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Research on the Precision Competency Indicator System for Smart Logistics Talents in Higher Vocational Education Based on Big Data Analysis

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Abstract: With the rapid development of smart logistics technologies, the industry's demand for multi-skilled, data-driven talents is increasing. Addressing the current issues in vocational colleges—such as inconsistent competency evaluation standards and mismatched curricula with industry requirements—this study constructs a systematic competency indicator framework for smart logistics talents in higher vocational education. A total of 11,500 valid job postings were collected from online recruitment platforms, enterprise surveys and expert interviews. Text mining and cluster analysis were applied to identify five core competency dimensions: technical skills, data analytics, process management, collaborative communication, and comprehensive literacy. Furthermore, the Analytic Hierarchy Process (AHP) combined with the Entropy Method was utilized to assign weights to each dimension and sub-indicator, resulting in a three-tier quantitative framework. An empirical verification was conducted on students majoring in smart logistics at a selected vocational college, using dual-source evaluation from corporate HR and teachers to test its validity and applicability. The results proved that the indicator system can be effectively applied to curriculum development, student competency assessment, and recruitment evaluation, providing a feasible pathway for integrating education with industry in the smart logistics domain. This study not only bridges the gap in standardized competency assessment in this field but also offers references for other emerging technology areas in vocational education.

1. Introduction

1.1 Research Background

Since the 21st century, the global trend of digital transformation in manufacturing and service industries has become evident. Supply chain integration, artificial intelligence, and Internet of Things (IoT) technologies have injected new vitality into the logistics industry. Smart logistics, as a product of the deep integration of new-generation information technology and the modern logistics industry, operates with data-driven processes and intelligent decision-making at its core. The application of technologies such as big data, cloud computing, AI, and blockchain has enabled logistics systems to achieve real-time monitoring, dynamic optimization, intelligent scheduling, and self-learning capabilities. Against this backdrop, the traditional logistics talent training model clearly struggles to meet industry demands. Higher vocational education, as a crucial stage for cultivating application-oriented, technical, and skilled talents, should have teaching objectives that flexibly respond to industry changes, supplying the smart logistics system with talents possessing comprehensive technical capabilities and intelligent operation and maintenance qualities. However, the curriculum content in higher vocational institutions still focuses on traditional transportation management, warehouse operations, and logistics cost control, lacking training in core competencies such as intelligent equipment operation, big data application, and system collaborative optimization. This contradiction leads to a "structural mismatch" between graduates and enterprise job requirements. Therefore, scientifically constructing a competency indicator system for smart logistics talents in higher vocational education, based on actual industry needs, can not only clarify teaching objectives but also provide systematic guidance for curriculum reform, teacher training, and student self-development [1-6].

1.2 Research Significance

(1) Theoretical Significance

This research integrates big data analysis methods into the field of educational evaluation, achieving interdisciplinary integration between pedagogy and data science, and provides new theoretical support for talent assessment in vocational education. Simultaneously, by systematically modeling the occupational competency structure of smart logistics, it can further enrich the research system concerning "job competency" and "learning outcomes" in vocational education, providing a foundational model for the quality assurance mechanism in higher vocational education [7-8].

(2) Practical Significance

At the practical level, the research results can be used for:

1. Revising professional standards and curriculum systems in higher vocational colleges.
2. Designing employee training standards and career progression paths in enterprises.
3. Formulating guidelines for the construction and evaluation of smart logistics majors by educational authorities.
4. Aligning with the policy direction of "industry-education integration" and "school-enterprise cooperation," this indicator system helps realize a closed-loop talent cultivation process from the education end to the industry end.

1.3 Current Research Status at Home and Abroad

Foreign countries began researching logistics occupational competency models as early as the end of the 20th century. For example, APICS (The Association for Supply Chain Management) in the United States proposed the SCOR model to measure the competencies required for various positions in supply chain operational efficiency. The European vocational education sector has built skill standards at different levels according to the EQF (European Qualifications Framework). In recent years, Japan and South Korea have also actively integrated information technology capabilities into logistics vocational education, emphasizing data decision-making, simulation, and digital twin thinking in their curriculum systems. Domestically, since the concept of "New Logistics" was proposed, academia has conducted extensive exploration into logistics talent training. Most research focuses on traditional skills and management qualities, while research targeting the smart logistics direction often concentrates on intelligent warehouse management, unmanned delivery technology, or information system operation. However, overall, China currently lacks a systematic indicator model that integrates big data analysis, local industry characteristics, and the reality of higher vocational education. In particular, research on big data-driven "precision profiling" and dynamic evaluation mechanisms for talents is still in its infancy.

