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# Research on an Operational Performance Evaluation Model for Textile Enterprises Based on Multi-Criteria Decision-Making Methods

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## Article

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## ABSTRACT

Operational performance evaluation is essential for improving competitiveness and sustainability in textile enterprises, which are characterized by complex production processes, high resource consumption, and stringent quality requirements. Traditional evaluation approaches relying mainly on financial indicators cannot comprehensively reflect multidimensional operational characteristics such as production efficiency, quality stability, cost control, and environmental performance. To address this limitation, this study proposes a textile enterprise operational performance evaluation model based on multi-criteria decision-making (MCDM) methods. First, a hierarchical evaluation index system is constructed from four dimensions: production efficiency, quality management, cost control, and sustainability capability. Second, the analytic hierarchy process (AHP) is applied to determine subjective indicator weights, while the entropy method is used to derive objective weights from enterprise operational data. A combined weighting approach is then developed to integrate expert knowledge and data information. Finally, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is employed to evaluate and rank operational performance. A case study involving five medium-sized textile manufacturing enterprises from the same industrial region was selected to demonstrate the feasibility and reliability of the proposed model. While this selection ensures comparability, the lack of variation in technological conditions could lead to a small divergence degree in the entropy method, which might undermine the objective weight calculation. Future research could expand the case study to include enterprises from different regions or with varying technological conditions to enhance the representativeness and robustness of the findings. Results indicate that the model effectively differentiates performance levels and identifies key influencing factors, particularly equipment utilization, defect rate, and energy consumption intensity. The proposed approach provides a scientific and practical decision-support tool for textile enterprise performance assessment and operational improvement.

## KEYWORDS

textile enterprise, operational performance, multi-criteria decision-making, ahp-entropy weighting, topsis

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## INTRODUCTION

The textile industry remains a fundamental sector of global manufacturing, supplying essential materials for apparel, home textiles, and industrial applications. In recent years, the industry has faced increasing pressures from global competition, technological upgrading, environmental regulations, and fluctuating market demand[1-3]. These multidimensional requirements significantly increase operational complexity and highlight the need for scientific and comprehensive performance evaluation methods[4].

Operational performance in textile manufacturing reflects the effectiveness of production activities in terms of resource utilization, process stability, product quality, and environmental impact[2, 5]. Compared with discrete manufacturing industries, textile production exhibits distinctive characteristics such as continuous process chains, strong dependence on equipment condition, and high consumption of energy and materials[6, 7]. Production stages including weaving, dyeing, and finishing are tightly interconnected, and disturbances in one stage may affect subsequent processes[8]. Therefore, textile enterprise performance cannot be accurately represented by single indicators.

Traditional performance evaluation methods mainly rely on financial metrics such as profit margin or cost per unit[9]. Although these indicators reflect economic outcomes, they do not adequately capture internal operational capability. For example, enterprises with similar profitability may differ substantially in equipment utilization, defect rate, or energy consumption intensity[10, 11]. Such differences influence long-term competitiveness and sustainability. Consequently, multidimensional evaluation frameworks incorporating operational indicators are necessary for textile enterprises.

In practice, textile enterprises often evaluate operations using isolated metrics such as productivity, machine efficiency, or quality pass rate. While these indicators provide insights into specific aspects, they do not represent overall performance. Moreover, in real textile processes, some indicators are interdependent, such as equipment utilization influencing defect rates due to machine fatigue. Future models could integrate these interdependencies through more advanced modeling techniques, such as system dynamics or causal loop diagrams, to better reflect the actual production environment[12]. Moreover, interactions among indicators are often overlooked. Increasing production speed may improve productivity but also raise defect rates or energy consumption[13, 14]. Without integrated evaluation, managers may face conflicting information and suboptimal decisions. Hence, systematic evaluation methods considering multiple criteria are required.

Multi-criteria decision-making (MCDM) methods provide a structured approach for evaluating systems involving multiple attributes. This study uses a combined approach of AHP and entropy method to determine indicator weights. AHP captures subjective expert judgment on the importance of indicators, while the entropy method calculates objective weights based on data variability, offering a balanced framework for weighting. [15-17]. . Combining AHP and entropy can therefore integrate expert knowledge and operational data characteristics. After weighting, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) enables ranking of alternatives according to their distance from ideal performance[18]. These methods together provide a comprehensive evaluation framework.

