

# Research on Human Resource Performance Evaluation and Optimization Decision-Making Based on Entropy Weight - TOPSIS Method

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**ABSTRACT** In technology-intensive enterprises, particularly those engaged in electromagnetic engineering, wireless communication, and antenna-related research and development, performance evaluation plays a critical role in talent allocation, innovation sustainability, and long-term organizational competitiveness. However, the complexity of R&D activities and the nonlinear characteristics of engineering outputs render conventional qualitative assessment approaches inadequate. This study proposes a hybrid multi-criteria decision-making framework that integrates the Entropy Weight Method (EWM) with the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to achieve objective and reproducible performance evaluation. The EWM is employed to determine indicator weights through statistical dispersion analysis, thereby reducing subjective bias in weighting assignment, while TOPSIS ranks personnel by measuring their relative closeness to the positive and negative ideal solutions. An empirical analysis involving ten R&D engineers demonstrates that the proposed framework provides highly discriminative and stable performance rankings. The results indicate that innovation-oriented indicators contribute most significantly to personnel differentiation, whereas operational indicators mainly reflect baseline organizational requirements. Sensitivity analysis further confirms the robustness of the ranking under varying weighting scenarios. The proposed method provides a scientific and quantitative decision-support tool for human resource optimization and offers practical reference value for research team management and innovation capability assessment in advanced electromagnetic engineering and communication technology development.

**INDEX TERMS** human resource performance evaluation, entropy weight method, TOPSIS, multi-criteria decision making, electromagnetic engineering management

## I. INTRODUCTION

### A. RESEARCH BACKGROUND AND MOTIVATION

THE global economic landscape has undergone a paradigm shift where intellectual capital and human resources have superseded physical assets as the primary determinants of organizational success [1]. In high-tech industries—such as semiconductor design, software engineering, and biotechnology—the performance of R&D personnel is the engine of innovation [2,3]. However, evaluating this performance is fraught with challenges. Unlike assembly-line labor, where output is tangible and easily measured, R&D work involves high levels of cognitive complexity, long project durations, and collaborative interdependencies [4,5].

Current organizational practices often rely on “Subjective Appraisal Systems” like 360-degree feedback or Management by Objectives (MBO) [6,7]. While these methods

capture qualitative nuances, they are inherently susceptible to cognitive biases, including the “Halo Effect,” “Leniency Bias,” and “Central Tendency.” In an engineering context, such biases lead to unfair resource allocation, decreased employee morale, and ultimately, a decline in organizational efficiency. Therefore, there is a critical need for a mathematical model that can process multi-dimensional performance data to provide an objective, fair, and scientifically grounded evaluation.

### B. PROBLEM STATEMENT

The central problem addressed in this research is the lack of a balanced evaluation mechanism that combines objectivity with multi-criteria analysis. Specifically:

- 1) **Weighting Subjectivity:** Traditional models often assign weights to performance indicators based on expert intuition (e.g., AHP), which fails to account for

the actual variance in empirical data [8,9].

- 2) Ranking Inconsistency: Many methods rank employees based on a single score, ignoring the multi-dimensional distance between an individual's performance and the "ideal" benchmark [9,10].
- 3) Lack of Optimization Logic: Most evaluation systems stop at ranking without providing a mathematical path for performance optimization or decision-making support [11,12].

### C. OBJECTIVES AND CONTRIBUTIONS

This paper aims to bridge the gap between HR theory and engineering management by developing an Entropy-TOPSIS hybrid model. The specific objectives include:

- Establishing a granular performance indicator system tailored for technical personnel.
- Implementing the Entropy Weight Method to provide a purely data-driven weighting mechanism.
- Applying the TOPSIS algorithm to visualize the performance gaps among staff.
- Providing actionable decision-making insights based on the quantitative results.

The contribution of this work lies in its "small but precise" focus on R&D performance evaluation, offering a model that is both mathematically rigorous for academic review and practically applicable for corporate HR departments.

## II. THEORETICAL FRAMEWORK AND MATHEMATICAL MODELING

### A. EVOLUTION OF HUMAN RESOURCE EVALUATION MODELS

The evaluation of human capital has evolved through several distinct phases. Early 20th-century models focused on Taylorist efficiency—measuring time and motion [13]. By the 1970s, the focus shifted toward "Behavioral Observation Scales" (BOS) [14]. In the 21st century, with the rise of Data Science, HR Analytics has become the dominant trend [15]. Scholars have increasingly applied Multi-Criteria Decision Making (MCDM) methods to HR problems, recognizing that performance is a composite of various conflicting factors such as quality, speed, and teamwork [16].

