B^k \mid w^k \sim multinomial\left(\frac{1}{w^k}\right), \forall k = 1, \ldots, K. \quad (10)$$

The Dirichlet distribution is adopted as the prior distribution for the multinomial distribution of weight because it satisfies non-negativity and unit-sum properties, as shown in Equation (11):

$$Dir(w\,||\,\alpha) \sim \frac{1}{B(\alpha)}\prod_{j=1}^{n} w_j^{\alpha_j - 1}, \quad \alpha \in \mathrm{R}^n. \tag{11}$$

Therefore, we can get the value of w^k when w^{agg} is given, according to Equation (12):

$$w^k \,||\, w^{BBWM} \sim Dir(\gamma \times w^{BBWM}), \quad \forall k = 1,\ldots,K \tag{12}$$

For parameter γ, the gamma distribution is used to simulate the distribution of γ as in Equation (13):

$$\gamma \sim gamma(a,b) \tag{13}$$

Here, a and b represent the shape parameters of the gamma distribution, which can be determined through either maximum likelihood estimation or Bayesian estimation.

Finally, the prior distribution over w^{BBWM} is shown in Equation (14):

$$w^{BBWM} \sim Dir(\alpha) \tag{14}$$

Where the parameter α is set to be 1.

Step 5: Credal ranking for indicators.

For the indicator set $M = \{m_1, m_2, \ldots m_n\}$, the credal raking is the set of confidence orders for each pair of indicators (m_i, m_j), while $m_i, m_j \in M$.

A Bayesian-based approach is proposed to evaluate and quantify the certainty associated with each confidence ranking.

The test is designed with the posterior distribution of w^{BBWM}. The mathematical equation of m_i is more important than m_j is shown as in Equation (15):

$$P(m_i > m_j) = \int I_{(w_i^{BBWM} > w_j^{BBWM})} P(w^{BBWM}) \tag{15}$$

Where $P(w^{BBWM})$ represents the posterior probability of w^{BBWM}, I denotes a logic parameter that evaluates to 1 when the subscript condition of I is true, and 0 otherwise.

Equations (16) and (17) express the confidence level in terms of Q samples drawn from the posterior distribution.

$$P(m_i > m_j) = \frac{1}{Q}\sum_{q=1}^{Q} I\left(w_i^{BBWM_q} > w_j^{BBWM_q}\right) \tag{16}$$

$$P(m_j > m_i) = \frac{1}{Q}\sum_{q=1}^{Q} I\left(w_j^{BBWM_q} > w_i^{BBWM_q}\right) \tag{17}$$

Where w^{BBWM_q} denotes the qth sample of w^{BBWM} in the MCMC sample.

Consequently, for each pair of indicators, the confidence level indicating the extent to which one indicator exceeds the other in importance can be calculated as described above. These confidence levels can subsequently be translated into conventional ranking orders. Thus, $P(c_i > c_j) + P(c_j > c_i) = 1$.

4.4 CoCoSo

The CoCoSo (Combined Compromise Solution) method represents an advanced multi-attribute group decision-making framework grounded in probabilistic linguistic term set theory. It extends and synthesises elements from established methodologies, namely the Approximate Ideal Solution (TOPSIS), Grey Relational Analysis (GRA), the Dombi operator, and the Heronian mean operator, to construct a decision-making model capable of processing probabilistic linguistic evaluation data. This structure enables the precise quantification and interpretation of expert assessments, even under conditions where attribute weighting information is partial or entirely absent [14].

By integrating the computational principles of Simple Additive Weighting (SAW), Weighted Aggregation and Product Assessment (WASPAS), and Multiplicative Exponential Weighting (MEW), CoCoSo delivers enhanced analytical robustness, producing results of higher accuracy than those derived from the constituent methods independently. This methodological synergy facilitates comprehensive modelling, improves evaluative precision, and strengthens the reliability of group decision outcomes [9]. The versatility of CoCoSo has led to its adoption across multiple domains, including the evaluation of third-party service providers, waste management systems, and strategic planning in environmental and energy resource management [25].

Step 1: Construct the preliminary decision matrix, as specified in Equation (18), using the established evaluation indicators and the corresponding raw data. In this study, the raw data are obtained from DEMATEL and BBWM, as outlined in the preceding steps.

$$x_{ij} = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{pmatrix}; i = 1, 2, \ldots, m; j = 1, 2, \ldots n \tag{18}$$

Step 2: Apply max–min normalisation to the constructed matrix, as presented in Equations (19) and (20).

$$r_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \tag{19}$$

$$r_{ij} = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \tag{20}$$

Step 3: Determine the total of the weighted comparison sequences for each alternative, along with the corresponding weights of these sequences, in accordance with Equations (21) and (22).

$$S_i = \sum_{j=1}^{n} \left(w_j r_{ij} \right) \tag{21}$$

$$P_i = \sum_{j=1}^{n} \left(r_{ij} \right)^{w_j} \tag{22}$$

The value of S_i is calculated based on the gray correlation method. The value of P_i is calculated based on the WASPAS method.