It can be seen that big data analysis has become an important tool for promoting precision in education, and smart logistics, as a emerging industry strongly supported by the state, requires talents with composite skills. Constructing a scientific and reasonable talent competency indicator system can not only improve the quality of talent cultivation in higher vocational colleges but also help optimize the allocation of educational resources and visualize academic outcomes. On this basis, the next chapter will further explore relevant theories such as smart logistics, big data, and competency assessment, laying a theoretical foundation for subsequent empirical research.

2. Analysis of Smart Logistics Job Competency Demands in Higher Vocational Education Based on Big Data

2.1 Dataset Overview

The original data selected for this study mainly comes from three types of sources: online recruitment platforms, enterprise survey questionnaires, and expert interviews. After preliminary data collection and preprocessing, a total of 11,500 valid job samples were obtained, covering large and medium-sized smart logistics enterprises and institutions in 31 provinces and municipalities across the country. The distribution of job types is as follows, as show in Table 1:

Table 1. Job Type Distribution Table

Job Category	Sample Size	Percentage (%)
Intelligent Warehouse Management	3,800	33.0
Transportation & Scheduling Optimization	2,100	18.3
System Data Analysis & Operation	2,700	23.5
Intelligent Equipment Operation & Maintenance	1,900	16.5
Supply Chain Collaborative Management	1,000	8.7

From the overall sample, technical and data analysis roles account for over 60% combined, indicating that the smart logistics industry's demand for composite skills and information management capabilities is significantly higher than for traditional operational roles.

2.2 High-Frequency Keyword Analysis of Job Postings

Using Python text mining technology to segment the job description texts, the top 50 high-frequency words were statistically obtained. The top ten keywords include: "Data Analysis, System Operation, Process Optimization, Collaborative Management, Intelligent Warehouse, ERP, IoT, Transportation Scheduling, Equipment Maintenance, Customer Service". The word frequency results show that:

1. Data analysis and information processing have become core competencies.
2. System operation and process optimization reflect the need for comprehensive technical application skills.

3. The high frequency of management-related keywords indicates that enterprises value coordination and communication skills.

4. Intelligent warehouse and IoT equipment maintenance reflect the industry's technological intelligence trend.

Synthesizing these keywords, the competency demands can be preliminarily divided into three directions: technical skills, management coordination, and comprehensive literacy.

2.3 Job Competency Clustering Results

Based on the high-frequency keyword analysis, the K-means clustering method was used to classify job competency elements. The results show that smart logistics jobs can be divided into five main competency types, as show in Table 2:

Table 2. Five main capability types for the intelligent logistics position table

Cluster ID	Competency Type Name	Core Keywords	Sample Proportion
C1	Technical Execution Ability	Automated equipment, robot control, RFID, MES system	21%
C2	Data Analysis & Information Processing Ability	Data collection, modeling, visualization, prediction algorithms	26%
C3	Process Design & Optimization Ability	Work standardization, route planning, inventory optimization	19%
C4	Collaborative Management & Communication Ability	Team collaboration, cross-department coordination, customer relationship management	22%
C5	Comprehensive Professional Literacy & Learning Innovation Ability	Learning awareness, problem-solving, service awareness, professional ethics	12%

It can be seen that the skill structure of smart logistics positions shows a clear composite trend—technical execution and data analysis have become foundational cores, while management coordination and innovation/learning qualities determine long-term career potential.

2.4 Analysis of Demand Differences Across Job Types

Further cross-comparison of different job types (warehouse management, transportation scheduling, system operation, etc.) revealed that:

1. Warehouse management positions focus on automated equipment operation and safety procedure execution.

2. Transportation scheduling positions emphasize data-driven decision-making and understanding of route optimization algorithms.

3. System operation positions require strong programming and system monitoring skills.

4. Supply chain coordination positions focus on cross-department collaboration and supply chain node management.

5. Customer service positions involve more communication, coordination, and emergency handling skills.

This differentiation implies that cultivating smart logistics talents in higher vocational education cannot adopt a single model; it should customize course modules for different job types to achieve "competency-oriented" teaching.

2.5 Analysis of Job Competency Demand Trends

Through time-series statistics (2021–2024), the following trends were observed, as show in Table 3:

Table 3.2021 - 2024 Position Capability Demand Trend Table

Year	Frequency of "Data Analysis" Keyword	Frequency of "Intelligent Equipment Operation" Keyword
2021	0.56	0.48
2022	0.63	0.52
2023	0.70	0.59
2024	0.78	0.65

The data indicates that with the popularization of smart logistics systems, the enterprise demand growth rate for "data-driven talents" exceeds 20%. Meanwhile, skills like "intelligent equipment operation" and "system maintenance" show a steady growth trend, indicating the industry is accelerating its intelligent transformation.

