# Design & Algorithm Optimization for Talent Evaluation Management System of Skilled Higher Vocational Institutions under the New Dual-High Plan

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**Abstract: Under the New-Dual High Plan (2025-2029),the way colleges and universities evaluate skilled talent is being quietly recast away from crediting what a person has already accumulated, and toward weighing what they can still contribute going forward. This study investigates a framework for differentiated evaluation models targeting three types of talents: technological breakthrough and process improvement-oriented, technical service and promotion-oriented, and standard development and teaching transformation-oriented. A seven-dimensional evaluation indicator system is designed, encompassing demand responsiveness, problem-solving capability, service contribution, outcome transformation, standard development, educational feedback, and collaborative construction. Through data sample analysis and algorithmic optimization reasoning, the adaptability and superiority of AHP, TOPSIS, and GWO-KELM in the two core processes of scoring and prediction are demonstrated. Finally, a management information system covering six major modules talent profiling, ranking engine, trajectory prediction, task mapping, differentiated evaluation, and performance application is designed, forming a complete business circle from data collection to decision support.**

**Keywords: Indicator System; Scientific and Technological Talent Evaluation; AHP; TOPSIS; GWO-KELM**

## 1. Introduction

With the evolution of both domestic and international situations, China's higher vocational education faces new developmental requirements. Skill-oriented higher education institutions, with their richer connotations, are increasingly assuming a strategically important position within China's higher education system. Their core competitiveness is no longer teaching scale or program count; increasingly it rests on what their scientific and technological workforce actually delivers technological breakthroughs [1], outcome transformation, industrial services. Since the New Double High-Initiative launched in 2025, more institutions have moved scientific and technological service capacity into their core evaluation indicators, making explicit that vocational education should serve industrial upgrading and technological progress [2]. That move has, at root, reset the institutional environment and value compass against which scientific and technological talents at such institutions are judged.

Yet practice still trails the policy. Drawing on data collection, survey analysis, and online crawling, our team surveyed 23 Double High-Initiative construction institutions and found that roughly 76% of skill-oriented institutions still lean on evaluation frames built around academic metrics publication counts, project tiers, award titles. That frame sits awkwardly against the institutions' own positioning and talent mix [3–5], and the fallout runs in several directions. People doing technical service and industrial promotion get little institutional incentive, because their outputs rarely register inside a traditional frame. The system also reads development poorly: annual and contract-term reviews are essentially retrospective, offering little forward guidance for how a talent should grow. Beneath both lies a lag in technique. Judging a scientific and technological talent means weighing heterogeneous information across research, teaching, and industrial service; the manual review still in use averages about 18 minutes per person not only slow, but easily bent by subjective bias [6,7].

These are the pain points which this paper sets out to address, and it does so as a connected solution rather than a single fix. Section 2 works from institutional logic to set out the direction and business requirements for evaluating scientific and technological talents at skill-oriented institutions under the New Double High-Initiative. Section 3 moves to theory, building an indicator system and a weight scheme that fits the differing needs of the three talent types. Section 4 turns to algorithm level: it demonstrates the adaptability and superiority of AHP-TOPSIS and GWO-KELM in the two core links of scoring and prediction. Section 5 takes an engineering view and lays out a deployable system architecture. Section 6 puts the design against experimental data, and Section 7 closes.

## 2. Ease of Use

### 2.1 From Stock Recognition to Incremental Contribution: A Deep Transformation of Evaluation Orientation

In its policy design, the first Double High-Initiative reads more like a stock assessment. The evaluation logic clusteres around what an institution already has existing educational foundations, flagship achievements, overall conditions. Metrics such as technical-service income, enterprise-training scale, and the dual-teacher ratio does enter the data collection, but they mostly describe standing capability rather than forecasting future contribution. Look at as institutional evolution, a stock-oriented model of this kind makes sense at the construction stage: it helps locating and locking in the resources in hand. The New Double High-Initiative breaks with that logic [8,9]. Two dimensions recur through its policy documents alignment with social demand, and the effectiveness of outcome contribution and the signal is clear: evaluation is sliding from retrospective statistics toward forward-looking identification [10].

For the individual scientific and technological talent, this means the system has to tell apart incremental gains in work effectiveness, not just total up output quantities [10]. Our team's time-series work on scientific and technological talent data from ten Double High-Initiative institutions, covering 2020–2024 and build again from data collection, survey analysis, and online crawling, for about 62% of talents the total research output held steady, yet the coefficient of variation in the annual growth rate of their technical-service income ran as high as 0.47. A cross-section, in other words, cannot show on its own capture how a talent's contribution actually moves. The finding shapes how the Double High-Initiative task-mapping module designing inside the architecture: it has to carry task decomposition top-down and contribution aggregation bottom-up at the same time, so that the two directions could form a single bidirectional data channel.