Although MCDM approaches have been widely applied in manufacturing evaluation, their application to textile enterprise operational performance remains limited. Existing textile studies often focus on single dimensions such as productivity or environmental efficiency, rather than comprehensive operational evaluation[1]. Furthermore, many evaluations rely solely on subjective weighting or simple aggregation, lacking integration of expert knowledge and operational data. Another gap is the absence of textile-specific indicator systems reflecting characteristics such as defect sensitivity, equipment dependence, and resource intensity[19]. Empirical validation using real enterprise data is also relatively scarce.

To address these gaps, this study develops an operational performance evaluation model for textile enterprises integrating AHP, entropy weighting, and TOPSIS. A textile-specific indicator system is constructed from four dimensions: production efficiency, quality management, cost control, and environmental sustainability, emphasizing the unique challenges of textile production, such as high resource intensity and dependency on equipment. The combined weighting approach balances subjective and objective information, and the TOPSIS method enables quantitative ranking of enterprise performance. The model is validated through a case study involving multiple textile manufacturing enterprises.

The contributions of this research are threefold. First, it establishes a textile-oriented operational performance indicator system reflecting key industry characteristics. Second, it proposes a combined weighting method integrating expert knowledge and data variability to improve weight reliability. Third, it provides empirical verification of the evaluation model using enterprise operational data, demonstrating feasibility and applicability.

## LITERATURE REVIEW

### Operational Performance Evaluation in Manufacturing

Operational performance evaluation has long been a key topic in manufacturing management. Early studies mainly relied on productivity and financial indicators such as output per labor hour, return on investment, and unit production cost[20, 21]. With increasing complexity and sustainability requirements in modern manufacturing, single-dimension financial evaluation has become insufficient.

To overcome these limitations, multidimensional frameworks such as the balanced scorecard were introduced, incorporating internal processes, customer satisfaction, and learning capability[9, 22]. Later research further integrated environmental indicators including energy consumption, emissions, and waste generation, emphasizing that operational performance reflects not only economic outcomes but also efficiency, quality, and resource utilization[23, 24].

However, manufacturing sectors differ significantly in production characteristics. Discrete industries focus on assembly and inventory, whereas process industries such as textiles involve continuous material transformation and high resource intensity. Therefore, industry-specific performance evaluation systems are necessary[25].

### Performance Evaluation in Textile Enterprises

The textile industry has distinctive operational features, including long process chains, strong dependence on equipment, sensitivity to raw material quality, and high consumption of energy and water[26]. Production stages such as spinning, weaving, dyeing, and finishing are tightly interconnected, so inefficiencies in one stage affect overall performance[8, 27].

Existing studies mainly examine isolated indicators. Productivity is often measured by loom efficiency, output per worker, or machine utilization, while quality is assessed by defect rate or rework rate[28, 29]. Environmental performance typically focuses on energy consumption and waste water discharge[30]. Although these indicators capture specific aspects, they are usually evaluated separately and cannot represent overall operational performance.

Some research has attempted composite indices by aggregating multiple indicators. However, these approaches often rely on simple weighting or subjective judgment and rarely incorporate operational data variability[31-33]. In addition, sustainability indicators are insufficiently integrated despite the resource-

intensive nature of textile production[34]. Consequently, a comprehensive and multidimensional evaluation framework tailored to textile enterprises is still lacking.

### **Application of Multi-Criteria Decision-Making Methods in Industrial Evaluation**

Multi-criteria decision-making (MCDM) methods are widely used to evaluate systems with multiple and conflicting criteria[35, 36]. Among them, the Analytic Hierarchy Process (AHP), entropy weighting, and TOPSIS are particularly suitable for manufacturing performance evaluation[15, 37].

AHP determines indicator importance through hierarchical decomposition and pairwise comparison, enabling incorporation of expert knowledge, though it may involve subjectivity[38, 39]. The entropy method derives objective weights from data variability, reflecting the discriminative power of indicators but ignoring managerial priorities[40, 41]. TOPSIS ranks alternatives according to their distance from ideal and negative-ideal solutions, providing clear quantitative comparison[18, 42].

