



Construction and Application of an Intelligent Matching System for Vocational Education Internship Resources in the Context of Digital Transformation

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Abstract. Aiming at the issues of internship resource mismatch, low allocation efficiency, and delayed dynamic adjustment in vocational education, this paper constructs an intelligent internship resource matching system based on multi-dimensional data modeling and weight optimization algorithms, using a Kunpeng Industrial College in Wuhan as a case study. By integrating three core data types—job requirements in the Kunpeng ecosystem, student competencies, and resource characteristics—a resource allocation strategy is designed involving similarity calculation, weight assignment, constraint verification, and feedback iteration. This achieves precise matching among positions, students, and resources. Experimental results show a matching accuracy of 93.2% and a 40.5% improvement in resource utilization compared to manual allocation, effectively addressing the shortcomings of high subjectivity and poor adaptability in traditional models. This provides technical support and a practical paradigm for the digital transformation of internship teaching in the Kunpeng ecosystem and similar industrial colleges.

Keywords: Digital Transformation; Vocational Education; Intelligent Matching; Resource Allocation Strategy; Industry-Education Integration

1 Introduction

In the context of digital transformation and the integration of information technology, artificial intelligence is a core driver for reconstructing the allocation of vocational education resources and enhancing teaching effectiveness [1][2]. Particularly under the development of emerging industries like the Kunpeng ecosystem, using AI to achieve dynamic adaptation between internship resources and industrial demands helps resolve the dilemma of resource idleness and shortage, enhances the alignment between student skills and industry needs, and is of great significance for promoting the high-quality development of vocational education and deepening industry-education integration [3].

Current domestic and international research has formed diverse explorations in the field of vocational education internship resource matching [4]. International research

focuses on building immersive internship environments through technologies like digital twins and virtual simulation, and establishing multi-party collaborative industry-education integration mechanisms supported by legislation [5][6]. Domestic research has made progress in the construction of intelligent matching platforms and policy drivers, such as developing five-party linkage mini-programs and establishing AI empowerment centers [7]. However, existing research mostly concentrates on general fields or theoretical courses, with a clear lack of studies on internship scenarios for specific technological ecosystems like Kunpeng. Furthermore, issues like single dimensions and insufficient collaboration persist, making it difficult to support precise matching needs under rapid industrial iteration.

The study addresses three key challenges in Kunpeng ecosystem internship matching: building a multi-dimensional position-student-resource matching mechanism, developing quantitative models for competency and adaptability weighting, and establishing a dynamic feedback loop to keep pace with technological evolution.

This system tackles these challenges through multi-dimensional data modeling and AHP-based weight optimization, prioritizing Kunpeng core competencies. Its "similarity-constraint-feedback" mechanism dynamically generates precise matches among positions, students, and resources, enabling adaptive alignment within the specific technological ecosystem.

2 Basic Definitions

2.1 Internship Teaching Management Data

The experimental dataset established in this study is derived from the Kunpeng Industrial College (September 2024 to June 2025) and comprises three core components. Job demand data from 15 partner enterprises quantifies skill requirements for 160 positions using the following formula:

Job Demand Quantification Formula:

$$\text{Skill Requirement} = D \times P \quad (1)$$

where D represents demand intensity (high: 0.8-1.0; medium: 0.5-0.7; low: 0.1-0.4) and P denotes technical proficiency.

Student Competency Assessment Model:

$$C = A_{\text{practical}} \pm 3 + C_{\text{cert}} + P_{\text{project}} \quad (2)$$

Where the C is the cert and has a pass rate of 68%.

The 52 resources in the dataset are systematically annotated with capacity constraints and support strength values aligned with the predefined numerical intervals (0.1-0.4, 0.5-0.7, 0.8-1.0). This structured approach ensures temporal relevance and methodological validity, establishing a reliable foundation for system implementation and experimental verification.

2.2 Decision Problem Definition for Internship Teaching

The internship allocation system at Kunpeng Industrial College optimizes position-student-resource matching under industrial demand, resource capacity, and student competency constraints. It ensures each student receives one position-resource pairing while maintaining resource capacity limits. The system prioritizes aligning student competencies with position requirements, achieving dual optimization of person-position and person-resource compatibility. The matching score integrates position-student alignment (40%), student-resource compatibility (30%), and position-resource correspondence (30%). This industry-driven approach prioritizes enterprise needs while balancing student development and resource utilization efficiency within the ecosystem's operational framework.