Step 4: Compute the relative weights of the alternatives using the designated aggregation procedure, following the formulations presented in Equations (23)–(25).

$$k_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m} \left(P_i + S_i \right)} \tag{23}$$

$$k_{ib} = \frac{S_i}{\min_i S_i} + \frac{P_i}{\min_i P_i} \tag{24}$$

$$k_{ic} = \frac{\lambda\left(S_i\right) + \left(1-\lambda\right)\left(P_i\right)}{\left(\lambda \max_i S_i + \left(1-\lambda\right)\max_i P_i\right)} \tag{25}$$

Equation (23) expresses the arithmetic mean of the cumulative scores derived from WSM and WPM, while Equation (24) calculates the sum of the relative scores of WSM and WPM in relation to the optimal alternative. Equation (25) determines the compromise between the WSM and WPM scores, where the trade-off coefficient λ is typically set to 0.5. Alternative λ values can be employed within CoCoSo to improve flexibility and strengthen the robustness of the ranking outcomes.

Step 5: Combine the following formulas to determine the value of k_i and calculate the final weighted ranking of each program (the larger the k_i, the better the program), as shown in Equation (26).

$$k_i = \left(k_{ia}k_{ib}k_{ic}\right)^{\frac{1}{3}} + \frac{1}{3}\left(k_{ia} + k_{ib} + k_{ic}\right) \tag{26}$$

5. Case Study

5.1 Case Background

The development of NQPF offers a crucial impetus for the transformation and upgrading of the logistics sector. By advancing NQPF, express delivery enterprises can enhance operational efficiency, optimise supply chain processes, and elevate service quality, thereby improving competitiveness and supporting sustainable growth [20]. Within express delivery enterprises, NQPF fundamentally revolves around innovation, exhibiting attributes of high technology, elevated efficiency, and superior quality. This necessitates that enterprises enhance the quality and efficiency of logistics services by adopting new technologies, novel operational modes, innovative business practices, and synergistic organisational management mechanisms, which collectively foster economic and social development [26]. Evaluating NQPF provides enterprises with a clear framework to identify strengths and weaknesses, enabling the formulation of targeted transformation strategies. Furthermore, comparative analysis of different enterprises' NQPF performance allows organisations to glean insights from leading practices, thereby reinforcing overall competitiveness.

5.2 Data Sources and Data Pre-Processing

The data employed in this study were sourced from the annual reports and ESG reports of A-share listed express delivery enterprises covering the period 2019–2023. Realistic values for each indicator were extracted using text analysis and related methods. No further pre-processing, such as normalization, was applied, since the CoCoSo method is capable of handling data with differing magnitudes directly.

5.3 Weights Determination

5.3.1 The 1st Level Indicators

By integrating the DEMATEL method with expert judgments, the evaluation matrix was constructed as shown in Equation (19), where D represents the direct influence matrix, K denotes the normalized direct influence matrix, and T corresponds to the total impact matrix.

$$D = \begin{pmatrix} 0 & 1 & 3 \\ 1 & 0 & 3 \\ 2 & 2 & 0 \end{pmatrix} \Rightarrow K = \begin{pmatrix} -1 & -0.33 & 1 \\ -0.33 & -1 & 1 \\ 0.33 & 1 & -1 \end{pmatrix} \Rightarrow T = \begin{pmatrix} -0.46 & 0.06 & 0.30 \\ -0.06 & -0.34 & 0.30 \\ 0.06 & 0.34 & -0.30 \end{pmatrix}$$

Using the constructed total impact matrix, the influence levels of the first-level indicators—technological innovation, strategy leading, and development support—were quantified. Additionally, the centrality and causality of these indicators were derived from the survey data, as illustrated in Figure 2. Moreover, Figure 2 illustrates that, from a centrality perspective, development supports exhibits markedly higher values compared to the other first-level indicators. This suggests that development support functions as a critical driver for technological innovation and strategic initiatives, often facilitating or leading related activities. Consequently, development support holds greater significance within the overall evaluation framework. Conversely, technological innovation displays substantially lower centrality, indicating that its advancement is frequently influenced by external factors such as market demand or prior technological accumulation, and its impacts may manifest with a temporal lag. Regarding causality, the analysis identifies development support as a cause indicator, whereas technological innovation and strategy leading function as effect indicators. Following Step 4 of the DEMATEL procedure, the weights of the first-level indicators can be determined as follows:

$$w_{technology\ innovation} = 0.521 \quad w_{strategy\ leading} = 0.129 \quad w_{development\ support} = 0.350$$