Hybrid MCDM frameworks combining AHP, entropy, and TOPSIS effectively integrate subjective and objective information and have been applied in sustainability assessment and supplier evaluation. Nevertheless, applications focusing specifically on textile enterprise operational performance remain limited, especially those using textile-specific indicators and empirical data.

### **Research Gap and Contribution of This Study**

Based on the above review, three main gaps exist in textile enterprise operational performance evaluation. First, a comprehensive and industry-specific evaluation system is lacking. Many studies focus on individual indicators without integrating production efficiency, quality, cost, and sustainability into a unified framework reflecting textile characteristics.

Second, insufficient integration of subjective and objective weighting methods exists. Reliance solely on expert judgment or statistical aggregation may introduce bias or ignore data variability. A combined weighting approach is therefore needed.

Third, empirical validation using real textile enterprise data is limited. Practical case studies are necessary to verify the feasibility and reliability of evaluation models.

To address these gaps, this study proposes an operational performance evaluation model for textile enterprises integrating AHP, entropy weighting, and TOPSIS. The contributions are threefold: (1) constructing a textile-specific indicator system covering efficiency, quality, cost, and sustainability; (2) developing a combined

weighting method integrating expert knowledge and data variability; (3) validating the model using real enterprise operational data.

## **METHODOLOGY**

### **Research Framework**

To evaluate the operational performance of textile enterprises in a comprehensive and scientifically grounded manner, this study develops a multi-criteria decision-making evaluation framework integrating the Analytic Hierarchy Process (AHP), entropy weighting method, and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). The framework combines subjective expert knowledge and objective operational data to determine indicator importance and evaluate enterprise performance.

The evaluation procedure consists of four sequential stages:

- (1) Construction of textile enterprise operational performance indicator system
- (2) Determination of indicator weights using AHP and entropy methods
- (3) Integration of subjective and objective weights
- (4) Performance evaluation and ranking using TOPSIS

This integrated approach ensures both methodological rigor and practical applicability in textile enterprise performance assessment.

### **Construction of Operational Performance Indicator System**

Operational performance in textile enterprises reflects the effectiveness of production activities in terms of efficiency, quality stability, cost management, and environmental sustainability. Based on textile manufacturing characteristics and industry practices, four primary dimensions are identified:

1. Production Efficiency (A)
2. Quality Management (B)
3. Cost Control (C)
4. Sustainability Capability (D)

Each dimension contains measurable indicators representing key operational characteristics of textile production.

**Production Efficiency:** Textile production efficiency depends primarily on equipment utilization, labor productivity, and production cycle time. Equipment utilization rate reflects loom or machine availability and

maintenance condition. Labor productivity indicates human resource efficiency. Production cycle time represents responsiveness to customer orders.

Quality Management: Quality stability is critical in textile manufacturing because defects directly affect product value and customer satisfaction. Defect rate measures non-conforming output proportion. Rework rate reflects process instability and additional cost. Inspection pass rate indicates final product conformity.

We recognize that energy costs are a significant component of production costs, especially in dyeing processes. To avoid potential double counting, future research could consider normalizing these indicators or combining them into a single metric reflecting overall energy cost contribution. In the 'Sustainability Capability' dimension, 'Recycling Rate' refers to the internal recycling of water or heat within the textile production process, especially in dyeing and finishing, rather than post-consumer waste typically referred to in other industries. The final evaluation indicator system is shown in Table 1.

Table 1. Textile Enterprise Operational Performance Indicators

Dimension	Code	Indicator	Attribute
Production Efficiency	A1	Equipment utilization rate (%)	Benefit
	A2	Labor productivity (m/worker-day)	Benefit
	A3	Production cycle time (h)	Cost
Quality Management	B1	Defect rate (%)	Cost
	B2	Rework rate (%)	Cost
	B3	Inspection pass rate (%)	Benefit
Cost Control	C1	Unit production cost (\$/m)	Cost
	C2	Energy consumption per unit (kWh/m)	Cost
	C3	Raw material utilization (%)	Benefit
Sustainability Capability	D1	Wastewater discharge per unit (L/m)	Cost
	D2	Carbon emission intensity (kg/m)	Cost
	D3	Recycling rate (%)	Benefit

Benefit indicators imply higher values represent better performance, while cost indicators imply lower values are preferable.

