Employment Ability Modeling and Path Optimization Algorithm Design for Higher Vocational Students in the Textile and Garment Industry

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ABSTRACT To address the mismatch between the employability of higher vocational students and the evolving requirements of the textile and garment industry, this study proposes an employment ability modeling framework and path optimization algorithm based on a dual-helix competency model integrating craft inheritance and digital innovation. A capability–job coupling matrix is established by incorporating regional industrial characteristics, industry-specific coefficients, and practical training constraints, while an improved NSGA-II algorithm with three-dimensional objective functions and a skill transfer probability mechanism is developed to generate personalized competency enhancement paths. Considering the increasing deployment of intelligent manufacturing systems, industrial Internet platforms, and wireless information acquisition technologies, efficient capability modeling and adaptive decision-making have become essential for supporting digital industrial ecosystems and future smart education infrastructures. Experimental results demonstrate that the proposed method achieves a matching accuracy of 89.2% with superior path diversity and stability compared with shortest-path, greedy, rule-based, and industry recommendation approaches, while effectively balancing resource consumption and optimization efficiency. The proposed framework provides a scalable solution for intelligent vocational education and offers methodological references for data-driven talent cultivation and information interaction in next-generation industrial environments related to electromagnetic-enabled communication and sensing systems.

INDEX TERMS employability modeling, path optimization, NSGA-II, intelligent manufacturing, industrial internet

I. INTRODUCTION

CURRENTLY, the textile and apparel industry is accelerating toward a new stage of digitalization, flexibility, and globalization. This trend has created an increasingly urgent demand for high-quality technical and skilled talents [1–3]. The industry's need for professionals with emerging capabilities, such as digital design and intelligent production, has risen significantly. However, the education system lags behind in the pace of talent training, resulting in a significant gap between supply and actual job demand. As an important channel for the output of technical and skilled talents [4–6], higher vocational colleges cannot update their curriculum content at a pace that matches industrial change, resulting in the coexistence of employment pressure for graduates and difficulty in enterprise recruitment [7–9].

Especially in the application of digital tools, software operation capabilities such as three-dimensional modeling and intelligent typesetting have become industry standards. However, most teaching institutions are still insufficient in terms of practical training equipment and opportunities, and the frequency of students' exposure to real work scenarios is far below industry expectations. At the same time, emerging positions such as cross-border e-commerce, intelligent manufacturing, and intangible heritage inheritance are constantly appearing, requiring course content to respond quickly to market changes. In the current vocational education system, the iteration cycle of teaching modules is generally too long, making it difficult to integrate cutting-edge technologies and job standards in a timely manner, further exacerbating the mismatch between the talent structure and industry needs. Existing research largely focuses on capability assessment or path recommendation, lacking closed-loop supply–demand optimization [10–12], which hinders meeting the needs of higher vocational populations. The structural contradiction mentioned here operates at two interrelated levels: a macro-level imbalance between the speed of industrial upgrading and the talent cultivation cycle, and a micro-level mismatch between the specific skill structures of graduates and evolving job requirements. By incorporating industry and regional coefficients into the capability–job coupling matrix, the proposed enhanced NSGA-II algorithm addresses both, ensuring that individual path optimizations collectively reduce the overall talent–demand gap.

To simulate cross-border e-commerce demand fluctuations and equipment failures, this paper creatively integrates industry coefficients (such as Gerber certification and CLO3D proficiency weights) and realistic training constraints (equipment turnover rate, time limits), all based on the NSGA-II multi-objective genetic algorithm. It creates a framework for "industry demand–education shortfall–algorithm breakthrough" to accomplish resource recommendation, path optimization, and dynamic closed-loop capability assessment. Several models and algorithms have been proposed in previous research to address the employment of higher vocational students in the textile and apparel industry. Through the optimization of teaching facilities and practical curricula, Ego et al. [13] increased students' willingness to select majors; Terzieva [14] promoted modular vocational training and emphasized industry–education collaboration; and Hidayat et al. [15] confirmed the beneficial effects of internships and teaching methods on design ability. Regarding unclear career paths, Hébert and Jenson [16] showed that interdisciplinary practice improves technical literacy, while Mawonedzo et al. [17] demonstrated the gap between conventional instruction and industry demands. To aid in accurate talent selection, Danişan et al. [18] developed a multi-criteria decision-making model for resource allocation optimization. Despite advancements in resource allocation, capability training, and school–enterprise collaboration, challenges remain, including limited sample coverage, inadequate algorithm robustness, and a lack of evaluation for intangible cultural heritage skills.

Recent research on career path planning through algorithm modeling and technology empowerment has supplemented earlier studies. Although Azonuche et al. [19] confirmed the influence of teaching facilities and career prospects on undergraduate major selection, they did not address vocational skill training. Kohli [20] pointed out the deficiency of digital technology integration in fashion education curricula and the need to improve students' job adaptability. An et al. [21] created an AI clothing design process that increased course satisfaction, with an emphasis on design thinking but no connection to career pathways. Tantawy et al. [22] suggested virtual fashion design techniques but lacked dynamic industry matching mechanisms. Wei et al. [23] reviewed advancements in sensory engineering, but did not create a closed loop between ability assessment and job matching. Lin [24] investigated digital fashion education without addressing vocational skill gaps. Wu et al. [25] used GANs to generate knitted fabric patterns, but only for design material generation. Despite these advancements, difficulties still exist.

This study proposes an employment ability modeling and path optimization approach for vocational textile students, focusing on "ability–job demand matching and path optimization." Building on the integration of deep learning and evolutionary algorithms for path recommendation by Fang et al. [26], indicator weighting by Qi et al. [27], job label classification by Mousavian Anaraki et al. [28], the use of cosine similarity and TF-IDF to build matching matrices by Januzaj [29], and regression-based resource modeling by Maulud et al. [30], this study constructs a coupling matching model and path generation algorithm based on job demands, student abilities, and resource conditions. Superior performance is demonstrated by validation using data from 500 students, supporting the reform of vocational education and providing individualized employment counseling.

II. ALGORITHM DESIGN

CONSTRUCTION OF THE CHARACTERISTIC ABILITY INDEX SYSTEM FOR HIGHER VOCATIONAL COLLEGES IN TEXTILE AND CLOTHING

This study proposes a "craft inheritance–digital innovation" double helix capability model based on industry transformation needs, emphasizing both traditional methods and digital applications to build a framework for modeling vocational student capabilities.