2.3 Definitions Related to the Matching System

The intelligent matching system for Kunpeng Industrial College employs a four-module architecture to optimize resource allocation. The data processing module executes sequential operations of data cleaning, standardization, and feature extraction, utilizing expert screening and principal component analysis to reduce dimensionality from 21 to 9 features while preserving 92.3% variance. The matching algorithm incorporates enhanced weighting for core competencies according to:

$$W_{\text{core}} = 1.2 \times W_{\text{base}} \quad (3)$$

Multi-dimensional matching follows the weighted scheme:

$$S_{\text{total}} = 0.4S_{\text{position}} + 0.3S_{\text{student}} + 0.3S_{\text{resource}} \quad (4)$$

The optimization module enforces hard constraints via suboptimal substitution (maintaining $\geq 85\%$ initial adaptability), while quarterly parameter updates ensure continuous alignment with evolving industrial requirements.

3 Matching System Design

To address the specific requirements for internship resource allocation at Kunpeng Industrial College, a six-step allocation strategy was developed, guided by industry demand, supported by data algorithms, and refined through practical feedback. This approach accounts for the college's strong technical orientation, precise position requirements, and diverse resource types. The specific implementation steps are outlined as follows:

Data Preprocessing: Following data cleaning, standardized processing is applied to position demands, student competencies, and resource characteristics. The Min-Max normalization method transforms skill scores and resource support levels into the $[0,1]$ interval, with predefined mappings for categorical values (e.g., strong=0.9,

medium=0.6, weak=0.3). Principal component analysis reduces the feature set to 9 key dimensions, achieving a dimensionality reduction of:

$$R_{\text{reduction}}(\text{Rate}) = (21 - 9) / 21 \times 100\% = 66.7\% \quad (5)$$

This preprocessing strategy improves computational efficiency by over 50% while maintaining critical information integrity.

Multi-dimensional Similarity Calculation: Quantify the correlation between "position - student", "student - resource", and "position - resource". Tailored for the Kunpeng ecosystem, students passing the HCIA-Kunpeng certification are given an additional weight of 0.15; the similarity between students proficient in cloud-native development and corresponding resources is increased by 0.2; cloud-native development positions are prioritized to match resources supporting Cloud Native 2.0, ensuring technical adaptation accuracy.

Weight Coefficient Determination using AHP: Ten experts construct a judgment matrix to establish the weights for position demand, student ability, and resource characteristics as 40%, 30%, and 30% respectively. A technology iteration coefficient of 1.1 is introduced for emerging positions to promptly respond to industrial technology trends.

The matching system employs a weighted scoring model:

$$S_{\text{total}} = 0.4S_{\text{PS}} + 0.3S_{\text{SR}} + 0.3S_{\text{PR}} \quad (6)$$

where S_{PS} , S_{SR} , and S_{PR} represent position-student, student-resource, and position-resource compatibility, respectively. Candidates are ranked by composite scores, with top-tier matches (≥ 85 th percentile) receiving priority allocation. This approach ensures optimal tripartite matching while maintaining operational efficiency through its balanced weighting scheme.

Constraint Verification and Dynamic Adjustment: Focus on verifying student assignment uniqueness, resource capacity limits, and position preference matching. When resource overstaffing occurs, students with lower matching scores are adjusted to suboptimal resources, ensuring their adaptability is no less than 85% of the initial plan.

Establish "Monthly Collection - Quarterly Optimization" Feedback Iteration Mechanism: Regularly collect data such as resource utilization rate, enterprise satisfaction, and student adaptability. Adjust system parameters promptly based on feedback results to ensure continuous adaptation to industrial changes and technological development needs.

4 Experimental Verification

4.1 Experimental Setup

This study employs the Kunpeng Industrial College at a Wuhan vocational institution as its research context, adhering to principles of industrial authenticity, pedagogical objectivity, and technical relevance. Data were systematically gathered through enterprise interviews, campus training documentation, and platform exports to ensure

practical applicability. Position requirements were obtained via semi-structured interviews with 15 corporate experts, detailing skill demands and technical competencies for 160 roles. Student capabilities were assessed through practical evaluations, certification records, and project performance from 350 participants. Resource data encompassed technical specifications and usage patterns of 52 assets. During preprocessing, numerical features underwent Min-Max normalization while categorical variables were one-hot encoded. Dimensionality reduction through principal component analysis retained 9 features with 92.3% cumulative variance, optimizing computational efficiency without compromising data integrity.

4.2 Comparative Experiments

This study evaluates the proposed system's effectiveness in the Kunpeng Industrial College context by comparing it against three prevalent allocation methods used in vocational education. The traditional manual approach relies on experienced instructors' subjective judgment without algorithmic support. The single-dimension matching method considers only position-student compatibility while neglecting resource constraints. The basic Deep Q-Network (DQN) model prioritizes resource utilization but lacks domain-specific optimizations for the Kunpeng ecosystem.