Trends:

1. Information technology and algorithm application skills will become basic requirements.
2. Automated equipment maintenance skills remain core practical abilities.
3. Although management and communication skills are soft skills, they are increasingly included in recruitment priorities, reflecting the enterprise preference for composite talents.

2.6 Competency Demand Model Construction

Integrating the high-frequency word results and cluster analysis, this study established a smart logistics job competency demand model. The model translates industry demands into educational goals for competency cultivation, providing a theoretical basis for the subsequent construction of the indicator system.

The model reveals the core competency structure of smart logistics talents, consisting of "five main dimensions":

1. Technical Skill Dimension → Intelligent operation and system maintenance;
2. Data Analysis Dimension → Modeling and algorithm application;
3. Management Coordination Dimension → Process design and team collaboration;
4. Comprehensive Literacy Dimension → Professional ethics and learning ability;
5. Innovative Thinking Dimension → Process improvement and efficiency enhancement.

Using big data methods, this section conducted an in-depth analysis of smart logistics industry jobs. Through high-frequency word statistics and cluster analysis, five core competency demands for talents were identified: technical execution, data analysis, process optimization, collaborative communication, and learning innovation. The analysis results show that the smart logistics industry has upgraded from a single operational type to a comprehensive technical and innovative type, placing higher demands on higher vocational education.

3. Construction of the Competency Indicator System for Smart Logistics Talents in Higher Vocational Education

3.1 Construction Approach

Based on the previous job competency demand analysis, this study maps industry requirements into the talent training objectives of higher vocational education. The construction of the indicator system follows these principles:

1. Systematic Comprehensiveness Principle - Covers all dimensions of smart logistics talents: technology, data, management, and comprehensive literacy, without omitting key information.
2. Measurability Principle - Indicators can be objectively assessed through scales, practical assessments, or data analysis.
3. Adaptability Principle - Can be adjusted promptly with industry technology updates (e.g., new automated equipment, big data tools).
4. Combination of Subjective and Objective Principles - Combines subjective expert evaluation via AHP with objective information quantity calculation via the entropy method to enhance weighscientificity.

3.2 Indicator Hierarchical Structure

Combining the previous five types of competency demands, a three-level hierarchical structure was constructed: Level 1 indicators (competency dimensions), Level 2 indicators (refined competency categories), Level 3 indicators (specific measurable elements).

3.2.1 Level 1 Indicators (Competency Dimensions)

Level 1 Indicator Code	Level 1 Indicator Name
T	Technical Skill Ability
D	Data Analysis Ability
M	Process Design & Management Ability
C	Collaborative Communication Ability
S	Comprehensive Literacy & Innovation Ability

3.2.2 Level 2 and Level 3 Detailed Indicators

Example Structure Table 4:

Table 4. Example Structure Table of Secondary Indicators and Sub-indicators at the Tertiary Level

Level 1	**Level 2**	**Level 3 (Examples of Measurable Elements)**
T Technical Skills	T1 Intelligent Equipment Operation	RFID read/write modules, proficiency in operating automated sorters, application of robot control commands
T Technical Skills	T2 System O&M and Maintenance	ERP system maintenance, MES system fault diagnosis and repair ability
D Data Analysis	D1 Data Collection & Cleaning	Python data scraping, SQL data cleaning
D Data Analysis	D2 Model Building & Prediction	Regression analysis, time series prediction model building
M Process Design & Mgmt	M1 Work Standardization Design	SOP compilation and optimization

Level 1	Level 2	Level 3 (Examples of Measurable Elements)
M Process Design & Mgmt	M2 Route & Inventory Optimization	Transportation route planning algorithm application, inventory turnover rate optimization schemes
C Collaborative Comm	C1 Team Collaboration	Department meeting participation rate, cross-department project success rate
C Collaborative Comm	C2 Customer Communication	Customer satisfaction survey results, order exception handling timeliness
S Comp. Literacy & Innov.	S1 Continuous Learning Ability	Number of industry skill certifications obtained
S Comp. Literacy & Innov.	S2 Innovation & Improvement Ability	Number of process optimization suggestions submitted and adoption rate

3.3 Indicator Weight Calculation Method

3.3.1 AHP Subjective Weight

Ten industry experts and heads of higher vocational programs conducted pairwise comparison scoring (1-9 scale method). After forming the judgment matrix, the consistency ratio was calculated ($CR \leq 0.1$).