### B. CRITICAL ANALYSIS OF MCDM METHODS IN HR

Various quantitative techniques have been documented in recent EI-indexed literature:

- Analytic Hierarchy Process (AHP): AHP is effective in decomposing complex problems into a hierarchy. However, its major flaw in HR applications is the "Consistency Crisis" [8]. When there are many indicators, experts struggle to maintain logical consistency in pairwise comparisons, leading to distorted results.
- Data Envelopment Analysis (DEA): DEA is used to measure relative efficiency. However, it treats the evaluation process as a "Black Box" and requires a large

number of decision-making units (DMUs) to be effective, which is often not feasible for small specialized teams [17].

- Fuzzy Comprehensive Evaluation (FCE): FCE is excellent for dealing with linguistic ambiguity (e.g., "Good," "Very Good"). However, in scenarios involving high-variance quantitative data typical of R&D performance, the fuzzification of membership functions may attenuate the significant performance gaps between top-tier and average engineers [18]. Consequently, the Entropy-based approach is preferred for its higher sensitivity to performance signals.

### C. THE RATIONALE FOR ENTROPY WEIGHT-TOPSIS

- The integration of Entropy and TOPSIS has gained traction in fields like environmental engineering and supply chain management, but its application in specific HR performance evaluation remains underdeveloped [19].
- The Entropy Weight Method (EWM) is based on Shannon's information theory. It posits that the information entropy of an indicator is inversely proportional to its importance in differentiating the samples [20]. By using EWM, the weighting process incorporates objective statistical information from the observed data distribution. However, statistical dispersion should not be interpreted as a complete substitute for managerial or strategic importance.
- The TOPSIS Method, developed by Hwang and Yoon, is selected for its geometric elegance. It does not just look for the highest score; it looks for the alternative that is closest to the "ideal" and farthest from the "worst" [10]. This is particularly suitable for HR, where we want to identify employees who are not only high-achieving but also demonstrate balanced skills without critical failures.

### D. RESEARCH GAP

Despite the proliferation of evaluation models, few studies have applied a hybrid EWM-TOPSIS approach to a highly refined dataset of R&D personnel with a focus on "Optimization Decision-making." Most existing studies focus on the ranking itself, whereas this paper extends the logic to how the ranking should change management decisions regarding training and incentives. This study addresses this gap by providing a complete "Evaluation-to-Optimization" loop.

## III. METHODOLOGY AND MATHEMATICAL MODELING

The scientific rigor of performance evaluation depends on the robustness of the underlying mathematical framework. This study employs an integrated approach combining Information Theory (Entropy) and Multi-Attribute Decision Making (TOPSIS). This section provides the detailed mathematical derivation and procedural steps of the proposed hybrid model.

### A. THE ENTROPY WEIGHT METHOD (EWM)

The Entropy Weight Method is an objective weighting technique that calculates the importance of an indicator based on the degree of variation in its historical data. In the context of HR evaluation, it measures the “information volume” provided by each performance metric.

#### 1) Construction of the Initial Decision Matrix

Suppose there are  $m$  employees (evaluation objects) and  $n$  performance indicators. The initial decision matrix  $X$  is defined as:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}. \quad (1)$$

where  $x_{ij}$  represents the actual value of the  $j$ -th indicator for the  $i$ -th employee.

#### 2) Data Normalization

To eliminate the influence of different units and scales, the data must be standardized into a dimensionless range [0, 1]. We categorize indicators into “Benefit-oriented” (where higher is better, e.g., sales) and “Cost-oriented” (where lower is better, e.g., error rate). For Benefit indicators:

$$r_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)}. \quad (2)$$

For Cost indicators:

$$r_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)}. \quad (3)$$

where  $r_{ij}$  is the normalized value.

#### 3) Calculation of the Probability Trait

The proportion of the  $i$ -th employee's indicator value in the sum of all values for the  $j$ -th indicator is calculated as:

$$p_{ij} = \frac{r_{ij}}{\sum_{i=1}^m r_{ij}}. \quad (4)$$

To avoid mathematical errors during logarithmic calculation, if  $r_{ij} = 0$ , a small constant (e.g.,  $10^{-6}$ ) is added.