Four key performance metrics were established to assess system performance. Matching accuracy measures the percentage of position-student-resource combinations satisfying both enterprise requirements and student competency thresholds. Resource utilization rate specifically tracks the usage efficiency of core technical assets. Enterprise satisfaction, scored by ecosystem partners, evaluates skill alignment and problem-solving capabilities. Student satisfaction, collected through standardized surveys, assesses perceived matching quality and skill development outcomes.

The experimental framework ensures comprehensive evaluation across multiple dimensions, with particular emphasis on the system's ability to balance industrial requirements with educational objectives while maintaining operational efficiency in resource allocation.

4.3 Experimental Results and Analysis

The proposed system was tested alongside the three comparison models for one internship semester (4 months). All models operated based on the same Kunpeng position demand, student ability, and resource data during the experiment. The results are shown in the Table 1 below:

Table 1. Performance Comparison of Different Models in Internship Resource Matching

Model	Matching Accuracy (%)	Resource Utilization Rate (%)	Enterprise Satisfaction (Points)	Student Satisfaction (Points)
Traditional Manual Allocation	62.8	48.5	68.2	70.5

Single-Dimension Matching	79.3	65.2	76.8	78.3
Basic RL Model (DQN)	86.5	74.8	82.5	84.7
Our Intelligent Matching System	93.2	89.0	90.3	92.6

The experimental results demonstrate that the proposed intelligent matching system achieves superior performance across all evaluation metrics in the Kunpeng Industrial College context. The system attained 93.2% matching accuracy, representing substantial improvements over traditional manual allocation (30.4 percentage points) and basic reinforcement learning models (6.7 percentage points). This enhancement stems from the integrated approach that coordinates position requirements, student capabilities, and resource characteristics through specialized weighting mechanisms.

Resource utilization reached 89.0%, with core technical assets showing particularly significant gains from 52% to 91%. Enterprise satisfaction scores improved to 90.3 points, reflecting better skill alignment and project adaptation. Student satisfaction reached 92.6 points, with 85% of participants acknowledging effective position-skill matching. These comprehensive improvements validate the system's practical value and scalability potential for specialized technological ecosystems.

To verify the necessity of the system's core modules (especially those optimized for the Kunpeng scenario), an ablation experiment was designed. The core modules—"Kunpeng-specific weight optimization", "resource technical adaptability constraint verification", and "feedback iteration"—were sequentially removed, and the changes in system performance were tested. The results are shown in the Table 2 below:

Table 2. Impact of Individual Modules on System Performance in Ablation Experiments

Experimental Scenario	Matching Accuracy (%)	Resource Utilization Rate (%)	Enterprise Satisfaction (Points)	Student Satisfaction (Points)
Complete System	93.2	89.0	90.3	92.6
Remove "Kunpeng-specific Weight Optimization"	85.7	83.2	81.5	86.4
Remove "Resource Tech Adaptability Constraint"	88.1	76.5	83.8	87.9
Remove "Feedback Iteration"	90.5	85.3	87.2	90.1

Ablation studies confirm each module's critical role in the Kunpeng ecosystem. Removing weight optimization reduced matching accuracy by 7.5% and enterprise

satisfaction by 8.8 points, demonstrating its decisive role in industrial alignment. Eliminating resource verification decreased utilization by 12.5%, causing server inefficiencies. Disabling feedback iteration lowered enterprise satisfaction by 3.1 points and hindered adaptation to Cloud Native 2.0 updates. These findings validate the modules' synergistic operation, with customized weight optimization contributing most significantly to industrial relevance while maintaining system adaptability to technological evolution.

5 Conclusion

This study develops an intelligent internship resource matching system for vocational education, implemented through the Kunpeng Industrial College case. Integrating multidimensional data modeling with weight optimization and closed-loop feedback, the system achieves precise alignment among positions, students, and resources. Experimental results demonstrate significant improvements in matching accuracy, resource utilization, and enterprise satisfaction compared to conventional approaches. The system's innovations include industry-specific metric design, demand-driven weighting mechanisms, and adaptive iteration capability. This methodology offers extensible solutions for similar industrial college contexts including smart manufacturing and artificial intelligence domains, demonstrating substantial practical applicability.

Future research will focus on three directions: integrating large language models like Huawei's Pangu to predict emerging positions; establishing cross-provincial platforms to share scarce resources among Kunpeng colleges; and utilizing real-time training data to enable dynamic matching. These advancements will support intelligent, industry-aligned precision in vocational internship education.

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