Example weight results (Level 1 indicators):

Level 1 Indicator	**AHP Weight**
Technical Skill (T)	0.28
Data Analysis (D)	0.26
Process Management (M)	0.20
Collaborative Communication (C)	0.14
Comprehensive Literacy (S)	0.12

3.3.2 Entropy Method Objective Weight

Enterprise survey questionnaire results were collected, and the standardized information entropy value for each Level 2 indicator was calculated to derive objective weights. For example:

Level 2 Code	**Entropy Method Weight**
T1 Intelligent Equipment Operation	0.15
T2 System O&M and Maintenance	0.13
D1 Data Collection & Cleaning	0.12
D2 Model Building & Prediction	0.14
...	...

3.3.3 Weight Synthesis Formula

Let the final weight be W_i

$$W_i = \alpha \times W_{AHP} + (1-\alpha) \times W_{Entropy}$$

Where α is the subjective evaluation weight coefficient (set to 0.6 in this study), balancing expert experience with data objectivity.

3.4 Complete Indicator System Table (Partial)

Level 1 Indicator	Level 2 Code	Level 2 Name	Synthetic Weight
T Technical Skill	T1	Intelligent Equipment Operation Ability	0.16
T Technical Skill	T2	System O&M and Maintenance Ability	0.14
D Data Analysis	D1	Data Collection & Cleaning Ability	0.13
D Data Analysis	D2	Modeling & Prediction Ability	0.15
M Process Management	M1	Work Standardization Design Ability	0.11
M Process Management	M2	Route & Inventory Optimization Ability	0.09
C Collaborative Communication	C1	Team Collaboration Ability	0.07
C Collaborative Communication	C2	Customer Communication & Handling Ability	0.07
S Comp. Literacy & Innov.	S1	Continuous Learning Ability	0.05
S Comp. Literacy & Innov.	S2	Innovation & Improvement Ability	0.03

From the table, it can be seen that the synthetic weights of technical skill and data analysis indicators are greater than those of other dimensions, aligning with the industry's positioning of smart logistics talents as "technology-driven + data-driven."

3.5 Application Scenario Examples

(1) Curriculum Development Reference
Based on the indicator system, courses can be divided into:
1. Technical Courses: Intelligent Equipment Training, ERP/MES System Operation
2. Data Courses: Data Mining, Logistics Big Data Visualization
3. Management Courses: Process Optimization, Supply Chain Collaboration
4. Soft Skill Courses: Team Management, Business Communication

(2) Student Learning Evaluation
Introduce this indicator system into the graduation comprehensive assessment, conducting

multi-dimensional scoring based on synthetic weights to form a quantified "Smart Logistics Talent Profile."

(3) Enterprise Recruitment Alignment

Enterprises can design recruitment assessment forms based on this system, directly mapping job requirements to specific skill evaluation items, thereby improving matching precision.

Based on big data demand analysis, this section constructed a competency indicator system for smart logistics talents in higher vocational education, adopting a three-level hierarchical structure and a combined subjective-objective weight calculation method. This system not only covers various abilities such as technical skills, data analysis, process management, and collaborative communication but also achieves measurability, providing an implementable standard tool for higher vocational college program development and enterprise recruitment.

4. Indicator System Verification and Teaching Application Case Study

4.1 Verification Purpose and Approach

Purpose：

Although the indicator system constructed in this study is based on industry big data and expert opinions, its validity and operability still need testing through practical application at the theoretical level. The verification in this chapter has two objectives:

1. Test Scientificity: Confirm that each indicator dimension accurately reflects the core competencies of smart logistics talents.
2. Test Usability: Determine that the indicator system is suitable for talent cultivation and evaluation in higher vocational colleges.

Select students from the smart logistics track of a logistics management program in a higher vocational college as the sample. Use the Chapter 3 indicator system to conduct a comprehensive graduation competency assessment. Have enterprise HR and course teachers conduct cross-evaluation of the assessment results. Finally, use statistical methods to analyze consistency and differences.

The verification process is as follows:

Step 1: Select student samples from the higher vocational smart logistics major.
Step 2: Design assessment tools based on the indicator system.
Step 3: Conduct comprehensive competency assessment.
Step 4: Cross-evaluation by enterprise HR and teachers.
Step 5: Statistical data analysis.
Step 6: Draw conclusions on scientificity and usability.

4.2 Sample and Background Information

1. School: X Provincial Communications Vocational College (Smart Logistics Track)
2. Sample Size: 60 students (have completed all course studies, expected to graduate this semester)
3. Gender Ratio: Male 38, Female 22
4. Internship Experience: 85% have more than six months of enterprise internship experience.
5. Participating Enterprises: JD Logistics Branch, SF Technology Department, Local Smart Warehouse Center.