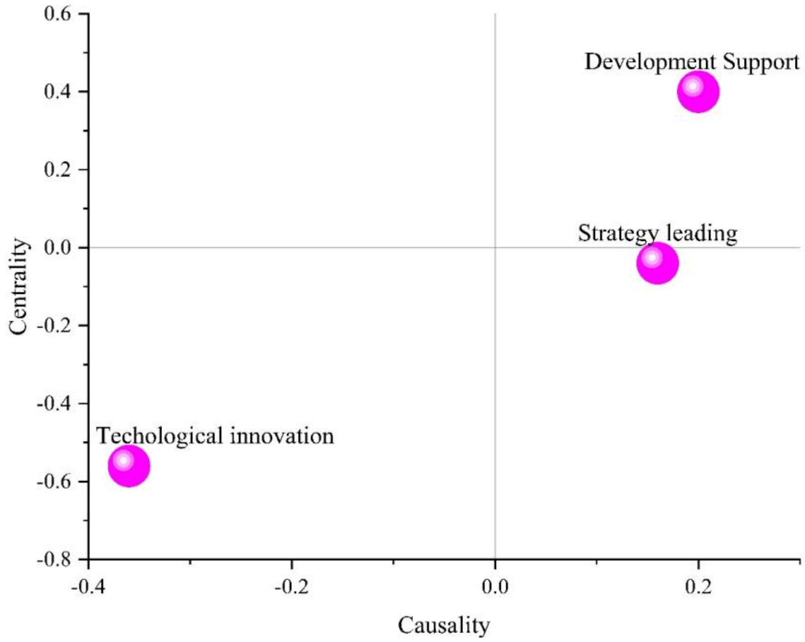

Fig.2: Centrality and Causality Analysis

5.3.2 The 2nd Level Indicators

The experts involved in this study were required to possess either an academic background in logistics research or professional experience in express delivery enterprises, along with a sufficient understanding of the evaluation objective, specifically the assessment of NQPF development in express delivery enterprises. A total of 16 experts participated in this research, comprising 8 logistics scholars and 8 enterprise practitioners. The evaluation outcomes derived from their input are presented in Figure 3.