Craft inheritance and digital innovation are the two axes defined by the model, which also covers cross-border e-commerce modules, intelligent manufacturing, digital design, traditional skills, and intangible heritage. Several rounds of expert consultation using the Delphi method are employed to determine competency elements. A three-round Delphi consultation with ten vocational curriculum designers and fifteen industry experts produced the initial axis weights (40% for craft inheritance and 37% for digital innovation). These figures were determined using the Analytic Hierarchy Process (AHP), and to ensure the weights represented both expert opinion and the contribution of statistical variance, they were then adjusted using principal component analysis (PCA) on regional industrial data in conjunction with entropy weighting. Zhejiang, Guangdong, and Shandong student data were used for cross-validation, which verified that the weight settings remain constant across various industrial clusters.

An improved AHP model introduces a regional industrial coefficient λ_i, adjusting the original weight w_i as $w_i' = w_i \times (1 + \alpha\lambda_i)$.

The coefficient λ_i is derived from PCA on industrial data and refined by entropy weighting, ensuring strong alignment between capability indicators and regional industry characteristics.

To quantify ability levels, a standardized capability vector is defined as follows:

$$V_j = \frac{X_j - \mu_j}{\sigma_j} \times \sqrt{\lambda_{\text{region}}} \tag{1}$$

where X_j is the raw score, and λ_{region} integrates regional manufacturing development and educational resource indices.

Data sources include skill assessments, digital tool usage logs, and practical training evaluations, supporting model input and path optimization. The double helix competency index system and regional adaptation weights are shown in Table 1. The unit resource consumption values for time, funds, courses, and external training are derived from a survey of 12 vocational institutions.

TABLE 1. Double Helix Capability Index System and Regional Adaptation Weight Table

Dual-Spiral Axis	Secondary Indicator	Base (%)	Weight	Regional Adjustment
Craft Heritage Axis	Fabric Identification	26		+9% (Yangtze Delta)
	Traditional Techniques	–		–
	Intangible Cultural Heritage	10.5		Regional emphasis
Digital Innovation Axis	Smart Equipment	24		-3% (Yangtze Delta)
	Digital Tools	–		–
	Cross-border E-commerce	9.5		+0.8% (Pearl River)
Integrated Competencies	Digital-Craft Integration	20		Dynamic adjustment
Core Competencies	Professional Ethics	10		Stable weighting
Total	–	100		–

DYNAMIC EXTRACTION OF INDUSTRY JOB REQUIREMENTS

This section focuses on constructing a job demand vector suitable for the capability–demand coupling matching model, applying multi-source heterogeneous data and a dynamic weight mechanism to enhance the model's responsiveness to the emerging occupational structure in the textile and apparel industry. The job demand feature extraction process is illustrated in Figure 1, which comprises five primary stages: data collection, text preprocessing, skill keyword extraction, vector representation construction, and job label classification.

Data collection is based on traditional platforms, supplemented by representative subdivision and cross-border job samples covering design and development, intelligent manufacturing, digital fabrics, and accessories, with a focus on high-frequency positions and job descriptions published by cross-border e-commerce companies. A Python-based multi-threaded crawler utilizes Requests and BeautifulSoup to extract structured data, performing deduplication and template text removal on job titles, requirements, and descriptions to construct a corpus.

Text preprocessing employs Jieba segmentation combined with a professional terminology dictionary, executing stop word removal, symbol elimination, word normalization, and part-of-speech filtering, retaining only nouns and verbs to ensure semantic purity.

Skill keyword extraction integrates BERT embeddings with TF-IDF for hybrid feature modeling. To improve the recognition of emerging skill terms, contextual semantic vectors are obtained through BERT encoding and then term weights are computed using TF-IDF. To enhance the model's adaptability to industry trends, dynamic keyword weights are adjusted using the textile industry prosperity index.

The keyword set is subjected to K-Means clustering, with the silhouette coefficient and Davies-Bouldin index determining the number of clusters. A pre-trained Word2Vec model encodes the cluster center words, which each represent a capability theme. The job demand matrix is generated by normalization after maximum pooling aggregates the text vectors for every job.

A multi-label classification model is added to the initial label assignment based on job title, industry category, and responsibility phrases to finish unlabeled items. This creates a highly consistent job label library that forms the foundation for later capability matching and path planning.

COUPLING MATCHING MODEL OPTIMIZATION

To increase the accuracy of matching measurement and its adaptability to real-world scenarios, this section builds a capability–position matching model that incorporates the weights of industry factors and the features of enterprise differences. The method framework carries out four stages: vector unified expression, matching function design, matrix construction, and constraint mechanism processing. Tables 2 and 3 display the variables and formulas used.

TABLE 2. Description of the Matching Degree Calculation Formula

Formula No.	Mathematical Expression	Explanation
(2)	$x_{\text{norm}} = \dfrac{x - x_{\min}}{x_{\max} - x_{\min}}$	Linear normalization of ability/demand values into the [0, 1] interval
(3)	$S(A, B) = \dfrac{A \cdot B}{\lVert A \rVert \cdot \lVert B \rVert}$	Cosine similarity measuring directional consistency between student and job vectors
(4)	$S_w(A, B, W) = \dfrac{(A \cdot W) \cdot (B \cdot W)}{\lVert A \cdot W \rVert \cdot \lVert B \cdot W \rVert}$	Weighted cosine similarity emphasizing key competency dimensions
(5)	$S_{\text{adj}} = S_w(A, B, W) \times Q$	Adjusted similarity incorporating industry-specific qualification coefficients Q

TABLE 3. Variable Description of Matching Degree Calculation Formula

Symbol	Definition
A	Normalized student ability vector
B	Normalized job demand vector
W	Job-specific weight vector for key competencies
Q	Qualification adjustment coefficient (e.g., $1.5\times$ for Gerber certification)
$S(A, B)$	Unweighted matching score
$S_w(A, B, W)$	Weighted matching score considering key skills
S_{adj}	Final adjusted matching score with industry factor
$\lVert A \rVert, \lVert B \rVert$	Euclidean norms of vectors A and B
$\cdot$	Dot product operator between vectors

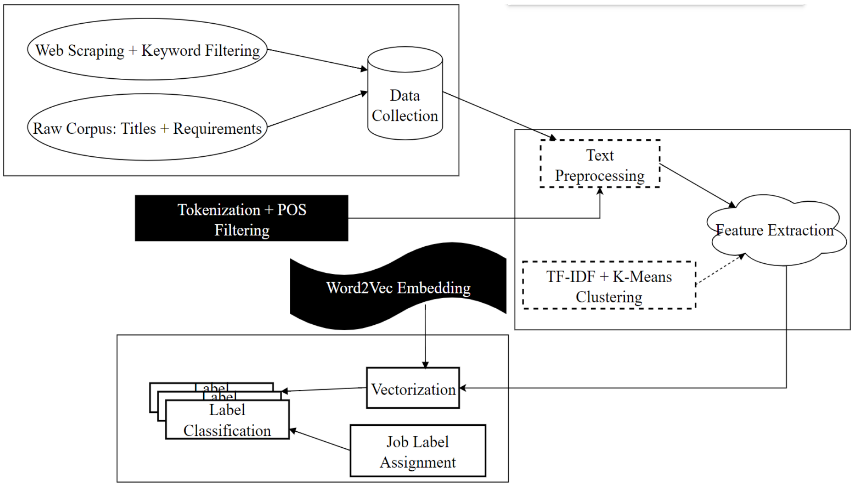

FIGURE 1. Flowchart of Demand Feature Extraction

Student capability and job requirement vectors undergo linear normalization to the [0, 1] range; missing job dimensions are filled with the industry average lower bound.