### 2.2 Classification Logic for Three Talent Types

Inside the industry-education integration ecosystem, the scientific and technological workforce at skill-oriented institutions sorts into three basic types by different roles: type of technological break through and process improvement-oriented; type of technical service and promotion-oriented; type of standard development and teaching transformation-oriented. They are not interchangeable. The first type works deep on enterprise production lines, dissolving concrete technical problems in equipment operation and process optimization; their deliverables are mostly technical solutions and improvement reports written for partner enterprises, on cycles that typically run three to six months. The second type carries the industry-facing load technical consulting, testing and diagnostics, promotion of new technology and their value shows up in service coverage and customer satisfaction. The third type turns technical experience and job standards into reproducible industry standards and training resources; from project initiation to release the cycle usually takes fourteen to eighteen months, which easily lag behind in evaluation. Through system design, these differential requirements are dynamically switched through weight templates and the rules for result recognition are flexibly configured.

### 2.3 Five Business Requirements for Closed-Loop Governance

The evaluation management system needs to meet the business requirements at five levels Multi-dimensional talent archiving requires to pull together the scattered records sitting in personnel, research, and teaching systems into one unified scientific and technological talent profile. Full-process outcome management requires to follow the whole chain, from needs assessment through delivery to application feedback. Task-contribution mapping requires to break institutional-level Double High-Initiative goals all the way down to the individual. Multi-stakeholder evaluation requires to embed layered review and permission control, so that enterprise experts, peer scholars, and administrators each work within their own evaluation authority. And application of resultsrequires to interoperate with personnel management, performance allocation, and professional-title review. The five demands point to one goal: to upgrade the evaluation system from a passive data collection tool to an active governance empowerment platform.

## 3. Using the Template

### 3.1 Four-Layer Structure of the Evaluation Model

The evaluation model proposed in this paper consists of four interconnected layers. The bottom-line constraint layer, located at the lowest level, is responsible for conducting preliminary reviews of red-line issues including teaching ethics, academic integrity, funding compliance, and intellectual property rights. Once any item on the negative list is triggered, the system automatically restricts the talent's evaluation grade for that year or suspends evaluation eligibility. The classification and identification layer is responsible for automatically matching the appropriate talent type and weight template based on the talent's job responsibilities, characteristics of outcome composition over the past three years, and historical classification records. The core evaluation layer employs the seven-dimensional indicator framework to conduct quantitative assessments of talent contributions, representing the main body of the evaluation process. The result validation layer performs cross-validation of preliminary evaluation results using multi-source information including enterprise feedback, financial data, and subsequent impact, preventing material-driven evaluation distortion. Run end to end, the four layers form a standardized pipeline review, classification, scoring, validation and every step along it stays traceable and verifiable.

### 3.2 Detailed Explanation of the Seven-Dimensional Indicator System

The seven dimensions demand responsiveness, problem-solving capability, service contribution, outcome transformation, standard development, educational feedback, and collaborative construction cover what a scientific and technological talent actually contributes. Demand responsiveness asks whether the work really starts from an industrial need. Problem-solving weighs whether a technical solution is workable and whether it closes the loop. Service contribution counts paid technical services but also credits the social value of public-benefit work. Outcome transformation keeps the two states outcome formed and outcome applied apart, and weights the second higher. Standard development watches how well technical experience gets standardized and exported. Educational feedback looks at how efficiently scientific and technological outcomes are turned into teaching resources and training projects. Collaborative construction reads how deep a talent sitting inside industry-education integration platforms and the surrounding organization. Each dimension is accompanied by 3 to 5 specific quantitative indicators and supporting material requirements to ensure the operability and traceability of the evaluation process Initial weights for the five criteria layers are calculated by collecting the judgment matrices of 15 experts through the AHP method. The CR values are all lower than 0.1, meeting the consistency checking standard.

## 4. Overall System Architecture and Functional Design

### 4.1 Technical Approach of the Five-Layer Architecture

The system is layered and decoupled. The basic data layer is connected to four heterogeneous sources the research management system, the academic affairs system, the outcome transformation platform, and the university-enterprise collaboration database through ETL tools that extract, clean, and standardize, processing about 2,500 incremental records per day. The business support layer provides forfull lifecycle of core objects: talents, projects, outcomes, standards, teaching transformation. The evaluation computation layer wraps three algorithmic engines AHP weight calculation, an improved TOPSIS evaluation, and GWO-KELM prediction and exposes them upward through standardized RESTful APIs, to support independent upgrade and replacement of algorithms The application presentation layer hands each role its own dashboard: institutional leaders, college administrators, research personnel, evaluation experts. The security governance layer runs through all levels and carries permission control, operational auditing, and data protection uniformly.