This background ensures that the sample has some industry practice, which is conducive to testing the explanatory power of the indicators in real job scenarios.

4.3 Assessment Tool Design

4.3.1 Tool Composition

Based on the previous three-level indicator system, a comprehensive assessment form containing 20 specific evaluable items was designed. Data for each item is obtained through the following three assessment methods:

1. Theoretical Test Questions (hard indicators like technical skills, data analysis)
2. Practical Tasks (practice indicators like system operation, equipment operation)
3. Scenario Simulation and Interviews (soft indicators like communication, collaboration, innovation awareness)

4.3.2 Scoring Mechanism

Each Level 3 indicator is set with a maximum score of 5 points. The final score is jointly completed by teacher scoring (hard skills) and enterprise HR scoring (soft skills), using a weighted average method to combine both opinions.

4.4 Verification Process and Data Collection

Step 1: Students complete theoretical tests and simulated system operations on campus, teachers record hard skill scores.

Step 2: Students participate in real business at their internship units, enterprise HR evaluates according to soft skill items.

Step 3: Collect data from both ends and import it into SPSS software for statistical analysis.

Step 4: Calculate the average score and standard deviation for each dimensional competency, analyzing the consistency of each indicator across different raters.

4.5 Verification Result Analysis

4.5.1 Scores for Each Level 1 Indicator

From the table, it can be seen that, as show in Table 5:

Table 5. Table of Score of the first-level indicators

Level 1 Indicator	Average Score	Standard Deviation	Enterprise HR Avg. Score	Teacher Avg. Score
Technical Skill (T)	4.21	0.52	4.18	4.24
Data Analysis (D)	4.05	0.47	4.01	4.08
Process Management (M)	3.88	0.51	3.90	3.86
Collaborative Communication (C)	3.94	0.49	4.02	3.86
Comprehensive Literacy (S)	3.75	0.44	3.80	3.70

1. Technical skills scored the highest, indicating a clear advantage for talents from this college in equipment operation and system maintenance.
2. Data analysis ability ranked second, aligning with industry demand.
3. Process management and communication skills were slightly weaker, suggesting a need to strengthen cross-department collaborative training in courses and practice.

4. Comprehensive literacy scores were relatively low, meaning there is still room for improvement in innovation and continuous learning areas.

4.5.2 Consistency Analysis

The Pearson correlation coefficient was used to test the evaluation consistency between enterprise and teacher raters. The correlation coefficients for the five Level 1 indicators were all between 0.72–0.85 with p-values < 0.01, indicating that this indicator system has good cross-rater consistency and can be used as a common evaluation tool for both parties.

4.6 Application Case Sharing

Case One: Curriculum Improvement

Based on the assessment findings that the score for "Application and Management of Intelligent Logistics Equipment" was relatively low, the institution will add a new course, "Application and Management of Smart Logistics Facilities and Equipment", to bring the operation and maintenance scenarios of intelligent logistics equipment into the classroom, enabling students to practice the application and management of intelligent logistics equipment in real work scenarios on campus.

Case Two: Enterprise Recruitment Assessment

A smart warehousing enterprise redesigned its recruitment assessment form based on this study's indicator system. It introduced a system operation practical session in the initial stage and added data analysis case studies in the interview stage, thereby improving matching precision. The enterprise reported that the onboarding adaptation time for hired candidates was reduced by approximately 30%.

By selecting higher vocational smart logistics students and combining dual-source evaluation from enterprise HR and teachers, this section empirically verified the indicator system constructed in Chapter 3. The results show that the system can effectively reflect the key competencies of smart logistics talents and can be practically applied in teaching improvement and recruitment evaluation. Although sample limitations exist, the overall feasibility and application potential have been fully demonstrated.

5. Conclusion and Outlook

This thesis, set against the background of the smart logistics industry and starting from actual industry demands, constructed a competency indicator system for smart logistics talents in higher vocational education through big data analysis and expert review. This system has not only undergone rigorous theoretical derivation but also demonstrated high consistency and applicability in practical application. It provides a concrete and feasible tool for higher vocational colleges to achieve deep "industry-education" integration and offers a scientific basis for the smart logistics industry to reserve talents that meet developmental needs. Ultimately, this study emphasizes that talent cultivation must keep pace with industry technological development, treating "technical skills + data capability" as the core driver while simultaneously fostering process management and soft skills to achieve the transformation of talents in the smart logistics field from "knowing how to do" to "knowing how to think."

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