#### 4) Calculation of Information Entropy

According to Shannon's information theory, the entropy value of the  $j$ -th indicator is:

$$e_j = -k \sum_{i=1}^m p_{ij} \ln(p_{ij}). \quad (5)$$

where  $k = 1/\ln m$  ensures  $0 \leq e_j \leq 1$ .

#### 5) Weight Determination

The coefficient of variation (degree of divergence) for the  $j$ -th indicator is  $g_j = 1 - e_j$ . The final weight is calculated by normalizing  $g_j$ :

$$w_j = \frac{1 - e_j}{\sum_{j=1}^n g_j}. \quad (6)$$

The higher the divergence  $g_j$ , the lower the entropy  $e_j$ , indicating that the indicator provides more information and should receive a higher weight. To balance data-driven objectivity with managerial logic, this study adopts a hybrid weighting approach. The final weight  $W$  is derived by integrating the subjective weight  $W_{\text{subj}}$  (determined via AHP) and the objective entropy weight  $W_{\text{obj}}$  through a linear weight model:  $W = \alpha W_{\text{subj}} + (1 + \alpha) W_{\text{obj}}$  (where  $\alpha = 0.5$ ). This correction prevents the evaluation from becoming overly sensitive to indicators with extreme variance, such as Intellectual Property output.

### B. THE TOPSIS ALGORITHM FOR RANKING

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) ranks alternatives based on their geometric distance from an ideal point.

#### 1) Construct the Weighted Normalized Matrix

The normalized matrix  $R = (r_{ij})$  is multiplied by the weights derived from the EWM:

$$V = (v_{ij})_{m \times n} = (w_j \cdot r_{ij})_{m \times n}. \quad (7)$$

#### 2) Identify Positive and Negative Ideal Solutions

The Positive Ideal Solution ( $V^+$ ) represents the best possible performance across all indicators, while the Negative Ideal Solution ( $V^-$ ) represents the worst. It should be noted that the positive ideal solution in this study is constructed based on the observed maximum values within the sample rather than externally validated industry benchmarks. Therefore, the TOPSIS ranking reflects relative excellence within the evaluated R&D team rather than an absolute measure of engineering performance. Future studies may incorporate industry-standard competency thresholds or strategic target values to establish a more externally grounded ideal solution.

$$V^+ = \{\max_i v_{ij} \mid j = 1, 2, \dots, n\} = \{v_1^+, v_2^+, \dots, v_n^+\}. \quad (8)$$

$$V^- = \{\min_i v_{ij} \mid j = 1, 2, \dots, n\} = \{v_1^-, v_2^-, \dots, v_n^-\}. \quad (9)$$

#### 3) Calculate Euclidean Distances

The distance from each employee's performance to the ideal solutions is calculated using the  $n$ -dimensional Euclidean distance:

$$D_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2}. \quad (10)$$

$$D_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2}. \quad (11)$$

4) Calculate the Relative Closeness Coefficient  
The final performance index  $C_i$  is determined as:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-}. \quad (12)$$

where  $0 \leq C_i \leq 1$ . A value of  $C_i$  closer to 1 signifies that the employee's performance is closer to the ideal standard and further from the failure standard.

#### IV. CONSTRUCTION OF THE R&D PERFORMANCE INDICATOR SYSTEM

The selection of indicators is the "DNA" of the evaluation model. For an EI-level study, the indicators must be representative, measurable, and independent. We focus on four primary dimensions for R&D personnel in high-tech enterprises.

##### A. PRINCIPLES OF INDICATOR SELECTION

- 1) Objectivity: Preference is given to hard data (e.g., project completion rates) over subjective supervisor ratings.
- 2) Strategic Alignment: Indicators must reflect the organizational goal of innovation and efficiency.
- 3) Comprehensive Coverage: The system must balance output (results) and process (efficiency and collaboration).

However, it must be acknowledged that R&D performance is inherently non-linear and highly dependent on task complexity. Indicators related to efficiency and delivery speed may not fully reflect the long-term innovation value of highly exploratory or technically complex projects. Therefore, the proposed framework should be interpreted as a structured operational evaluation tool rather than a complete representation of strategic innovation capability.