Basic matching employs cosine similarity (formula (3)) between student vector A and job vector B. A core competency weight vector W is introduced to construct weighted similarity (formula (4)), enhancing responsiveness to key capabilities. The industry-specific qualification coefficients Q are determined by analyzing three years of job posting data from the China Textile Talent Network, cross-border e-commerce recruitment platforms, and industry association reports. Keyword weighting is applied to identify high-demand qualifications, followed by PCA to extract the most significant contributing factors. Entropy weighting is then used to assign quantitative coefficients, ensuring that the final values reflect both industry frequency and discriminative importance.

Considering industry entry requirements, a job correction factor Q is defined, forming the adjusted matching formula (5). If a job requires specific equipment qualifications (e.g., Gerber, Lectra, Yin Cutter) and the student meets these, the matching score is multiplied by an equipment weight (e.g., $1.5\times$), reflecting job preference. The results form a two-dimensional matching matrix $M \in R^{n\times m}$, where $M(i,j)$ each entry denotes the adjusted matching degree S_{adj} between student i and job j. In the matching matrix construction, enterprise-scale-dependent thresholds are set: 90% for large enterprises and 80% for SMEs. However, in the algorithm implementation and experimental filtering, a unified threshold of 0.85 is applied to ensure consistency in cross-method comparison. Note that SME matches with scores between 0.80 and 0.85 are still considered valid in practice but are excluded from the experimental analysis to maintain a stringent evaluation standard.

If a student scores below the threshold in any core dimension, the matching score $M(i,j)$ is set to zero, creating a "capability threshold mask matrix."

Job assignment follows a highest matching priority strategy. For multiple jobs with score differences under 0.02, a candidate set is retained for subsequent path optimization.

Final outputs include the adjusted matching matrix M, job candidate set, enterprise threshold control matrix, and equipment mask matrix.

RESOURCE CONSTRAINT MODELING

To improve the feasibility of the path optimization algorithm, this paper models four key resources in the process of capacity improvement as constraint variables: time (R_i^T), funds (R_i^C), course resources (R_i^L) and external training (R_i^E), forming a student resource vector $R_i = \{R_i^T, R_i^C, R_i^L, R_i^E\}$, and normalizing it to the interval [0, 1]. The total resource constraint is: $R_i \leq R_{\max}$, $\forall i \in [1, n]$.

The parameters for time, budget, course resources, and external training constraints were obtained through a survey of 12 higher vocational institutions in major textile industrial regions. Data on laboratory equipment turnover rates, course scheduling patterns, and cooperative enterprise training cycles were collected and averaged to set realistic upper bounds. The unit resource consumption value is obtained from the survey data of twelve colleges and universities. The average consumption is 0.8 units of time per day, 500 yuan per module, 4 courses per semester, and 1 internship per quarter. The equipment failure rate is set to vary between 10% and 30%, and the demand fluctuation range is plus or minus 20%. Robustness testing shows that under these disturbance conditions, the algorithm can still maintain a stable output with a matching degree of no less than 85% and a resource utilization rate higher than 75%.

These quantified constraints are directly embedded into the feasibility function of the path optimization model, ensuring that recommended paths are both achievable within institutional conditions and aligned with enterprise training schedules.

Each capability improvement module sets a corresponding resource consumption vector $D_j = \{d_j^T, d_j^C, d_j^L, d_j^E\}$, and the cumulative resource consumption of the student path $P_i = \{j_1, j_2, \ldots, j_m\}$ is $\sum_{j\in P_i} D_j = \{\sum d_j^T, \sum d_j^C, \sum d_j^L, \sum d_j^E\}$. The path resource feasibility determination function is:

$$f(P_i) = \begin{cases} 1, & \text{if } \sum_{j\in P_i} D_j \leq R_i \text{ and } D_j \neq \infty, \\ 0, & \text{otherwise.} \end{cases} \tag{6}$$

The course resource constraint is implemented through the capability–course matrix $M \in R^{k\times l}$. If a module is not offered during the current period, its resource consumption is set to ∞, which automatically excludes it (as a penalty term for infeasible solutions, forcing the exclusion of modules that are not offered). The external training constraint applies the position–training adaptation matrix $S \in R^{m\times q}$, and only allows training projects with a fitness of $s_{mq} \geq \theta$ ($\theta = 0.7$ is the preset threshold) to participate in path generation. s_{mq} represents the fitness of the m-th position and the q-th training project.

The funding and time resource model is in linear form. Assuming the unit resource consumption is γ_j and τ_j, the total path consumption is:

$$C(P_i) = \sum_{j\in P_i} \gamma_j, \quad T(P_i) = \sum_{j\in P_i} \tau_j \tag{7}$$

And satisfying: $C(P_i) \leq R_i^C$, $T(P_i) \leq R_i^T$.

All resource constraints are embedded in the fitness ev aluation of the NSGA-II algorithm in vector form. Soluti ons that violate the constraints have their fitness reduced t hrough a penalty mechanism and are automatically elimin ated in the non-dominated sorting, achieving feasible solut ion screening and solution space compression, thus improvi ng algorithm effi-ciency and practicality. The resource con straint framework is shown in Figure 2.

PATH OPTIMIZATION ALGORITHM DESIGN (IMPROVED NSGA-II)

The ability improvement path for higher vocational students is modeled as a multi-stage dynamic optimization problem under resource constraints. Unlike approaches that focus solely on personal skill enhancement, the proposed method integrates aggregated industry demand trends into the path generation process. This linkage allows the optimization of individual training sequences to be mapped back to systemic talent allocation improvements, thereby supporting both student-level and industry-level employment alignment. Starting from the initial ability $C_0 \in R^d$, the operation sequence $a_j \in A$ is planned so that the final ability $C_l = C_0 + \sum_{j=1}^{l} \Delta C_{a_j}$ maximally aligns with the job demand vector $D \in R^d$ while satisfying resource limits $R_j \in R_k$.