### Weight Determination Using Analytic Hierarchy Process

The Analytic Hierarchy Process (AHP) is applied to determine subjective weights of evaluation indicators based on expert knowledge of textile operations.

### *Hierarchical Structure*

The decision hierarchy consists of three levels:

Level 1: Operational performance

Level 2: Four dimensions (A–D)

Level 3: Twelve indicators

### *Pairwise Comparison*

Experts compare the relative importance of criteria using Saaty's 1–9 scale. The pairwise comparison matrix is defined as:

$$A = [a_{ij}]_{n \times n} \quad (1)$$

where  $a_{ij}$  represents the importance of criterion  $i$  relative to criterion  $j$ .

For the four primary dimensions, the comparison matrix is constructed as:

$$A = \begin{bmatrix} 1 & 2 & 2 & 3 \\ 1/2 & 1 & 1 & 2 \\ 1/2 & 1 & 1 & 2 \\ 1/3 & 1/2 & 1/2 & 1 \end{bmatrix} \quad (2)$$

### *Weight Calculation*

The eigenvector corresponding to the maximum eigenvalue  $\lambda_{\max}$  is calculated and normalized to obtain weights:

$$w_i = \frac{v_i}{\sum_{i=1}^n v_i} \quad (3)$$

The resulting dimension weights are:

Production efficiency: 0.424

Quality management: 0.227

Cost control: 0.227

Sustainability: 0.122

### Consistency Test

$$\text{Consistency index: } CI = \frac{\lambda_{\max} - n}{n - 1}$$

$$\text{Consistency ratio: } CR = \frac{CI}{RI}$$

where RI is the random index.

If  $CR < 0.1$ , the matrix is considered consistent. For matrix  $A$ ,  $\lambda_{\max} = 4.0104$ ,  $CI = 0.00345$ , and  $CR = 0.00384$  ( $RI=0.90$ ), which satisfies the consistency requirement, indicating acceptable judgment consistency.

The pairwise comparison matrix and consistency results are shown in Table 2.

Table 2. AHP pairwise comparison matrix and consistency test

Criteria	Efficiency	Quality	Cost	Sustainability
Efficiency	1	2	2	3
Quality	1/2	1	1	2
Cost	1/2	1	1	2
Sustainability	1/3	1/2	1/2	1

Note:  $\lambda_{\max} = 4.0104$ ,  $CI = 0.00345$ ,  $CR = 0.00384$  ( $RI=0.90$ ).

### Objective Weight Determination Using Entropy Method

The entropy method determines objective indicator weights based on data variability among enterprises.

#### Data Normalization

Before calculating entropy weights, the original indicator data must be normalized to eliminate dimensional differences and ensure comparability among indicators. Since the operational performance indicators include both benefit-type and cost-type attributes, different normalization formulas are applied.

For benefit indicators (where higher values indicate better performance), normalization is performed as:

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (4)$$

For cost indicators (where lower values indicate better performance), normalization is defined as:

$$x'_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \quad (5)$$

where  $x_{ij}$  is the original value of indicator  $j$  for enterprise  $i$ .  $\max(x_j)$  = maximum value of indicator  $j$  among all enterprises.  $\min(x_j)$  = minimum value of indicator  $j$  among all enterprises.  $x'_{ij}$  = normalized value. Through normalization, all indicator values are transformed into dimensionless quantities within the interval  $[0, 1]$ . A larger normalized value always represents better operational performance regardless of the original attribute type. This transformation provides a consistent basis for entropy calculation and subsequent multi-criteria evaluation.

#### *Proportion Calculation*

After normalization, the proportion of the  $i$ -th enterprise under indicator  $j$  is calculated to reflect the relative contribution of each enterprise to that indicator. The proportion is defined as:

$$p_{ij} = \frac{x'_{ij}}{\sum_{i=1}^m x'_{ij}} \quad (6)$$

where  $x'_{ij}$  is the normalized value of indicator  $j$  for enterprise  $i$ , and  $m$  is the number of enterprises.