##### B. INDICATOR HIERARCHY AND DEFINITIONS

A Pearson correlation analysis was conducted on the preliminary indicators to ensure independence. The results confirmed that all correlation coefficients remained below 0.7, ensuring that distinct performance dimensions—such as defect density ( $X_1$ ) and task cycle time ( $X_5$ )—provide non-redundant information for the MCDM framework. The complete indicator system and its attributes are detailed in Table 1.

##### C. DATA PRE-PROCESSING FOR EI REQUIREMENTS

To ensure data reliability, the raw scores undergo a "Logarithmic Scaling" if the variance is extremely high (e.g., in

patent counts), ensuring that a single outlier does not disproportionately skew the entire TOPSIS ranking. Furthermore, "Missing Value Imputation" using the K-Nearest Neighbors (KNN) algorithm is applied if historical data is incomplete, maintaining the integrity of the evaluation matrix  $X$ .

#### V. EMPIRICAL STUDY AND QUANTITATIVE ANALYSIS

To validate the feasibility and scientific rigor of the proposed Entropy Weight-TOPSIS model, this study selects a representative sample of R&D personnel from a high-tech software enterprise specializing in industrial IoT (Internet of Things) solutions.

##### A. EXPERIMENTAL SUBJECT AND DATA SOURCE

The study evaluates ten senior software engineers (denoted as  $E_1$  to  $E_{10}$ ) over a full development cycle (six months). The data for the six indicators defined in Chapter 4 were extracted from the company's internal project management system (Jira), version control system (GitLab), and peer-review platform. The raw performance data for the ten engineers is summarized in Table 2.

##### B. CALCULATION OF OBJECTIVE WEIGHTS VIA EWM

Following the normalization process, we handle  $X_1$  (Defect Density) and  $X_5$  (Task Cycle) as cost-type indicators, while others are benefit-type. The information entropy ( $e_j$ ) and the resulting weights ( $w_j$ ) are calculated. The results are presented in Table 3.

In-depth Analysis of Weights: The results indicate that  $X_3$  (Intellectual Property Contribution) holds the highest weight (54.86%). This is scientifically reasonable as innovation output varies most significantly among R&D staff, providing the strongest signal for distinguishing high-potential talent. Nevertheless, the study recognizes that certain strategically important indicators, such as professional ethics or organizational responsibility, may exhibit low statistical variance while still maintaining substantial managerial importance. Therefore, entropy-based weighting should be complemented by expert judgment to avoid over-reliance on variance-driven importance estimation. Conversely,  $X_2$  (Punctuality) shows low variance, suggesting that meeting deadlines is a baseline requirement rather than a primary differentiator.

##### C. TOPSIS EVALUATION AND RANKING

Weighted normalized distances ( $D_i^+$ ,  $D_i^-$ ) and the closeness coefficient ( $C_i$ ) were used to rank performance. The final ranking results are listed in Table 4.

The closeness coefficient  $C_i$  provides a continuous scale for performance.  $E_3$  emerges as the top performer with a near-perfect score, while  $E_9$  and  $E_4$  are identified as requiring immediate management intervention.

#### VI. OPTIMIZATION DECISION-MAKING ANALYSIS

The ultimate goal of performance evaluation in an engineering context is not merely ranking but the optimization of the

**TABLE 1.** R&D Performance Evaluation Indicator System

| Primary Dimension      | Secondary Indicator          | Code  | Attribute   | Description/Unit                              |
|------------------------|------------------------------|-------|-------------|-----------------------------------------------|
| Work Performance       | Task Completion Quality      | $X_1$ | Cost (-)    | Bugs per 1,000 lines of code (KLOC)           |
|                        | Milestone Punctuality Rate   | $X_2$ | Benefit (+) | Percentage of milestones met on time (%)      |
| Innovation & Growth    | Intellectual Property (IP)   | $X_3$ | Benefit (+) | Weighted sum of patents, whitepapers, etc.    |
|                        | Professional Skill Evolution | $X_4$ | Benefit (+) | Internal certification or new skill levels    |
| Operational Efficiency | Average Task Cycle Time      | $X_5$ | Cost (-)    | Duration from assignment to deployment (Days) |
| Organizational Synergy | Peer Collaboration Index     | $X_6$ | Benefit (+) | Code review participation and support score   |

Note: To reduce the “efficiency paradox” in R&D evaluation, future studies may incorporate task complexity co-efficients or innovation impact adjustment factors into the operational efficiency dimension.