### 4.2 Core Logic of the Six Functional Modules

Of the six functional modules, the comprehensive ranking module and the classification evaluation module constitute the technical core of the system The ranking module runs a five-stage pipeline picking indicators, calling weights, standardizing data, computing the composite score, generating the grade. At the weight-call stage it auto-switches the judgment matrix to match the talent type that client identified. The classification evaluation module handles the initial type identification and its yearly adjustment, including three information sources which refresh per year: job-characteristic match (weight 0.4), outcome-structure similarity (weight 0.4), and consistency with past classification (weight 0.2 The "Double High" task mapping module connects the construction tasks at the school level with the individual achievements and contributions, serving as a key hub for evaluating the upgrade from tools to governance functions.

## 5. Core Algorithm Adaptation and Experimental Validation

### 5.1 Technical Requirements of the System for Algorithms

The technical requirements of the scientific and technological talent evaluation management system for underlying algorithms can be summarized into four core dimensions. In the comprehensive evaluation capability dimension, algorithms need to process hierarchical data structures derived from twenty observational indicators across five criteria layers while supporting the effective integration of domain expert experience. In the weight flexibility dimension, algorithms need the ability to dynamically switch weight templates at runtime based on talent type, and such switching should not negatively impact the ranking consistency of evaluation results. In the predictive capability dimension, algorithms need to achieve high-precision predictions of talent development potential under conditions of 342 training samples and 15-dimensional time-series features, with a target prediction accuracy of no less than 90%. In the interpretability dimension, the decision logic of evaluation results should be transparent and traceable to both Evaluation object and administrators.

### 5.2 Demonstration of AHP-Improved TOPSIS Adaptability

The AHP method shares a natural structural isomorphism with the three-tiered indicator system constructed in this paper, making the weight generation process fully consistent with the logical framework of the indicator system. Our research team conduct pairwise comparisons of the relative importance of the five criteria layers and twenty observational indicators using the 1–9 scale method. Fifteen sets of judgment matrices were constructed, all with consistency ratios (CR) below 0.1.

The opposite applies for cost-type criteria. Calculating Distances

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

$$D_i^- = \sqrt{\sum_{j=1}^{n}\left(\left(v_{ij} - v_j^-\right)^2\right)} \tag{2}$$

To address the reversal problem that occurs with traditional TOPSIS when the set of evaluation objects changes dynamically, this paper proposes adopting an absolute ideal solution to replace the relative ideal solution. The absolute positive ideal solution is defined as the vector of theoretical optimal values for each indicator across the entire evaluation space, unchanged by variations in the set of evaluation objects, thereby fundamentally eliminating the reversal phenomenon on a mathematical basis. Another improvement involves introducing the entropy weight method to adaptively adjust AHP subjective weights based on data characteristics. The entropy weight method calculates objective weights based on the degree of variation of each indicator within the sample data; the greater the degree of variation, the stronger the discriminatory power of the indicator, and the higher the assigned weight. The comprehensive weight is the normalized product of subjective and objective weights, incorporating both expert experience and data characteristics as information sources.

Using sample data points from ten Double High-Initiative institutions, our team performed Spearman rank correlation analysis between the ranking results of AHP-improved TOPSIS and those of institutional expert review panels. The average correlation coefficient was 0.917 (p < 0.001). Under five-fold cross-validation, this coefficient remained stable within the interval of 0.902 to 0.931, and no ranking reversal anomalies occurred, fully validating the effectiveness and reliability of this improved scheme.

### 5.3 Demonstration of GWO-KELM Adaptability

By bringing kernel-function mapping over from ELM, KELM swaps the random hidden-layer output matrix for a kernel matrix, which sharpens the model's adaptability considerably. The data of the research team in the case of predicting the development potential of scientific and technological talents has the following three characteristics: the few training samples (342); the moderate feature dimension (15); and the high noise level due to the subjectivity of manual scoring.