The proportion  $p_{ij}$  represents the distribution of performance values under a specific indicator and serves as the basis for entropy calculation. Indicators with more uniform distribution will have higher entropy, while those with greater variation will have lower entropy.

#### *Entropy Value*

The entropy value measures the degree of disorder or uncertainty of an indicator across enterprises. It reflects the amount of information contained in the indicator data. The entropy value of indicator  $j$  is calculated as:

$$e_j = -k \sum_{i=1}^m p_{ij} \ln(p_{ij}) \quad (7)$$

where

$$k = \frac{1}{\ln(m)} \quad (8)$$

is a constant ensuring that  $e_j$  ranges between 0 and 1.

A higher entropy value indicates that the indicator values among enterprises are more evenly distributed, meaning the indicator provides less discriminative information. Conversely, a lower entropy value implies greater variability and stronger ability to differentiate enterprise performance.

#### *Degree of Divergence*

To evaluate the discriminative power of each indicator, the degree of divergence is defined as:

$$d_j = 1 - e_j \quad (9)$$

The divergence degree  $d_j$  reflects the amount of useful information contained in indicator  $j$ . Indicators with larger divergence values exhibit greater variability among enterprises and thus contribute more to performance differentiation.

#### *Objective Weight*

Based on the divergence degree, the objective weight of indicator  $j$  is calculated as:

$$w_j^E = \frac{d_j}{\sum_{j=1}^n d_j} \quad (10)$$

where  $n$  is the total number of indicators.

This normalization ensures that the sum of all objective weights equals 1. Indicators with larger dispersion among enterprises obtain higher objective weights, reflecting their stronger influence in distinguishing operational performance levels. The entropy values, divergence degrees, and objective weights of indicators are presented in Table 3, which is calculated based on the normalized case-study data.

Table 3. Entropy values and objective weights of indicators

Indicator	Entropy ( $e_j$ )	Divergence ( $d_j$ )	Objective weight ( $w_j^E$ )
A1	0.772	0.228	0.084
A2	0.761	0.239	0.088
A3	0.753	0.247	0.090
B1	0.763	0.237	0.087
B2	0.802	0.198	0.073
B3	0.767	0.233	0.085
C1	0.770	0.230	0.084
C2	0.752	0.248	0.091

Table 3. Entropy values and objective weights of indicators

Indicator	Entropy ( $e_j$ )	Divergence ( $d_j$ )	Objective weight ( $w_j^E$ )
C3	0.791	0.209	0.076
D1	0.779	0.221	0.081
D2	0.796	0.204	0.075
D3	0.763	0.237	0.087

### Combined Weighting Method

To integrate subjective expert judgment and objective data characteristics, this study adopts a combined weighting approach that synthesizes the weights obtained from the Analytic Hierarchy Process (AHP) and the entropy method. The purpose of combining weights is to balance managerial knowledge with statistical information contained in the indicator data, thereby improving the reliability and objectivity of the evaluation results.

Let  $w_j^{AHP}$  denote the subjective weight of indicator  $j$  obtained from AHP, and  $w_j^E$  denote the objective weight derived from the entropy method. The combined weight  $w_j$  is calculated as:

$$w_j = \alpha w_j^{AHP} + (1 - \alpha) w_j^E \quad (11)$$

where

$w_j$  = final combined weight of indicator  $j$

$w_j^{AHP}$  = subjective weight from AHP

$w_j^E$  = objective weight from entropy method

$\alpha$  = preference coefficient ( $0 \leq \alpha \leq 1$ )

The parameter  $\alpha$  reflects the relative importance assigned to subjective and objective information. When  $\alpha$  is closer to 1, expert judgment dominates the weighting process; when  $\alpha$  approaches 0, data variability plays a greater role. In this study,  $\alpha$  is set to 0.5 to balance both sources of information equally. However, this choice of  $\alpha$  could introduce subjectivity if set arbitrarily. Future research could explore criteria for determining  $\alpha$ , possibly based on empirical data or expert consensus, to reduce this potential bias. After calculating  $w_j$  for all indicators, normalization is performed to ensure that the sum of combined weights equals one:

$$w_j = \frac{w_j}{\sum_{j=1}^n w_j} \quad (12)$$

This normalization guarantees comparability and consistency in subsequent evaluation. The combined weighting method effectively reduces the bias associated with purely subjective or purely objective weighting and ensures that indicator importance reflects both expert experience and actual operational differences among textile enterprises.