An improved NSGA-II framework is constructed, incorporating the industry feature vector: $a_j = (\mathrm{Heritage}_j, \mathrm{DigitalLevel}_j)$, where Heritage denotes the degree of craft inheritance [0, 1], and DigitalLevel indicates digital skill level (1–5), enhancing industry fit in path generation.

The three-dimensional objective functions are:

Maximize matching degree:

$$f_1(P_i) = 1 - \cos(\theta(C_l, D)) = 1 - \frac{C_l \cdot D}{\|C_l\| \cdot \|D\|} \tag{8}$$

Minimize resource consumption:

$$f_2(P_i) = \sum_{m=1}^{l} \sum_{j=1}^{k} R_{a_j}^{(m)} \tag{9}$$

Minimize path length (i.e., the number of modules in the path, which implicitly reflects skill correlation and learning efficiency):

$$f_3(P_i) = l \tag{10}$$

Subject to resource constraints: $\sum_{j=1}^{l} R_{a_j}^{(m)} \leq B^{(m)}$.

A heuristic scoring function guides path generation:

$$\mathrm{Score}(a_j) = \frac{\|D - C_0\| - \|D - (C_0 + \Delta C_{a_j})\|}{\|R_{a_j}\|} \tag{11}$$

Genetic operations include SBX (simulated binary crossover) to maintain action validity and polynomial mutation combined with skill transfer probabilities (e.g., “Sewing $\rightarrow$ Smart Pattern Making” with probability 0.6). Mutation occurs only when conditions are met.

Individuals violating resource constraints are repaired via path pruning or low-resource alternatives; a local search module refines high-quality paths to improve Pareto frontier solutions.

The outputs include multi-path recommendation sets, process–digital dual-dimensional encoded paths, and the Pareto optimal solution set.

With modules that sequentially match algorithm logic, Figure 3 illustrates the full path optimization process, guaranteeing extensibility, clarity, and ease of implementation.

A job–skill correlation matrix and historical student skill progression data are used to derive the skill transfer probability mechanism. The likelihood of switching from one skill to another is represented by conditional probabilities, which are calculated (for example, “Sewing $\rightarrow$ Smart Pattern Making” has a probability of 0.6). The genetic algorithm incorporates these probabilities into the mutation stage to direct the creation of feasible paths, ensuring that suggested learning sequences correspond with practical skill acquisition patterns and industry demands. When resource limits are exceeded, constraint repair is initiated. Local search is applied to Pareto-optimal solutions to refine path quality.

Footnote 1: Skill transition probabilities were estimated from anonymized student training records and industry job–skill mappings. Detailed frequency matrices are not provided due to privacy and confidentiality agreements.

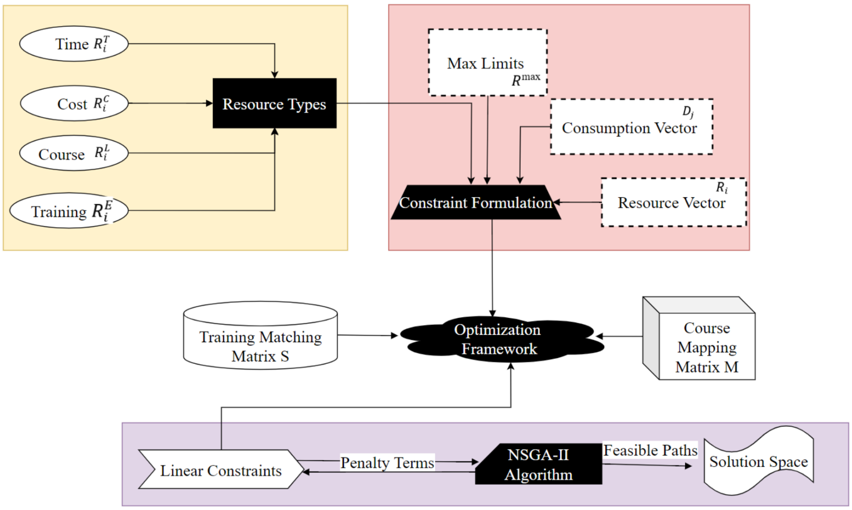

FIGURE 2. Resource Constraint Framework

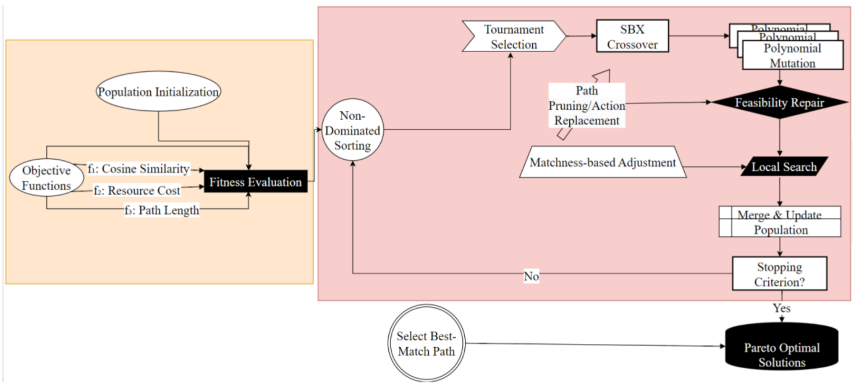

FIGURE 3. Path Optimization

ALGORITHM IMPLEMENTATION PROCESS

The improved NSGA-II path optimization is implemented in Python, comprising input construction, path initialization, fitness calculation, genetic evolution, feasibility judgment, and optimal path output, supporting multi-student parallelism.

Input includes student ability vector C_0, job demand vector D, resource limits R, resource consumption matrix M, and algorithm parameters: population size N, max generations $G_{\max}$, crossover probability P_c, mutation probability P_m, crowding distance threshold δ, resource tolerance ϵ_r, and convergence threshold t.

Path initialization uses the ability gap $\Delta C = D - C_0$ to calculate scores:

$$\text{score}(j) = \frac{\Delta C_j}{\|M_{j,:}\|_2}, \quad j = 1, 2, \ldots, n \tag{12}$$

High-score modules are selected to build resource-feasible paths P_i.

Fitness functions include matching degree, resource consumption, and path length:

$$f_1 = 1 - \frac{C_l \cdot D}{\|C_l\| \cdot \|D\|}, \quad C_l = C_0 + \sum_{j=1}^{l} \Delta C_{a_j} \tag{13}$$

$$f_2 = \sum_{j=1}^{l} M_{a_j,:} \cdot \mathbf{1}_k \tag{14}$$

Individuals violating resource limits are eliminated.