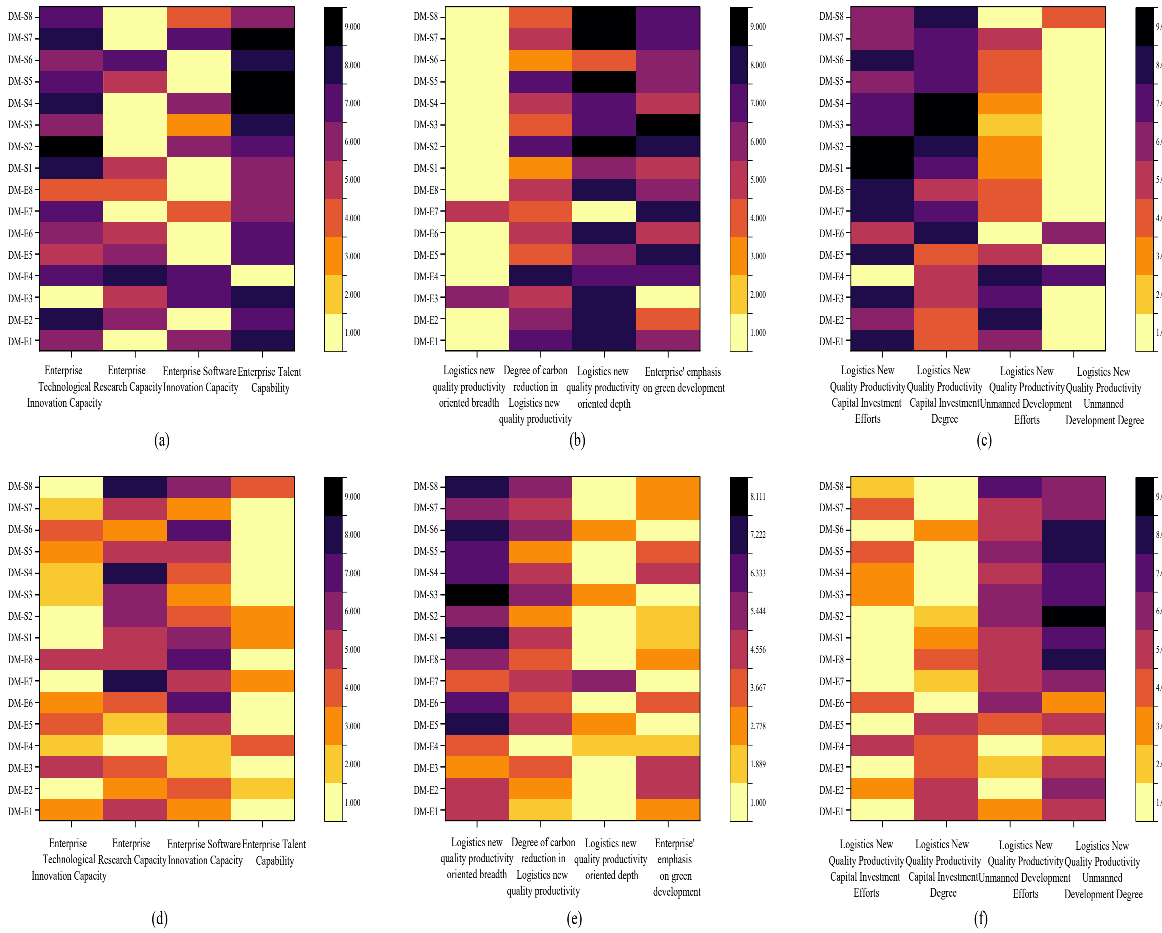

Fig.3: Evaluation Results from 16 DMs

Drawing on the experts' evaluations depicted in Figure 3, the BBWM was applied to conduct a group decision analysis. The prioritization of the confidence levels for each second-level indicator under their respective dimensions is illustrated in the weighted directed graph in Figure 4.

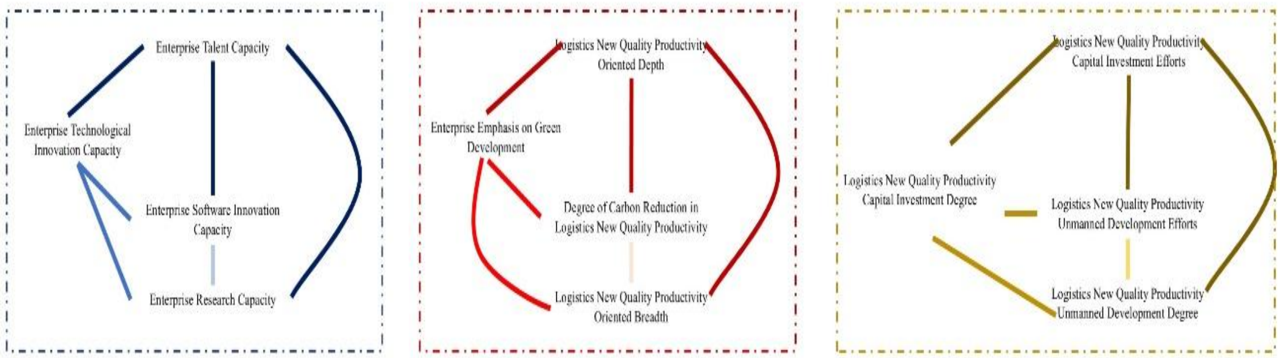

Fig.4: BBWM Results for NQPF Evaluation

The results indicate that Enterprise Talent Capacity, Logistics NQPF Orientation Depth, and Logistics NQPF Capital Investment Efforts emerge as the most critical indicators within their corresponding dimensions. The global weights were determined by integrating the weights of the second-level indicators obtained through BBWM with the first-level indicator weights derived from DEMATEL, as presented in Figure 5.

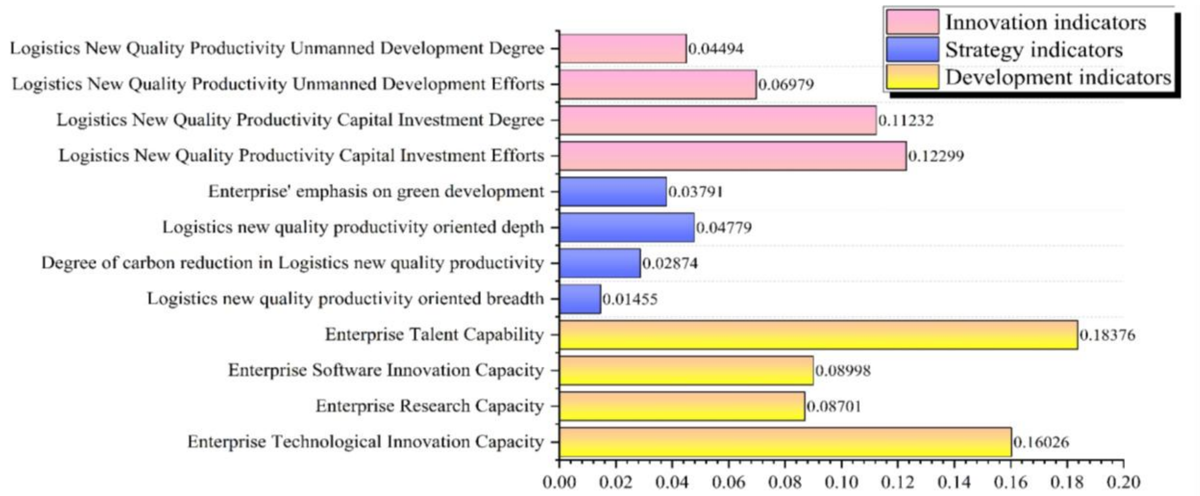

Fig.5: Global Weights for Each Indicator in NQPF Evaluation for Express Delivery Enterprises

5.3.3 CoCoSo Results and Analysis

5.3.3.1 Overall Results and Analysis

This section presents the outcomes of the CoCoSo analysis and the corresponding calculations, summarised in multiple tables. Initially, the actual performance data for 2019–2023 were extracted from the operational annual reports of the five major A-share listed express delivery enterprises: S.F. Express (SF), STO Express (ST), YTO Express (YT), Yunda Express (YD), and Deppon Express (DB). The indicator weights employed in the CoCoSo evaluation were derived from the previously determined DEMATEL and BBWM results. Based on the computed scores, a comparative illustration of the enterprises' performance is depicted in Figure 6.