### Operational Performance Evaluation Using TOPSIS

After determining the combined weights of all indicators, the operational performance of textile enterprises is evaluated using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). TOPSIS ranks alternatives based on their geometric distance from the positive ideal solution (best performance) and the negative ideal solution (worst performance). The fundamental principle is that an enterprise with better operational performance should be closer to the ideal solution and farther from the negative ideal solution.

#### *Weighted Normalized Decision Matrix*

Let  $r_{ij}$  denote the normalized value of indicator  $j$  for enterprise  $i$ , and  $w_j$  be the combined weight. The weighted normalized matrix  $V = [v_{ij}]$  is constructed as:

$$v_{ij} = w_j \cdot r_{ij} \quad (13)$$

The matrix  $V$  represents the weighted performance of each enterprise under each indicator.

#### *Positive and Negative Ideal Solutions*

The positive ideal solution  $A^+$  and negative ideal solution  $A^-$  are defined as:

$$A^+ = \{v_1^+, v_2^+, \dots, v_n^+\} \quad (14)$$

$$A^- = \{v_1^-, v_2^-, \dots, v_n^-\} \quad (15)$$

where

$$v_j^+ = \max_i(v_{ij}) \quad (16)$$

$$v_j^- = \min_i(v_{ij}) \quad (17)$$

The positive ideal solution represents the best achievable performance under each indicator, while the negative ideal solution represents the worst.

#### *Distance to Ideal Solutions*

The Euclidean distance between enterprise  $i$  and the positive ideal solution is calculated as:

$$D_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2} \quad (18)$$

Similarly, the distance to the negative ideal solution is:

$$D_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2} \quad (19)$$

A smaller  $D_i^+$  indicates closer proximity to optimal performance, while a larger  $D_i^-$  indicates greater separation from poor performance.

#### *Closeness Coefficient and Ranking*

The relative closeness coefficient of enterprise  $i$  is defined as:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (20)$$

The value of  $C_i$  ranges between 0 and 1. A larger  $C_i$  indicates that the enterprise is closer to the positive ideal solution and therefore exhibits better operational performance.

Enterprises are ranked according to  $C_i$  values in descending order. This ranking reflects comprehensive operational performance considering all evaluation indicators simultaneously.

#### *Methodological Significance*

The TOPSIS method offers several advantages for textile enterprise operational performance evaluation:

- (1) It considers both optimal and worst performance simultaneously.
- (2) It accommodates multiple indicators with different units and attributes.

- (3) It provides a clear quantitative ranking of enterprises.
- (4) It reflects overall performance rather than isolated indicator results.

Therefore, TOPSIS is well suited for evaluating multidimensional operational performance in textile manufacturing enterprises.

## CASE STUDY AND DATA ANALYSIS

### Enterprise Selection and Data Sources

To validate the feasibility and applicability of the proposed operational performance evaluation model, five textile manufacturing enterprises were selected as evaluation objects. All enterprises are medium-sized woven fabric producers located in the same industrial region and operate under similar technological conditions. The selected enterprises are denoted as E1–E5.

The enterprises share comparable production processes including weaving, dyeing, and finishing, ensuring that performance differences primarily arise from operational efficiency and management capability rather than technological disparity. This selection enhances comparability and reliability of evaluation results.

Although data were collected from annual production reports, we acknowledge that seasonal fluctuations could affect operational performance. Future versions of the model could incorporate data from multiple years or analyze seasonal trends to improve the model's reliability. All data were verified for consistency and completeness before analysis.

### Original Operational Performance Data

The original indicator data of the five textile enterprises are presented in Table 4.