Genetic evolution follows NSGA-II, with crowding distance:

$$d_i = \sum_{j=1}^{3} \frac{f_j^{(i+1)} - f_j^{(i-1)}}{f_j^{\max} - f_j^{\min}} \tag{15}$$

SBX crossover and polynomial mutation are applied; parent and offspring populations are merged and elitism selection is performed. Termination occurs when improvement in matching degree is below ϵ for t generations or $G_{\max}$ is reached.

Parallel multi-threaded optimization distributes job demands and resource pools, outputs optimal paths and metrics per student, and saves results in JSON format. The algorithm implementation process is shown in Figure 4.

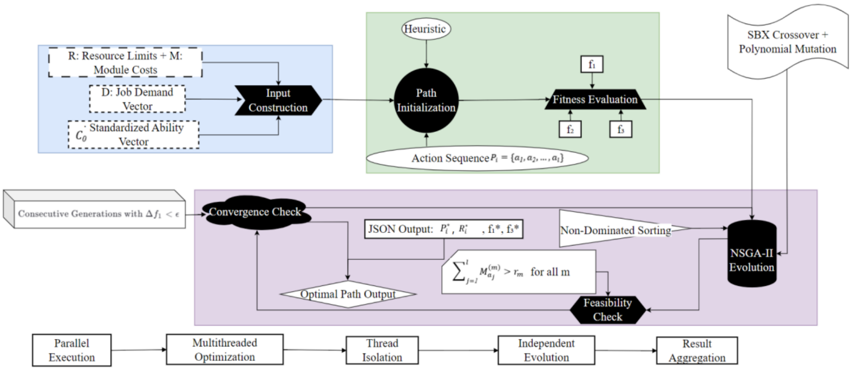

FIGURE 4. Algorithm Implementation Process

III. EXPERIMENT AND VERIFICATION

EXPERIMENTAL DESIGN

Based on ability assessment data of 500 vocational students from Zhejiang (40%), Guangdong (30%), and Shandong (30%), with a gender ratio of 1:1.2 (male: female), majors spanning textile design, intelligent manufacturing, and e-commerce, and grades predominantly in the second and third years, the dataset covers craft inheritance and digital innovation axes. Job requirements were sourced from the China Textile Talent Network, SHEIN, etc., with 300 samples classified into intelligent manufacturing, cross-border e-commerce, and traditional management. Job vectors were constructed using BERT-TF-IDF. This study was conducted in accordance with the requirements of the Ethics Committee of Hebei Art & Design Academy. Participants were informed of the study's purpose and data usage prior to participation, and responses were collected anonymously. No personally identifiable information was stored.

Comparison algorithms include NSGA-II, shortest path, greedy, rule-based matching, and the "Smart Education Cloud" collaborative filtering system. Each student was matched to manufacturing and e-commerce job categories, with three demand vectors per category. Resource constraints were set as time $\leq$ 30 days, budget $\leq$ 3,000 yuan, courses ≤ 8, and training sessions ≤ 3. The regional adaptation coefficient was dynamically generated.

Five-fold cross-validation was employed. The model was implemented in Python with NSGA-II parameters: population 120, generations 180, crossover 0.92, mutation 0.18. Solutions were filtered by matching degree ≥ 0.85 and resource consumption $\leq 85\%$. Metrics included matching degree, resource consumption, path length, regional coefficient, and matching success rate. Data processing complied with China's Personal Information Protection Law (PIPL) and Data Security Law (DSL). All student data were anonymized prior to analysis, and the study protocol was approved by the institutional ethics committee. Data are available upon reasonable request for research purposes subject to compliance with applicable laws.

The main experimental parameters and comparative techniques are presented methodically in Tables 4 and 5.

The vertical dimension shows how deeply the textile and apparel industry is integrated with educational practices, while the horizontal dimension comprises student samples, resource limitations, algorithm parameters, and optimization goals. The three main industrial clusters are represented in the student samples: Guangdong (30%), Shandong (30%), and Zhejiang (40%). In accordance with higher vocational teaching standards, resource constraints include a maximum of eight courses and three hands-on training sessions. Principal component analysis is used to dynamically generate the regional coefficient, creating a closed loop between capability training and industrial demand. With a crossover rate of 0.92 and a mutation rate of 0.18, NSGA-II parameter optimization enhances global search and improves convergence. While the shortest path algorithm and greedy strategy mimic cost-sensitive training programs, the Zhijiao Cloud Platform's collaborative filtering stands in contrast to NSGA-II's multi-objective optimization.

TABLE 4. Experimental Parameters

Parameter	Value/Description
Student Sample Size	500 students (5-fold cross-validation, regional distribution: ZJ 40%, GD 30%, SD 30%)
Resource Constraints	Time: $\leq$ 30 days; Budget: $\leq$ 3,000 yuan; Courses: $\leq$ 8 modules; Internships: $\leq$ 3
	λ: 0.8–1.2 Regional Adaptation Coefficient
NSGA-II Settings	Population Size: 120; Max Generations: 180; Crossover Rate: 0.92; Mutation Rate: 0.18
Matching Threshold	$\geq$ 0.85 (considered successful)
Optimization Targets	Maximize Matching Degree; Minimize Resource Cost; Maximize Regional Adaptation
Hardware Environment	Python 3.10, NumPy, SciPy, Scikit-learn, TensorFlow

TABLE 5. Comparison Method Table

Method	Description
Shortest Path Algorithm	Abstracts modules as nodes with resource-weighted edges to find minimal-cost paths
Greedy Strategy	Prioritizes actions with highest unit-resource matching improvement
Manual Rule-based Approach	Follows fixed curriculum-defined paths without adaptive optimization
Industry Recommendation	Jack Technology Zhi Jiao Cloud platform using collaborative filtering
NSGA-II	Standard multi-objective genetic algorithm without skill migration probability and regional adaptation constraints

EXPANSION OF MATCHING EVALUATION DIMENSIONS

The degree of alignment between an individual's capability and job demands is reflected in the matching degree, which is determined by taking the cosine similarity between the student's ability vector and the job requirement vector. The primary evaluation indicator is the matching error for each student–job pair following path optimization. When compared to control algorithms under the same conditions, the average matching degree shows the overall fitness across all samples. Higher model stability is indicated by a smaller standard deviation. To guarantee comparability, all algorithms are run with the same data input and job requirement configurations. Using skewness and kurtosis, the distribution properties of matching errors are examined, and the degree of approximation to a normal distribution is evaluated using normality tests. Lower matching deviation risk and a more symmetrical error distribution are implied by skewness values near zero.