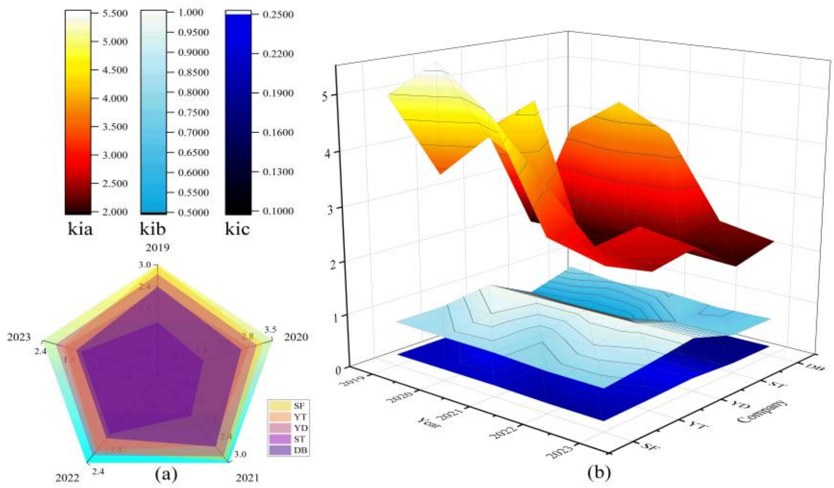

Fig.6: Evaluation Results for Different Express Delivery Enterprises' NQPF (2019-2023)

Figure 6 provides a comparative overview of the NQPF evaluation outcomes for the five major A-share listed express delivery enterprises—SF, ST, YT, YD, and DB—over the period 2019–2023. Figure 7 presents the temporal evolution of NQPF scores in a hexagonal format, where each vertex denotes a specific year and line colours differentiate the enterprises. The lengths and configurations of the lines represent the relative strength of each enterprise's NQPF performance annually. The analysis indicates that YD consistently maintained the leading position from 2019 to 2023, reflecting sustained investment in NQPF and tangible development outcomes. Its strategy of comprehensive digitalization has enhanced operational efficiency and service quality through technological capabilities and information systems. Notably, YD has independently developed tools such as the Digital Intelligent Dispatch System and the Fully Automated Sorting System, which have improved work efficiency and customer satisfaction.

SF led the sector from 2019 to 2021, with a marginal decline in 2022–2023. The enterprise has been at the forefront of digital transformation within the express industry, investing in technology R&D, exemplified by the release of the vertical large language model “Feng language” and the launch of the “Guangdong, Hong Kong, and Macao cross-city half-day delivery” service. The expansion and optimisation of its aviation network further support rapid delivery operations. Despite these achievements, SF faces challenges associated with rapid technological updates, increased data security risks, and a scarcity of digital talent, which may affect NQPF. Additionally, scaling operations and heightened market competition may increase labour, operational, and R&D costs, potentially constraining further NQPF development.

In contrast, ST exhibited comparatively weaker NQPF performance over the five-year period. Although ST is pursuing digital transformation, its progress lags behind competitors in transit centre construction and automation adoption. These deficiencies limit data processing capabilities, customer experience, and operational efficiency, ultimately affecting its NQPF. To enhance performance, ST must strengthen internal management, optimise incentive mechanisms, accelerate digital transformation, expand automation implementation, and reinforce brand positioning to navigate market competition and external environmental shifts.

Results of Kia and Analysis

Analysis of the kia values in Figure 7 indicates that all five enterprises exhibit a general upward trajectory in NQPF development. This trend may be attributed to internal growth and operational advancements, enhancements in industry standards, consolidation of relative competitive advantages, dynamic modifications in the evaluation metrics, and supportive external environmental conditions. These factors contribute to the sustained development of NQPF across the enterprises. Nonetheless, disparities in performance are evident. YD consistently demonstrates the strongest NQPF outcomes, followed by SF. Conversely, DB and ST exhibit relatively weaker performance, while YT occupies an intermediate position. These variations likely reflect differences in strategic approaches, R&D investment, technological application, and marketing efforts related to NQPF. For enterprises with lower performance, targeted enhancement of investment and innovation in NQPF is recommended to strengthen competitiveness. Simultaneously, high-performing enterprises should maintain their leadership, continually exploring new avenues and opportunities for NQPF advancement.