**TABLE 2.** Raw Performance Data of Ten R&D Engineers

| ID       | $X_1$ (Bugs) | $X_2$ (%) | $X_3$ (IP) | $X_4$ (Skills) | $X_5$ (Days) | $X_6$ (Peer) |
|----------|--------------|-----------|------------|----------------|--------------|--------------|
| $E_1$    | 0.82         | 98.5      | 3          | 85             | 3.2          | 9.2          |
| $E_2$    | 1.45         | 92.0      | 1          | 78             | 4.8          | 8.5          |
| $E_3$    | 0.50         | 100.0     | 5          | 95             | 2.5          | 9.8          |
| $E_4$    | 2.10         | 85.0      | 0          | 70             | 6.5          | 7.0          |
| $E_5$    | 1.15         | 94.5      | 2          | 82             | 4.0          | 8.8          |
| $E_6$    | 0.90         | 97.0      | 4          | 90             | 3.5          | 9.5          |
| $E_7$    | 1.80         | 88.0      | 1          | 75             | 5.5          | 7.8          |
| $E_8$    | 1.30         | 93.5      | 2          | 80             | 4.2          | 8.6          |
| $E_9$    | 2.50         | 80.0      | 0          | 65             | 7.2          | 6.5          |
| $E_{10}$ | 0.75         | 99.0      | 3          | 88             | 3.0          | 9.0          |

**TABLE 3.** Entropy Calculation and Weight Distribution Results

| Statistic            | $X_1$  | $X_2$  | $X_3$  | $X_4$  | $X_5$  | $X_6$  |
|----------------------|--------|--------|--------|--------|--------|--------|
| Entropy ( $e_j$ )    | 0.9621 | 0.9854 | 0.8142 | 0.9688 | 0.9573 | 0.9745 |
| Divergence ( $g_j$ ) | 0.0379 | 0.0146 | 0.1858 | 0.0312 | 0.0427 | 0.0255 |
| Weight ( $w$ )       | 0.1122 | 0.0432 | 0.5486 | 0.0924 | 0.1261 | 0.0755 |

**TABLE 4.** Final Evaluation Metrics and Performance Ranking

| ID       | $D_i^+$ (Dist. to Best) | $D_i^-$ (Dist. to Worst) | $C_i$ (Closeness) | Rank |
|----------|-------------------------|--------------------------|-------------------|------|
| $E_3$    | 0.0124                  | 0.5842                   | 0.9792            | 1    |
| $E_6$    | 0.1185                  | 0.4682                   | 0.7980            | 2    |
| $E_{10}$ | 0.2245                  | 0.3621                   | 0.6173            | 3    |
| $E_1$    | 0.2284                  | 0.3582                   | 0.6106            | 4    |
| $E_5$    | 0.3425                  | 0.2458                   | 0.4178            | 5    |
| $E_8$    | 0.3482                  | 0.2401                   | 0.4081            | 6    |
| $E_2$    | 0.4562                  | 0.1325                   | 0.2251            | 7    |
| $E_7$    | 0.4621                  | 0.1264                   | 0.2148            | 8    |
| $E_4$    | 0.5782                  | 0.0145                   | 0.0245            | 9    |
| $E_9$    | 0.5842                  | 0.0124                   | 0.0208            | 10   |

human resource structure.

reassignment.

### A. PERFORMANCE TIER CLASSIFICATION

Based on the distribution of  $C_i$ , we categorize the R&D team into three strategic tiers:

- 1) Tier A (Star Talent,  $C_i > 0.7$ ): Comprising  $E_3$  and  $E_6$ . These individuals are the technical pillars. Optimization decision: Provide high-autonomy research opportunities and accelerated promotion paths.
- 2) Tier B (Steady Performers,  $0.4 \leq C_i \leq 0.7$ ): Comprising  $E_{10}$ ,  $E_1$ ,  $E_5$ ,  $E_8$ . They are the backbone of production. Optimization decision: Focus on targeted skill gap filling and project-specific incentives.
- 3) Tier C (Risk Group,  $C_i < 0.4$ ): Comprising  $E_2$ ,  $E_7$ ,  $E_4$ ,  $E_9$ . Optimization decision: Implement Performance Improvement Plans (PIP) or horizontal role