By calculating the percentage difference in matching value before and after optimization, the matching change rate assesses how effective the optimization path was. Error control performance is visualized through density estimation and normal fitting curves, comparing the error distributions across different algorithms. The generalization ability of matching is analyzed by grouping jobs into four categories: technology, management, design, and sales. For each category, average error and quantile values are computed. Oneway ANOVA is applied to assess the algorithm's adaptability across job types.

The matching degree distribution is shown in Figure 5.

Figure 5 shows the error distribution of the five path optimization methods in the task of matching student capabilities with job requirements, and the corresponding smooth curves reflect the error fitting results. The results show that the error distribution of NSGA-II is the most concentrated, with a peak close to zero and the fastest tail decay, indicating that its matching error is the smallest and the stability is the highest; the error distribution of the greedy method and the manual rule method is right-skewed and has a large standard deviation; the error distribution of the shortest path method is relatively concentrated. The above differences verify that the NSGA-II algorithm has better error control and stability in matching tasks.

OPTIMIZATION EFFICIENCY VERIFICATION

Under a unified platform and dataset, the improved NSGA-II algorithm was compared with four methods across six metrics:

The running time indicator reflects the total time spent by the algorithm in the complete experimental process, including data preprocessing, multiple rounds of cross-validation, and result aggregation. The 4.3 seconds listed in Table 6 is the average time taken for a single path generation; the two statistics are different. NSGA-II takes an average of 1.7 hours for the complete experimental cycle, and a single optimization process takes an average of 4.3 seconds.

Convergence Speed: Converged within 180 generations with average improvement < 0.001, faster than others.

Resource Utilization: Achieved 79.3%, higher than Greedy (55%), Shortest Path (60%), and Manual Rule (60%).

Path Diversity: Levenshtein diversity index 0.62, low than Greedy (0.65) and better than Manual Rule (0.35).

Stability: Standard deviation below 0.08 over 10 trials, minimal fluctuation.

Statistical Significance: Matching degree and resource utilization significantly better than controls ($p < 0.01$). The results are shown in Figure 6.

Running time, convergence speed, resource usage, path diversity, stability, and statistical significance are the six dimensions on which the radar chart in Figure 6 displays the normalized scores (0–1) of different path optimization algorithms. With the outermost closed loop (e.g., running time 0.95, resource utilization 0.91), NSGA-II exhibits the best overall performance. Greedy Strategy and Manual Rule achieve moderate results, while the Shortest Path Algorithm exhibits lower scores in several dimensions (e.g., convergence speed 0.30). Although Industry Recommendation does reasonably well in terms of stability (0.70) and resource utilization (0.79), it still lags behind NSGA-II in other metrics.

VERIFICATION OF IMPROVEMENT EFFECT

Matching improvement is measured by the angular similarity change rate $\Delta_i = (S_i^{\mathrm{post}} - S_i^{\mathrm{pre}})/S_i^{\mathrm{pre}}$. The average and standard deviation of 500 students are calculated to assess overall optimization effectiveness. Job matching success rate is based on a threshold of 0.85, comparing the number of matched positions before and after optimization.

Employment rate prediction uses a logistic regression model to compare predicted probabilities pre- and post-optimization.

Satisfaction is evaluated via a five-dimension Likert-scale questionnaire, standardized to reflect subjective acceptance.

Resource consumption is represented by a normalized resource vector: $R = [r_1, r_2, r_3, r_4]$.

Differences before and after optimization are compared, and the proportion of students completing optimization within constraints is recorded.

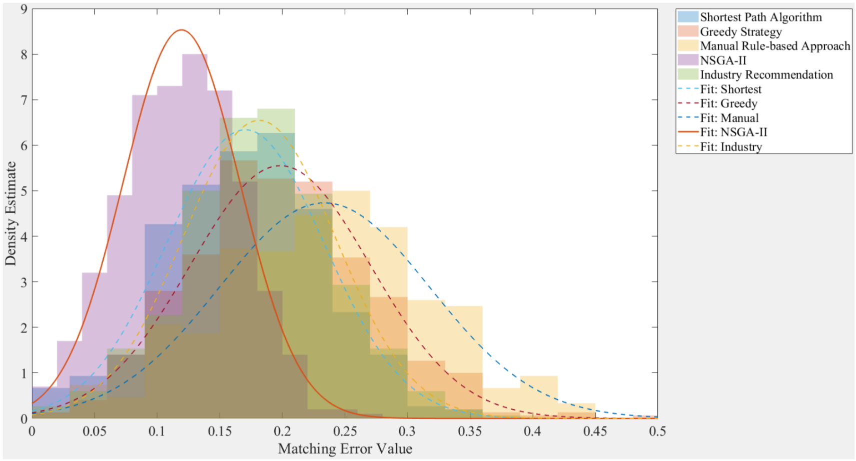

FIGURE 5. Matching Degree Distribution Histogram

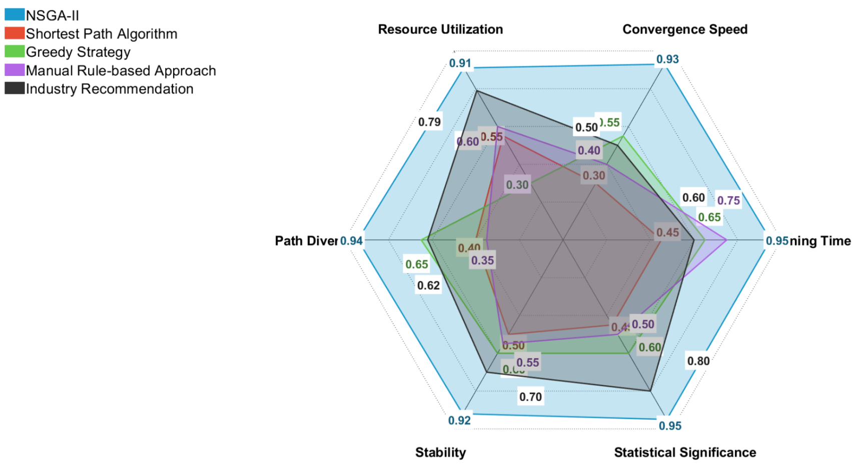

FIGURE 6. Comprehensive Comparison of Optimization Efficiency of Various Algorithms

The five indicators are standardized and clustered using K-Means (K = 3), yielding the mean characteristics of high, medium, and low improvement groups.

Overall validation is based on before–after comparison, forming a closed-loop evaluation using both subjective and objective indicators. Results are shown in Figure 7.