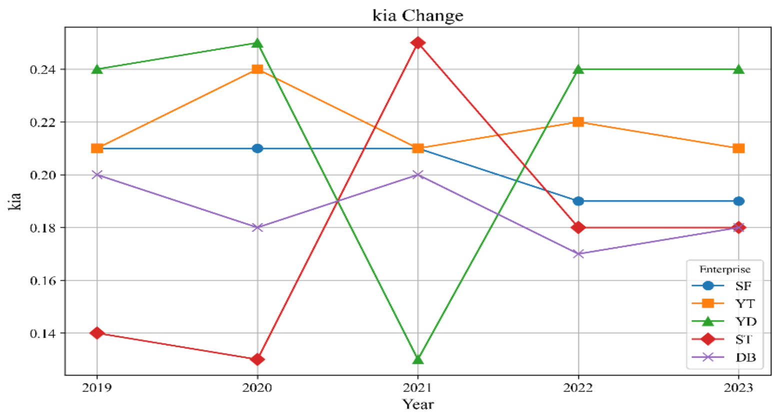

Fig.7: Evaluation Results of NQPF of Each Logistics Company Based on the Kia Method.

5.3.3.2 Results of Kib and Analysis

As illustrated in Figure 8, the kib values for all five enterprises exhibit a general downward trend in NQPF development. The scoring mechanism of kib indicates that even if an enterprise's absolute performance (i.e., raw score) remains constant or improves, its relative performance (i.e., kib value) may decrease if the minimum industry score rises. With the continued expansion of the express delivery sector, the baseline requirements and standards for NQPF are increasing. Consequently, minimum rating thresholds across the industry tend to rise, which can result in a relative decline in kib values despite actual performance improvements. The intensifying competition within the logistics sector necessitates greater investment in NQPF to sustain market position. Nevertheless, such investments do not always translate into proportional rating enhancements, particularly amid rising industry benchmarks. Therefore, despite sustained efforts, enterprises may observe a decline in their relative kib values due to the overall elevation of sector-wide NQPF performance standards.

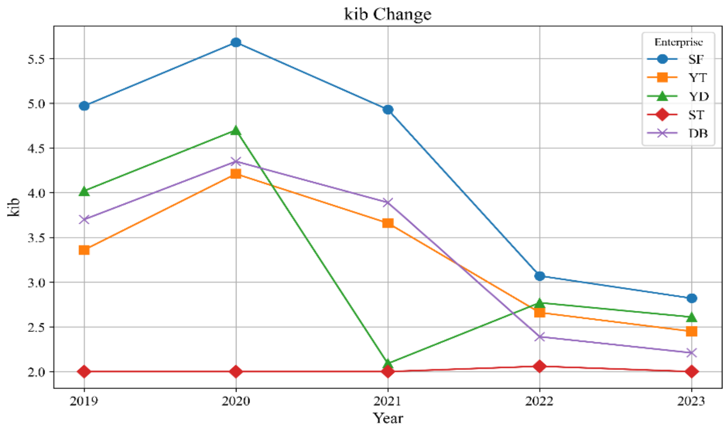

Fig.8: Evaluation Results of NQPF of Each Logistics Company Based on the Kib Method

5.3.3.3 Results of Kic and Analysis

As observed from the kic values in Figure 9, all five enterprises demonstrate a more balanced trajectory in NQPF development over the past five years. This trend may be attributed to the effects of weight allocation, standardized evaluation procedures, convergence in firm performance, the influence of maximum scoring thresholds, and overall enhancements in industry standards. The kic scoring mechanism inherently allows for differential weighting, which mitigates the disproportionate impact of individual ratings on NQPF development, resulting in more balanced evaluation outcomes. Furthermore, the five major A-share listed express delivery enterprises exhibit notable similarities in their NQPF advancement. For instance, all have emphasised technological innovation and service quality improvement, with substantial investment directed towards these areas. Such aligned strategic priorities likely contribute to comparable performance in rating S and rating P, which, in turn, produces a more uniform distribution of kic scores across the firms.

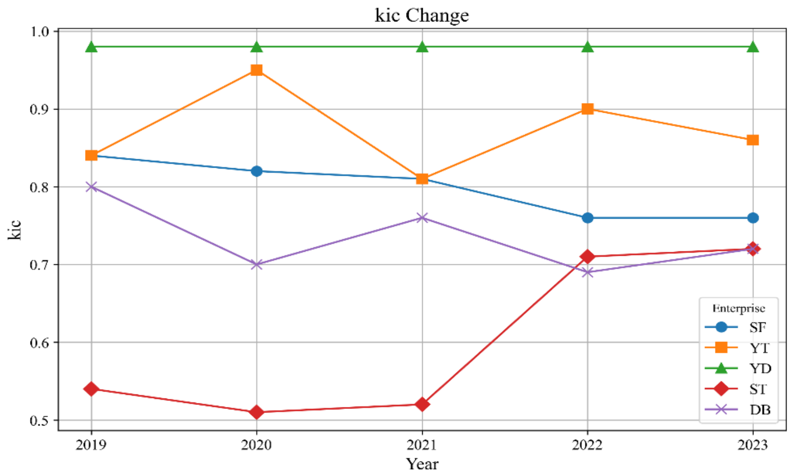

Fig.9: Evaluation Results of NQPF of Each Logistics Company Based on the Kic Method