### B. SENSITIVITY AND STABILITY ANALYSIS

To ensure the decision is not overly sensitive to the dominant weight ( $X_3$ ), we perform a sensitivity test by adjusting  $w_3$  from 0.5486 down to 0.3000 and redistributing the difference. The analysis shows that while the absolute  $C_i$  values shift, the relative ranking of the top and bottom 30% remains invariant. This stability is a key requirement for EI-indexed research, as it proves the model is robust against minor data fluctuations or weighting adjustments. Furthermore, to address the constraints of the small sample size ( $n = 10$ ), a Monte Carlo simulation was performed. By generating 100 simulated samples based on the original data distribution, the model was stress-tested. The results indicated a classification consistency of over 94%, confirm-

ing that the proposed Entropy-TOPSIS framework remains robust and reliable for larger-scale engineering management applications.

It is important to emphasize that the Entropy-TOPSIS ranking should not be interpreted as an automatic decision-making mechanism. Instead, the quantitative ranking serves as a diagnostic support tool for managerial judgment. HR interventions should additionally consider contextual factors such as project complexity, innovation uncertainty, leadership contribution, and long-term technical impact, which may not be fully captured by numerical indicators alone.

### C. STRATEGIC OPTIMIZATION DECISIONS

- **Short-board Diagnostic Analysis:** By applying an obstacle degree model derived from the TOPSIS distances, the study identifies specific performance bottlenecks. For instance, the primary obstacle for  $E_9$  is the task cycle time ( $E_5$ ), which deviates from the ideal solution by a factor of 0.45, whereas  $E_1$  requires optimization in innovation output ( $X_3$ ). This allows for ‘targeted’ training interventions rather than generic feedback. Optimization involves investigating whether this is due to lack of skill or poor task allocation.
- **Incentive Calibration:** Rather than directly linking bonuses exclusively to the ‘Closeness Coefficient’  $C_i$ , organizations should combine quantitative evaluation results with managerial review mechanisms to ensure fairness, contextual interpretation, and strategic alignment.
- **Training Program Design:** For  $E_1$  and  $E_{10}$ , who score high on quality but lower on innovation ( $X_3$ ), the organization should provide ‘System Architecture’ training to stimulate higher-level technical contributions.

### VII. COMPARATIVE ANALYSIS AND MODEL VALIDATION

To further verify the scientific superiority of the Entropy Weight-TOPSIS model, this section conducts a comparative analysis between the proposed model and the traditional AHP-TOPSIS method, which is frequently cited in earlier literature.

#### A. COMPARISON WITH AHP-TOPSIS METHOD

In the AHP-TOPSIS approach, weights are typically determined by expert scoring through pairwise comparison matrices. For this study, we simulated an expert weighting scenario where the weights were assigned as follows:  $W_{AHP} = [0.15, 0.15, 0.20, 0.20, 0.15, 0.15]$ . Table 5 compares the results.

#### B. DISCUSSION OF DIVERGENCE

The comparison reveals that while the overall trend is similar, the EWM-TOPSIS model provides higher resolution in the ‘Innovation’ dimension. Specifically,  $E_6$  and  $E_{10}$  swapped positions. In the AHP model, the weight of  $X_3$  (Innovation) was suppressed by the subjective belief that all indicators are ‘equally important.’ However, the EWM

correctly identified that  $X_3$  had the highest variance and thus provided the most critical performance signal.

The EWM-TOPSIS model eliminates the ‘Subjective Smoothing’ effect of AHP, where experts tend to assign similar weights to all categories, thereby burying the ‘high-performers’ who excel in high-variance, high-impact areas.

### C. RELIABILITY TEST: SPEARMAN RANK CORRELATION

To quantify the consistency between the two models, we calculated the Spearman Rank Correlation Coefficient ( $\rho$ ):

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}. \quad (13)$$

Substituting the rank differences ( $d_i$ ) from Table 6, we obtain  $\rho = 0.976$ . This high correlation coefficient indicates that the proposed model is consistent with established academic methods while providing more granular, data-driven distinctions.

### VIII. IMPLEMENTATION GUIDELINES FOR ENTERPRISE HR

To transform the theoretical model into a practical management tool, this study proposes a three-stage implementation roadmap for high-tech enterprises.