Figure 7 presents a comparison of the five core indicators before and after path optimization. As seen from the upper subgraph, the matching degree increased from 0.78 to 0.92, the employment rate increased to 0.84, the satisfaction rate rose to 0.86, resource consumption decreased to 0.48, and efficiency improved significantly. The lower subgraph applies K-Means clustering to divide students into three categories: high, medium, and low. Among them, the high group made the greatest progress, indicating that optimization is more effective for potential learners.

To enhance validation, two additional industry-side indicators are introduced in Figure 8. First, the time to job competence is reduced by 32%, aligning with the improved matching trend. Second, the training equipment turnover rate increases by 41% through batch-based path scheduling. These results align with student-side resource and ability indicators, demonstrating the synergistic effect of path optimization in both education management and enterprise training.

By integrating student and industry indicators, the proposed approach proves its value across the education–employment–enterprise chain, offering practical support for optimizing vocational education in the textile and garment industry.

As a hypothetical example, consider a student whose initial ability vector indicates strong craft heritage skills (fabric identification: 0.85; traditional techniques: 0.80) but limited digital competencies (CLO3D proficiency:

0.35; cross-border e-commerce: 0.30). The model matches this student to a target position in digital fashion design, which requires higher digital proficiency and moderate craft heritage. The optimized path recommends sequential modules—“Digital Pattern Making with CLO3D” (4 weeks), “Smart Equipment Operation” (3 weeks), and “Cross-border Marketing Basics” (2 weeks)—while retaining and slightly enhancing craft heritage skills through “Intangible Cultural Heritage Digital Integration” (2 weeks). Under resource limits (time $\leq$ 30 days, budget $\leq$ 3,000

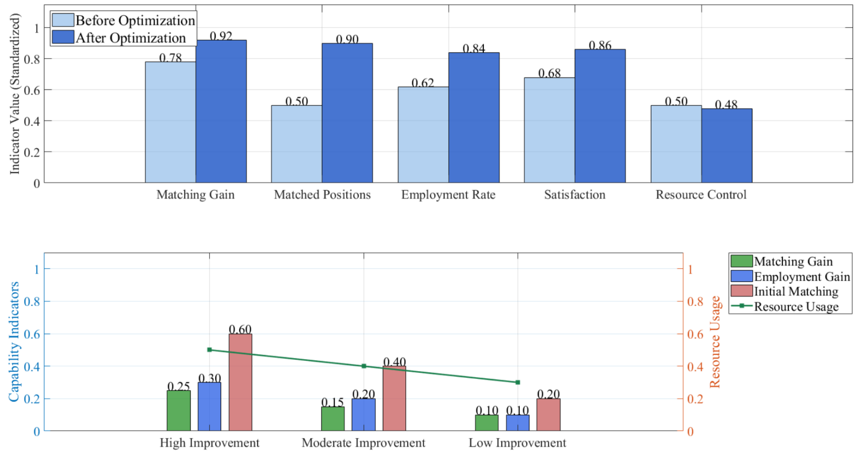

FIGURE 7. Comparison of Improvement Effects in Histogram

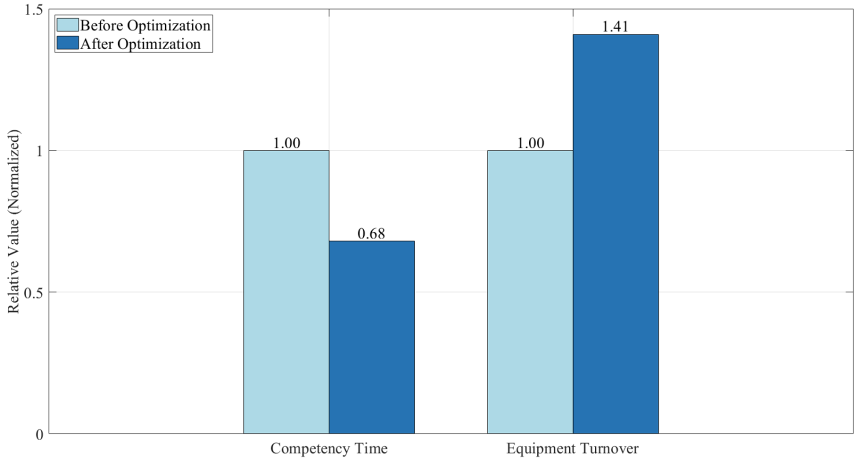

FIGURE 8. Comparison of Industry Indicators

yuan), this plan increases the matching degree from 0.72 to 0.91, illustrating the model's practical use in generating personalized improvement paths.

KEY PARAMETER ANALYSIS RESULTS

Using a controlled variable method, the sensitivity of the NSGA-II algorithm to key parameters and industry disturbances is analyzed in terms of matching degree, runtime, and path stability.

ALGORITHM PARAMETERS

Population Size: Matching stabilizes after 50; recommended value: 100.

Crossover Probability: Enhances path diversity; 0.9 is recommended.

Mutation Probability: Optimal within 0.1–0.2; too low causes early convergence, too high leads to instability.

Iterations: Solution set stabilizes after 180 generations.

Resource Upper Limit: Raising to 1.2× initial mean improves matching, but constraints must be maintained.

INDUSTRY DISTURBANCES

Job Weight Fluctuation (±20%): Significantly affects path structure; model is sensitive.

Device Failure Rate (10%–30%): Increases resource consumption and reduces stability.

Overall, the model exhibits sensitivity to mutation, resource constraints, and external disturbances. Proper configuration and adaptive tuning are essential for optimal performance. The analysis results of key parameters of NSGA-II path optimization are shown in Figure 9.

Figure 9 presents the parameter analysis of the NSGA-II algorithm. The horizontal axis shows seven parameters. The left vertical axis displays normalized mean matching degree and sensitivity coefficient, while the right vertical axis shows running time in seconds. Mutation probability achieves the highest matching degree (0.95), maximum iterations incur the longest runtime (180 s), and sensitivity analysis indicates mutation probability has the greatest impact (0.86), followed by resource limit (0.79), highlighting the key role of resource constraints and demand fluctuations in path optimization.