The optimization objective is to minimize the Root Mean Square Error (RMSE) on the training set:

$$fitness = \min_{C,\gamma}(RMSE) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \quad (3)$$

The RBF kernel function of KELM possesses good capability to capture the local structures of such data, making it a suitable candidate algorithm for this task scenario. However, the performance of KELM is sensitive to the values of the kernel parameter gamma and the regularization coefficient C. Traditional grid search methods for parameter tuning are inefficient in high-dimensional parameter spaces and prone to local optima. Concurrently employing the Grey Wolf Optimizer (GWO), which simulates the social hierarchy and collaborative hunting mechanisms of grey wolf packs, can achieve global optimization of gamma and C within thirty iterations.

## 6. Experimental Data Analysis and Visualization Validation

### 6.1 Description of Experimental Data and Analysis of GWO Convergence

Originating from technical means such as data collection, survey analysis, and online crawling, the data sources included four types of heterogeneous systems: research management systems (publication, project, and patent data), academic affairs management systems (teaching and competition outcomes), outcome transformation platforms (technology transfer and collaboration information), and university-enterprise collaboration databases (technical service and training records). The data preprocessing stage sequentially performed mean imputation for missing values, outlier detection and removal based on the 3σ principle (resulting in the removal of four anomalous samples), and Min-Max normalization standardization. The preprocessed valid sample set was randomly divided into a training set (239 samples) and a test set (103 samples) at a ratio of 7:3.

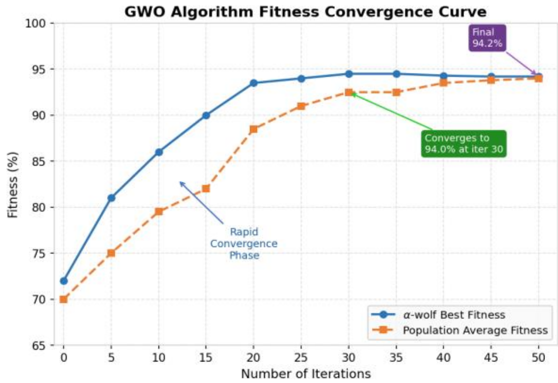


**Figure 1. GWO Algorithm Fitness Convergence Curve**

The behavioral trajectory of the GWO algorithm during the KELM hyperparameter optimization process is shown in Figure 1. The fitness of the alpha wolf (the current optimal individual) continuously increased from an initial state of 72.0%, experiencing a rapid climbing phase during the first fifteen iterations to reach 90.0%, followed by a slow fine-tuning phase, reaching approximately 93.5% by the 25th iteration and stabilizing at 94.2% by the 30th iteration. Seeing from the variation curve of the population's average fitness it rises in stepfrom the initial 70.0% to the final 93.4% As the iterations run, the gap between the two curves keeps narrowing which indicates the GWO algorithm could guide the convergence of the optimal individual and has a good driving effect on the evolution of the entire population as well. Three vertical dashed lines mark the stages respectively: the rapid-convergence window, the stable-convergence point, and the final convergence value.

Blue solid line: alpha wolf fitness; orange dotted line: population average fitness; convergence stabilizes at 30 iterations.

### 6.2 Comparative Analysis of Model Performance

Figure 2 lines up the five candidate models on the same test set. GWO-KELM ranks first at 93.4% accuracy, creating 4.3 percentage points comparing to the second-ranked manually adjusted parameter KELM (89.1%) this gap is directly attributed to GWO's global optimization of the kernel parameters and the regularization coefficient. From the perspective of error indicators, GWO-KELM posts an MAE of 0.062, the lowest in the field, means its predictions stands closest to the true values on average. Its RMSE of 0.098 cuts 47.6% off the BP neural network's 0.187. On the composite F1-score it leads again at 0.924. The performance gradient shows a clear regularity: the increase from kernel-function mapping (2.2 percentage points from ELM to KELM) and the increase from hyperparameter optimization (4.3 percentage points from KELM to GWO-KELM) have formed a superimposed effect, verifying the scientific nature of the algorithm combination scheme in this paper.

### 6.3 System Architecture Design

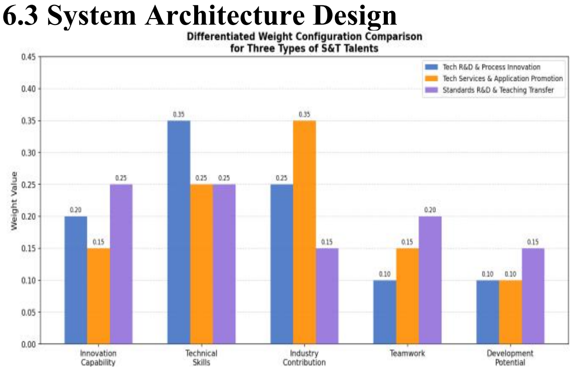


**Figure 2. Differentiated Weight Configurations across the Three Talent Types**

At the bottom, the basic data layer runs ETL tools to clean, transform, and standardize the four heterogeneous sources. On the second layer, the core computation layer wraps three engines AHP weight calculation, improved TOPSIS evaluation, GWO-KELM prediction coordinating through standardized data interfaces. On top, providing system application functions for different roles including six funtionalmodules: talent profiling, comprehensive ranking, trajectory prediction, task mapping, differentiated evaluation, performance application. The different layers interact each other through a RESTful API gateway, which keeps coupling down the degree of hierarchical coupling, enhancing the robustness of the system, and ensuring the security and auditability of data transmission at the same time.