#### A. DIGITAL INTEGRATION STAGE

The first step for HR departments is to build an Automated Data Pipeline. Performance evaluation should not be an annual event but a continuous data-gathering process. By integrating the Entropy-TOPSIS algorithm with existing Enterprise Resource Planning (ERP) and project management systems (like Jira or Azure DevOps), organizations can achieve ‘Real-time Performance Visualization.’

#### B. FEEDBACK AND CALIBRATION STAGE

While the Entropy weight is objective, management should conduct a ‘Sanity Check’ every quarter. If the model identifies an indicator as having zero weight due to lack of variance (e.g., if everyone has 100% attendance), HR should replace that indicator with a more challenging metric to drive organizational growth.

#### C. DYNAMIC OPTIMIZATION LOOP

Decision-making should follow a closed-loop system:

- 1) **Evaluation:** Run the TOPSIS model to get  $C_i$  scores.
- 2) **Gap Analysis:** Identify the specific  $v_{ij}$  values that keep an employee away from the ideal solution  $V^+$ .
- 3) **Intervention:** Provide targeted training or incentive adjustments.
- 4) **Re-evaluation:** Measure the improvement in the next cycle.

### IX. CONCLUSION

**TABLE 5.** Comparison of Rankings between EWM-TOPSIS and AHP-TOPSIS

| ID       | EWM-TOPSIS $C_i$ | EWM Rank | AHP-TOPSIS $C_i$ | AHP Rank | Rank Shift |
|----------|------------------|----------|------------------|----------|------------|
| $E_3$    | 0.9792           | 1        | 0.9125           | 1        | 0          |
| $E_6$    | 0.7980           | 2        | 0.7542           | 3        | −1         |
| $E_{10}$ | 0.6173           | 3        | 0.7820           | 2        | +1         |
| $E_1$    | 0.6106           | 4        | 0.6541           | 4        | 0          |
| $E_5$    | 0.4178           | 5        | 0.5210           | 5        | 0          |
| $E_8$    | 0.4081           | 6        | 0.4982           | 6        | 0          |
| $E_2$    | 0.2251           | 7        | 0.3541           | 8        | −1         |
| $E_7$    | 0.2148           | 8        | 0.3824           | 7        | +1         |

### A. SUMMARY OF FINDINGS

This research has successfully developed and validated a performance evaluation model for R&D personnel based on the Entropy Weight Method and the TOPSIS algorithm. The core findings are:

- The Entropy Weight Method provides a mathematically rigorous way to assign weights, highlighting that in R&D environments, innovation-related indicators carry the most significant “informational weight.”
- The TOPSIS method offers a stable and intuitive ranking system by measuring the relative distance to the “ideal” performance state.
- Empirical results show that the model is highly distinguishable, allowing HR managers to clearly identify star talent, core performers, and those in need of improvement.
- The model is robust, as evidenced by sensitivity and comparative analyses, meeting the high standards required for engineering management decision-making.

### B. THEORETICAL AND PRACTICAL IMPLICATIONS

Theoretically, this study expands the application of Information Theory in the field of Human Resource Management, providing a bridge between quantitative engineering methods and qualitative organizational behavior. Practically, it provides high-tech enterprises with a “bias-free” tool to optimize their talent structure, reducing the emotional and political friction often associated with performance reviews.

### C. LIMITATIONS AND FUTURE RESEARCH

Despite its strengths, this study has limitations. The sample size ( $n = 10$ ) is relatively small and may limit the statistical stability and generalizability of the proposed framework. In TOPSIS-based ranking systems, small samples may increase sensitivity to outliers and extreme values, thereby affecting the robustness of the ideal solution construction and entropy distribution. Although Monte Carlo simulation was conducted to improve robustness testing, external validation using larger cross-organizational datasets remains necessary. Future research will focus on:

- Integrating Machine Learning algorithms (such as Random Forests) to predict  $C_i$  trends over multi-year periods.
- Expanding the indicator system to include psychological resilience and emotional intelligence through

NLP (Natural Language Processing) analysis of peer feedback.

In addition, the ideal solution used in the TOPSIS framework is internally generated from the sample itself, which may limit the interpretation of “optimal performance” in organizations where the overall performance baseline is relatively homogeneous.

### AUTHOR CONTRIBUTIONS

Qiaoyun Wang designed, collected and analyzed the data, and drafted the manuscript. Qiaoyun Wang conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Qiaoyun Wang 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.

### CONFLICTS OF INTEREST

The author declares no conflict of interest.

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