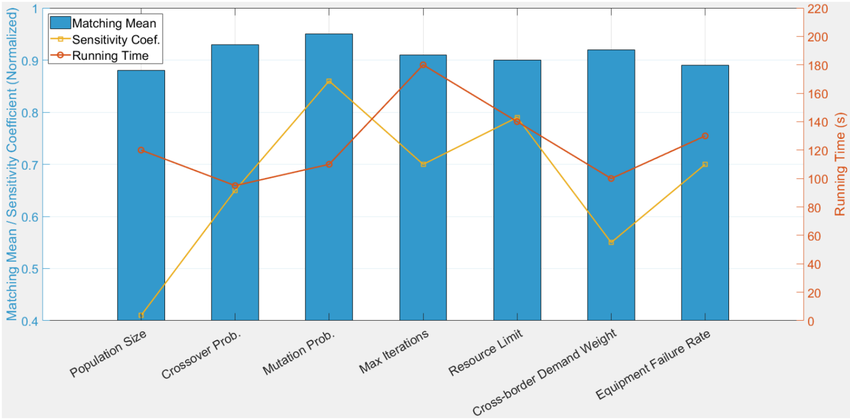

FIGURE 9. Analysis Results of Key Parameters of NSGA-II Path Optimization

COMPARISON WITH BASELINE METHODS

To evaluate the effectiveness of the proposed improved NSGA-II algorithm in job matching, four baseline methods are adopted:

Baseline-1: Shortest Path Algorithm—Competency modules are treated as nodes and resource consumption as edge weights; Dijkstra's algorithm is used to obtain the minimum-resource path.

Baseline-2: Greedy Strategy—At each step, the module with the highest unit resource efficiency is selected iteratively until the threshold is met or resources are exhausted.

Baseline-3: Manual Rule-based Approach—A fixed path template (e.g., basic skills $\rightarrow$ training $\rightarrow$ job adaptation) is applied without adjustment for individual differences.

Baseline-4: Industry Recommendation (ZhiJiao Cloud)—Based on collaborative filtering, job matches are recommended using historical data from similar users, lacking explicit resource constraints and path optimization.

The experiment involves 500 vocational students across five job categories, under unified constraints (time $\leq$ 30 days, funding $\leq$ 3,000 yuan, courses $\leq$ 8, training $\leq$ 3 sessions, $\lambda \in [0.8, 1.2]$). All methods are executed with identical inputs.

The closed-loop mechanism is realized through periodic data updates: job demand vectors are refreshed quarterly via API integration with recruitment platforms, and course offerings are adjusted annually based on path optimization outcomes and industry feedback, ensuring dynamic alignment between education and employment.

Evaluation metrics include matching score, resource utilization, path generation time, path diversity, and result stability. Each method is run five times, and average results are analyzed. The results are summarized in Table 6.

Table 6 shows NSGA-II performs best in key indicators: highest matching degree (89.2%), moderate resource utilization (79.3%), good diversity (0.62), and stability (0.024), with a generation time of only 4.3 seconds. Industry Recommendation responds faster (1.8 seconds) with moderate matching degree (82.4%), but exhibits weaker path diversity and stability. Other baselines show deficiencies in matching accuracy, diversity, or resource control. These results confirm the practical value of the improved NSGA-II in personalized ability improvement path planning.

Current enterprise training paths largely rely on manual mentors or experienced teams, involving demand research, course and practical training design, and phased evaluation and adjustment. This process is time-consuming and insufficiently responsive to market fluctuations in real time.

An example of the comparison results (simulated data/qualitative analysis) is shown in Table 7.

This algorithm has shown clear advantages in industry practice scenarios. Compared to current enterprise methods, this algorithm offers a high degree of automation, fast response speed, strong personalization, and diversity, enabling it to dynamically adapt to changes in market demand and uncertain risks. It supports large-scale applications and continuous optimization. After applying this algorithm, enterprises can significantly improve the efficiency of training and employment matching, reduce labor costs, shorten the time to job competency, and enhance the collaborative training effect between colleges and enterprises.

IV. CONCLUSIONS

Addressing the mismatch between employment abilities and job requirements of higher vocational students in the textile and garment industry's digital transformation, this paper proposes a solution based on the "craft inheritance–digital innovation" double helix capability model and an improved NSGA-II algorithm. A capability index system integrating industrial cluster characteristics is constructed, incorporating industry coefficients and practical training constraints to establish a capability–job coupling matching matrix. The algorithm is enhanced with a three-dimensional objective function and skill transfer mechanism to generate personalized improvement paths. Comparative experiments with baseline algorithms verify that the proposed method outperforms shortest path, greedy, rule-based, and industry recommendation approaches in matching accuracy, stability, and diversity, achieving a maximum matching degree of 89.2%, a resource utilization rate of 79.3%, and path diver-

TABLE 6. Comparison Results between the Baseline Method and the Proposed Method

Method	Matching Score (%)	Resource Utilization (%)	Time Cost (s)	Diversity Index (0–1)	Stability Std. (down)
NSGA-II	89.2	79.3	4.3	0.62	0.024
Baseline-1: Shortest Path Algorithm	71.6	65.5	0.9	0.09	0.081
Baseline-2: Greedy Strategy	75.9	88.2	2.1	0.24	0.053
Baseline-3: Manual Rule-based Approach	68.1	91.6	5.2	0.00	0.107
Baseline-4: Industry Recommendation (ZhiJiao Cloud)	82.4	72.0	1.8	0.15	0.066

TABLE 7. Comparison Results Example

Comparison Dimension	Proposed Algorithm	Current Industry Practice
Matching Accuracy	High (≈89%)	Moderate (≈70%)
Resource Utilization & Cost	Efficient (≈79% utilization; lower long-term cost via automation)	Lower efficiency (≈60–70%; high manual effort/cost)
Generation Time & Scalability	Fast (seconds; supports large-scale batches)	Slow (weeks; difficult to scale)
Diversity & Stability	High (Diversity Index ≈0.62; Std ≈0.024)	Low (template-based; high variability)
Adaptability & Robustness	Strong (real-time adjustments; handles demand shifts and equipment faults)	Weak (slow response; poor handling of sudden changes)
Long-term Improvement	Data-driven iterative optimization	Relies on periodic manual evaluation; slow feedback

sity of 0.62, effectively mitigating the talent supply–demand time–space mismatch. Limitations include sample coverage and intangible cultural heritage quantification. Future work will integrate 5G industrial Internet data, expand intelligent manufacturing talent training, and promote coordination between vocational education and industrial upgrading.

AUTHOR CONTRIBUTIONS

All work in this study was independently completed by Mengting LI.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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Not applicable.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

This study was conducted in accordance with the ethical guidelines for research involving human subjects as stipulated by the Ethics Committee of Hebei Art & Design Academy. All procedures were reviewed and approved by the ethics committee of the affiliated institution prior to data collection. The personal information of all participating students was anonymized before analysis to ensure confidentiality and compliance with national data protection regulations. Informed consent was obtained from all participants or their legal guardians, confirming their voluntary participation in the study without any coercion.

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