### 6.4 Comparison of Differentiated Weights for Three Talent Types and Functional Indicator Mapping Analysis

Technological breakthrough-oriented talents carry their heaviest weight on technical skills (0.35), followed by industrial contribution (0.25); the sum of the two take 60% of the total, in consistent with its positioning of taking on-site technical breakthroughs as the core responsibility. Technical service-oriented talents have the highest weight (0.35) on the dimension of industrial contribution, followed by technical skills (0.25) reflecting the responsibility characteristics of the service-and-promotion orientation. Standard development-oriented talents spread more in balance: innovation capability (0.25) and team collaboration (0.20) are both higher than the other two types, which is in line with the collaborative innovation characteristics required for standard development work. Once normalized, all three sets satisfy $\Sigma\omega = 1$, ensuring the fairness of cross-type comparison. The comprehensive ranking and differentiated evaluation modules bind strongly to all five dimensions (association strength no less than 4.0), covering widest in the system. The development-trajectory prediction module ties most tightly to the development-potential dimension (5.0), while its pull on the other four stays low (no more than 2.0) consistent with a module aimed at time-series data. The Double High-Initiative task-mapping module shows a strong correlation in the two dimensions of industrial contribution and team collaboration (4.5 and 4.0), reflecting its unique functional positioning as a bridge connecting between institutional strategy and individual outcome. Generally, the heat matrix provides a quantitative steer on direction of system function optimization.

### 6.5 System Performance Metrics

In performance testing, the full single-person evaluation ran, on average, in 3.2 seconds about 0.4 seconds to load and standardize data, 0.3 seconds for the AHP weight query, 1.1 seconds for the improved TOPSIS calculation, 1.2

seconds for the GWO-KELM prediction, and 0.2 seconds to render the result. Against the manual method (roughly 18 minutes per person), it has achieved an efficiency improvement of approximately 337 times in comparison.. A batch test of 500 clears in 14.8 minutes, with a throughput of 2,027 persons per hour, exceeding the design target of 1,800 people per hour. Under 50 concurrent users the average response held at 0.8 seconds with a 95th-percentile of 1.5 seconds, so the system ran steady.

## 7. Conclusion and Future Directions

Starting from the policy transformation of the New Double High-Initiative, this study works through the topic of evaluating scientific and technological talents in skill-oriented universities that is both theoretically deep and practically worth doing The work runs along four lines building the evaluation model, designing the indicator system, planning the system architecture, and fitting intelligent algorithms to the task. At the theoretical level, a logical framework for differentiated evaluation of three talent types and a quantitative scheme for the seven-dimensional indicator system are proposed. The Cronbach's alpha coefficient reached 0.892, and the Spearman rank correlation coefficient of the AHP-improved TOPSIS model reached 0.917, providing a methodological foundation for differentiated evaluation. At the technical level, the adaptability and superiority of GWO-KELM for the task of talent potential prediction are demonstrated. The test set accuracy of 93.4% and F1-score of 0.924 significantly outperformed four baseline models, validating the effectiveness of the technical pathway combining kernel function mapping with global parameter optimization. At the engineering level, a management information system featuring a five-layer architecture and six functional modules is designed. The measured throughput of 2,027 persons/hour represents a 337-fold improvement over manual methods.

During the research process, several directions worthy of further exploration were also identified. The weight configuration in the current evaluation model still relies primarily on expert judgment as the main information source. More dimensions of objective behavioral data for analysis and dynamic calibration could be considered to introduce in the future. On the algorithm side, although GWO-KELM predicts accurately, there is still room for improvement in the interpretability of its decision-making process. Integrating interpretability tools like SHAP values or LIME would make evaluation results more credible when they feed into personnel decisions. Cross-institutional data collaboration is another direction full of potential, but it needs to act carefully. The federated learning framework offers a way to expand the training sample while protecting data privacy, which helps enhance the model's generalization and its application values in practice.

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