6. Extended Discussion

Based on the correlation analysis between NQPF evaluation outcomes and financial performance across the express delivery enterprises, the study identifies a bidirectional dynamic relationship between NQPF and financial performance. The selected financial performance indicators include Revenue, Net Profit, Gross Margin, EPS, Debt-to-Equity Ratio, ROE, and Operating Margin. The performance of each indicator for the five enterprises from 2019 to 2023 is summarised in Figure 10. Integrating the financial performance data with the NQPF evaluation results, the following conclusions can be drawn:

1. NQPF exerts a positive driving effect on financial performance, enhancing operational efficiency, service quality, and profitability.
2. A vicious cycle exists wherein weak NQPF correlates with poorer financial performance, potentially limiting investment and innovation capabilities.
3. NQPF serves as a robust indicator for reflecting the developmental potential of express delivery enterprises, enabling strategic planning and long-term competitiveness.

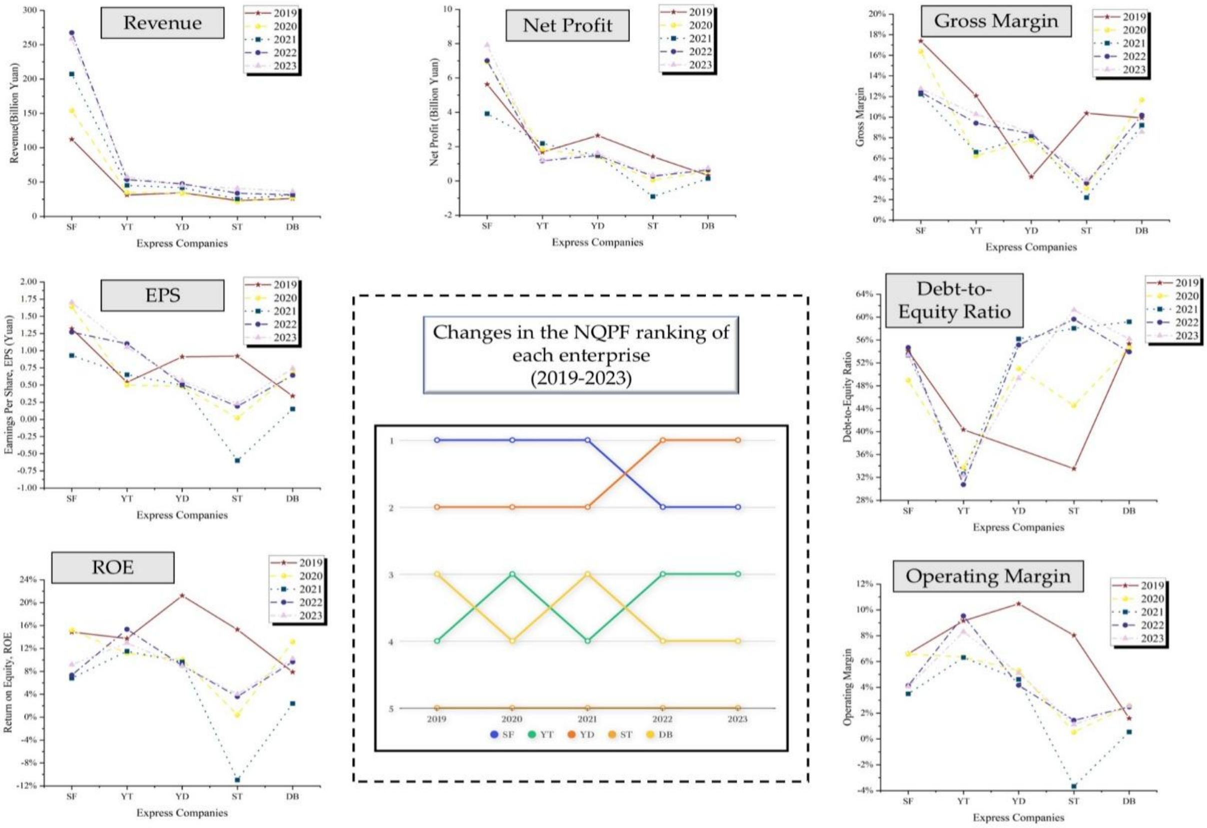

Fig.10: Changes in Financial Performance and NQPF Rankings for 5 Listed Express Delivery Enterprises (2019-2023)

6.1 Positive Driving Effects of NQPF on Financial Performance

The comparative analysis of Yunda Express and S.F. Express underscores the influence of NQPF on financial performance, highlighting the differential outcomes of technological investments and financial management strategies. Yunda Express, maintaining a leading position in NQPF, demonstrates a virtuous cycle between financial performance and technological investment. From 2019 to 2023, its gross profit margin increased from 4.21% to 8.52%, while the operating profit margin consistently exceeded 5%, reaching 5.10% in 2023. Concurrently, the asset-liability ratio improved from 50.99% in 2020 to 49.3% in 2023, reflecting the firm's ability to balance technical investments with financial risk through a light-asset operational model. In contrast, S.F. Express experienced a slight decline in NQPF ranking after 2021, corresponding with incremental financial pressures. Although its revenue rose from 112.19 billion Yuan in 2019 to 258.41 billion Yuan in 2023, the gross profit margin declined from 17.39% to 12.75%, indicating short-term profitability compression attributable to substantial asset investments.