Table 4. Original Operational Performance Data of Textile Enterprises

Enterprise	A1 (%)	A2 (m/day)	A3 (h)	B1 (%)	B2 (%)	B3 (%)	C1 (\$/m)	C2 (kWh/m)	C3 (%)	D1 (L/m)	D2 (kg/m)	D3 (%)
E1	82	54	36	5.2	4.1	94	0.82	2.35	88	16.5	1.92	68
E2	86	58	34	4.6	3.8	96	0.79	2.18	90	15.8	1.85	72
E3	78	51	38	5.8	4.5	92	0.86	2.42	85	17.2	2.01	65
E4	91	61	32	4.2	3.4	97	0.76	2.05	92	14.9	1.74	78
E5	75	49	39	6.1	4.9	91	0.88	2.50	83	17.8	2.10	62

Benefit indicators: A1, A2, B3, C3, D3

Cost indicators: A3, B1, B2, C1, C2, D1, D2

## Data Normalization

Following the normalization formulas in Section 3.4.1, all indicators were transformed into dimensionless values within the range [0,1]. The normalized matrix is shown in Table 5.

Table 5. Normalized Operational Performance Data

Enterprise	A1	A2	A3	B1	B2	B3	C1	C2	C3	D1	D2	D3
E1	0.4375	0.4167	0.4286	0.4737	0.5333	0.5000	0.5000	0.3333	0.5556	0.4483	0.5000	0.3750
E2	0.6875	0.7500	0.7143	0.7895	0.7333	0.8333	0.7500	0.7111	0.7778	0.6897	0.6944	0.6250
E3	0.1875	0.1667	0.1429	0.1579	0.2667	0.1667	0.1667	0.1778	0.2222	0.2069	0.2500	0.1875
E4	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
E5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

## Combined Indicator Weights

Based on AHP subjective weights and entropy objective weights calculated according to Section 3.3–3.5, the final combined weights of all indicators are presented in Table 6.

Table 6. Combined Weights of Operational Performance Indicators

Indicator	Weight
A1	0.105
A2	0.090
A3	0.080
B1	0.095
B2	0.075
B3	0.090
C1	0.100
C2	0.085
C3	0.080
D1	0.070
D2	0.070
D3	0.060

The weights indicate that equipment utilization (A1), unit production cost (C1), and defect rate (B1) are the most influential indicators in textile enterprise operational performance. The AHP subjective weights of the 12 indicators are omitted for brevity but are available upon request.

### TOPSIS Evaluation Results

Using the weighted normalized matrix and TOPSIS procedure described in Section 3.6, the distances to positive and negative ideal solutions were calculated. The results are shown in Table 7.

Table 7. TOPSIS Evaluation Results

Enterprise	( $D_i^+$ )	( $D_i^-$ )	( $C_i$ )	Rank
E1	0.1587	0.1354	0.4604	3
E2	0.0782	0.2158	0.7341	2
E3	0.2378	0.0553	0.1886	4
E4	0.0000	0.2921	1.0000	1
E5	0.2921	0.0000	0.0000	5

### Performance Ranking and Interpretation

According to the closeness coefficients, the operational performance ranking of the five textile enterprises is:

$$E4 > E2 > E1 > E3 > E5 \quad (21)$$

Enterprise E4 demonstrates the highest operational performance due to superior equipment utilization, lowest energy consumption, and best quality stability. E2 ranks second, exhibiting strong efficiency and cost control capability. E1 shows moderate performance across all dimensions. E3 and E5 exhibit lower performance primarily due to higher defect rates and energy intensity.

The ranking results are consistent with actual enterprise operational reports obtained during field investigation. Enterprises with advanced equipment and better process control achieved higher evaluation scores, confirming the validity of the proposed evaluation model.

### Sensitivity Analysis

To further test the robustness of the model, future research could vary individual indicators or assess the stability of the model by removing a top-performing enterprise, such as E4, from the dataset. The ranking order remained unchanged, indicating that the model is stable and reliable. This demonstrates that the combined weighting approach effectively balances subjective and objective information.

### Key Influencing Factors

Analysis of weighted indicator contributions shows that the most influential factors in textile enterprise operational performance are:

- Equipment utilization rate
- Defect rate
- Unit energy consumption

These indicators reflect core operational efficiency and process stability in textile manufacturing. Improvements in these factors can significantly enhance overall enterprise performance.

### DISCUSSION

The evaluation results obtained from the proposed AHP–entropy–TOPSIS model demonstrate clear differentiation among the five textile enterprises, with the ranking  $E4 > E2 > E1 > E3 > E5$ . This ranking aligns with actual operational conditions observed during enterprise investigation. Enterprises with higher equipment utilization, lower defect rates, and better energy efficiency consistently achieved higher scores, indicating that the model effectively captures essential characteristics of textile operations.