6.2 Vicious Circle between Weak NQPF and Poorer Financial Performance

The NQPF evaluation consistently ranked STO Express lowest, reflecting multiple financial constraints. The firm's profitability has been highly unstable, with net profit declining sharply from 142 million RMB in 2019 to a loss of 911 million RMB in 2021 and only recovering marginally to 333 million RMB by 2023. This volatility has constrained its capacity to allocate resources to technological investment. Moreover, the firm's leverage increased markedly, with the asset-liability ratio rising from 33.52% in 2019 to 61.24% in 2023, resulting in elevated debt levels that adversely affect R&D expenditure. This has reinforced a vicious cycle of "low technological investment → reduced competitiveness → sluggish revenue growth." In 2021, the operating profit margin fell to -3.67%, the lowest among the five firms, indicating misalignment with the management standards prescribed by the State Administration for Market Regulation.

6.3 NQPF Helps to Reflect Development Potential for Express Delivery Enterprises

The analysis reveals that variations in the NQPF rankings exhibit only a marginal correlation with firm size indicators, such as revenue. In contrast, stronger associations are observed with financial metrics including net profit, ROE, gross margin, and debt-to-equity ratio. Consequently, the NQPF evaluation outcomes presented in this study provide a more precise reflection of the operational efficiency and profitability stability of express delivery enterprises, offering valuable insights to inform strategic decisions and future development planning.

7. Conclusion

The assessment of NQPF development in express delivery enterprises constitutes a complex and systematic challenge. In this study, a scientifically grounded and methodologically robust evaluation index system and corresponding procedures have been developed to appraise NQPF in these enterprises. The framework, structured around technological innovation, strategic leadership, and development support, encompasses both the inputs and outputs of express delivery firms in areas such as technology research and development, managerial innovation, and service innovation. Using S.F.Express, STO.Express, Yunda Express, and Deppon Express as case studies, the proposed evaluation model and methodology are validated, highlighting disparities and bottlenecks in the NQPF development of each enterprise. This study further provides tailored developmental strategies and operational recommendations, thereby contributing substantively to the sustainable and high-quality growth of the sector. Additionally, the framework and methodology introduced here can be applied to other industries, such as warehousing and transportation firms, to assess their NQPF development.

7.1 Contributions

The contributions of this study can be summarised as follows:

(1) To evaluate the development of NQPF in express delivery enterprises, a novel evaluation index system and assessment model structured around technological innovation, strategic leadership, and development support are proposed. The index system distinctly captures both the inputs and outcomes of express delivery enterprises in technological research and development, managerial

innovation, and service innovation, as well as their impacts on financial performance and market competitiveness. This enables enterprises to gain a clearer understanding of their operational characteristics, identify strengths and weaknesses, and formulate more scientifically grounded and rational development strategies.

(2) This study presents the first integrated application of DEMATEL, BBWM, and CoCoSo for NQPF assessment. DEMATEL and BBWM are employed to determine indicator weights, while CoCoSo is used to rank enterprises. The hybrid DEMATEL-BBWM-CoCoSo approach enhances evaluation accuracy by leveraging the methodological advantages of each component. Moreover, this integrated method is extendable to future NQPF assessments in other sectors, effectively addressing challenges such as high inter-indicator correlation and incomplete indicator data.

(3) The study further analyses the correspondence between NQPF evaluation results and financial performance, revealing a synergistic relationship. The findings indicate that NQPF evaluation outcomes can serve as a proxy for an enterprise's future development potential and provide guidance for recognising developmental challenges.

7.2 Limitations

In the research process, the frequency of specific terms in the annual reports and ESG reports of the enterprises was employed as a proxy to gauge the degree of attention allocated to certain indicators. However, this approach does not precisely reflect the actual level of development achieved by the enterprises with respect to these indicators and is inherently subject to a degree of subjectivity. Future studies should aim to mitigate the subjectivity inherent in such assessment processes. In addition, the individual relationships between each financial indicator and NQPF were not examined in detail due to limitations in research capacity. Consequently, the study derived generalised patterns only from a macro-level perspective, and more granular, indicator-specific analyses may be undertaken in subsequent research.

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Data Availability

All experimental data and analysis scripts are available in the Annual Financial report and ESG report of listed express delivery enterprises in China.

Acknowledgments

None.

Conflicts of Interest

The authors declare no conflicts of interest.

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