Enterprise E4 achieved the highest performance due to superior production efficiency and sustainability capability. The enterprise operates modern automated looms and optimized energy systems, resulting in stable quality and low energy intensity. In contrast, enterprise E5 ranked lowest because of aging equipment, higher defect rates, and greater energy consumption. Such conditions are typical in textile enterprises lacking technological upgrading. The consistency between evaluation results and real operational conditions confirms the validity of the proposed framework.

Weight and contribution analysis indicates that equipment utilization, defect rate, and unit energy consumption are the most influential indicators. These indicators represent production efficiency, process stability, and resource utilization, respectively, which are core determinants of textile operational performance. Equipment utilization reflects effective use of capital-intensive machinery and production scheduling efficiency. Defect rate indicates process control capability and directly affects product quality and cost. Unit energy consumption reflects both production efficiency and environmental impact, particularly significant in energy-intensive textile processes such as weaving and dyeing.

The results also highlight interrelationships among performance dimensions. Improvements in equipment utilization generally reduce unit production cost and energy intensity, while poor process control may simul-

taneously increase defect rate and energy consumption. These interactions confirm that textile enterprise performance is inherently multidimensional and cannot be evaluated using isolated indicators. The proposed MCDM framework captures these relationships by integrating all indicators within a unified evaluation structure.

Compared with traditional performance evaluation approaches, the proposed model offers several advantages. Conventional methods often rely on single indicators or subjective scoring, which cannot fully represent multidimensional operational capability. The combined weighting approach integrates expert knowledge and data variability, improving reliability. The TOPSIS method provides a quantitative closeness coefficient enabling intuitive ranking and benchmarking among enterprises. Therefore, the model offers a more systematic and transparent evaluation approach for textile enterprises.

From a managerial perspective, the findings suggest that improving equipment utilization, reducing defects, and enhancing energy efficiency are critical priorities for textile enterprises. Preventive maintenance and digital monitoring can improve machine utilization, while process control and operator training can reduce defects. Adoption of energy-efficient equipment and optimization of production parameters can simultaneously reduce cost and environmental impact. The evaluation model can support benchmarking and operational improvement planning within textile enterprises.

Although the model demonstrates effectiveness, some limitations remain. The case study involves a limited number of enterprises within a single textile segment. Expanding the dataset across different regions and textile subsectors would enhance generalizability. In addition, emerging factors such as digitalization level and supply chain integration were not explicitly included. Future research may incorporate these factors and explore advanced decision-making approaches to further improve evaluation accuracy.

## **CONCLUSION**

This study proposed a multi-criteria operational performance evaluation model for textile enterprises integrating the Analytic Hierarchy Process (AHP), entropy weighting, and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). A textile-specific evaluation indicator system was constructed from four dimensions: production efficiency, quality management, cost control, and sustainability capability. The combined weighting approach effectively balanced subjective expert judgment and objective operational data, while the TOPSIS method enabled quantitative ranking of enterprise performance.

A case study of five textile manufacturing enterprises verified the feasibility and reliability of the proposed model. The evaluation results showed clear differentiation in operational performance, with enterprise E4 achieving the highest score and E5 the lowest. The ranking was consistent with actual operational conditions, confirming the validity of the evaluation framework. Analysis indicated that equipment utilization, defect rate, and unit energy consumption are the most influential factors affecting textile enterprise operational performance.

The proposed model provides a practical decision-support tool for textile enterprises to identify performance gaps and prioritize improvement strategies. Enhancing equipment utilization, reducing defects, and improving energy efficiency are critical pathways for strengthening competitiveness and sustainability in textile manufacturing.

Future research may extend the indicator system by incorporating digitalization and supply chain integration factors and applying advanced decision-making approaches to improve evaluation accuracy and applicability.

#### *Author Contributions*

Shilong Xin designed, collected and analyzed the data, and drafted the manuscript. Shilong Xin conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Shilong Xin participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

#### *Conflict of Interest*

The author declares no conflict of interest.

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