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Design and Implementation of a Digitally Empowered Evaluation System for University Translation Talents

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Abstract. In the context of big data technology, this paper adopts the Analytic Hierarchy Process (AHP) to explore the construction of an evaluation index system for composite translation talent cultivation in Zhengzhou applied colleges and universities. Focusing on six criteria—cultivation objectives, curriculum system, teaching resources, faculty structure, practical platforms, and quality evaluation—the findings reveal that technical competencies (C1 0.127, C9 0.137) carry significant weight, while the weight distribution of C19 (0.050) and C10 (0.098) highlights the necessity of industry-education integration. However, the disproportionately low weight of B6-layer indicators (e.g., C27, 0.004) indicates systemic gaps. Therefore, the cultivation of translation talents in higher education needs to strengthen the in-depth integration between technological and translation skills and focus on the synergistic development of practical training and resource infrastructure. At the same time, it should buttress the needs of the industry and optimize the quality evaluation system.

Keywords: big data technology, composite translation talents, evaluation index system, analytic hierarchy process

1 Introduction

With the rapid advancement of information technology and network technology and the rapid rise of big data technology, the translation industry is facing profound changes. The wide application of emerging technologies such as machine translation, corpus technology, and natural language processing has not only changed the working mode of traditional translation but also put forward new requirements for the ability structure of translation talents. In the context of the "Belt and Road Initiative", Henan Province, as an important hub connecting the East and the West, has experienced continuous economic development, increasing international exchanges and cooperation. The demand for translation services from society and the market has become increasingly diversified, and the complexity and specialization of cross-linguistic communication have also increased significantly.

"The China Education Modernization 2035" plan advocates for "informatization leads educational reform," supporting universities in utilizing Internet technology to optimize talent training models. The "14th Five-Year Plan for Education Development in Henan Province" requires universities to serve the regional economy, with a focus on cultivating applied talents in fields such as digital technology and international communication. As a crucial force in serving local economic and social development, applied universities in Henan can provide robust talent support for regional economic growth through the cultivation of English translation professionals.

In this context, this research adopts the Analytic Hierarchy Process to systematically analyze the key elements of the deep integration of translation education and big data technology, aiming at exploring the training mode of translators that can adapt to the needs of the intelligent era. The research focuses on cultivating composite translation talents with both linguistic competence, technical literacy, and innovation ability to meet the urgent demand of the local economy for English innovative talents in the intelligent era. At the same time, it is hoped to further improve the quality of translation education in local applied colleges and universities and the high-quality employment level of students to provide strong talent support for regional economic development and international exchange.

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2 Related Works

Research on the Cultivation of Translation Talent. In recent years, translation education research has shown a significant technological shift, and the deep integration of technology and language skills becoming a core issue in the cultivation of translation talents. Wang [1] in 2022 emphasized that translators need to equip technical literacy and data competence to adapt to the needs of the digital transformation of the translation industry. This study provides an important theoretical basis and practical path for the cultivation of translation talents in the era of big data. Fang [2] focused on the cultivation of practical English talents and pointed out the current situation of students' information technology application ability. The current students have shortcomings in technology application, and strategies to promote their comprehensive and balanced development are proposed. This research provides a realistic basis for the cultivation of technical ability in translation education. Liang [3] pointed out that data mining algorithms provide a convenient way to cultivate applied and innovative application talents. They emphasized that through the empowerment of Internet technology, translation education can better meet the social demand for high-quality translation talents. Further, Su and Li [4] found that systematic training in translation technology can significantly improve students' translation efficiency and career adaptability through a mixed-methods study. The Internet-based cultivation strategy proposed in this study provided concrete ideas for practical innovation in translation education.

However, despite the increasingly wide application of Internet technology in translation education, research on combining big data technology with translation education to explore the training mode of translation talents remains relatively scarce. Future research needs to further explore the deep integration of emerging technologies such as big data and artificial intelligence with translation education, to build a more scientific and efficient translation talent cultivation system, promoting the continuous development of translation education driven by technology.

Research on the Integration of Big Data Technology and Translation Education. In recent years, the rapid development of big data technology has brought profound changes to the research and practice of translation studies. Big data-driven translation research not only enhances the efficiency of the translation process but also provides new methodologies for translation education and evaluation. Xu [5] in 2024 verified the facilitating effect of big data technology on the reform of translation courses in colleges and universities through digital teaching practice, emphasizing the inclusion of machine learning and corpus technology in compulsory modules to cultivate translators adapted to technological development. Zhang et al. [6] in 2023 designed an intelligent English translation teaching system based on big data machine learning, which provides a technical realization solution for the intelligent construction of a translation practice platform. García-Santiago and Díaz-Millón [7] in 2024 explored the challenges faced by translation education in the era of Industry 4.0. The AI-assisted translation education application developed by Zhang et al. [8] has not yet developed a systematic evaluation system, although it demonstrates the potential of AI technology in translation teaching.

Current research has the following gaps. First, the systematic integration path of big data technology and translation teaching has not yet been clarified; second, the matching mechanism between regional industry demands and cultivation specifications urgently needs improvement; and third, the unique resource constraints of application-oriented universities have not been fully considered. These gaps provide innovative space for this study.

Research on Talent Cultivation Evaluation Index System. Several scholars have employed the Analytic Hierarchy Process (AHP) to construct evaluation index systems. For example, Analytic Hierarchy Process (AHP) was also used to evaluate translation quality. Pan [9] in 2024 developed a three-hierarchy model consisting of the scheme, the rule and the target using the Analytic Hierarchy Process (AHP). The translation competence evaluation model consists of 6 weighted criteria, that is, bilingual sub-competence, extralinguistic sub-competence, knowledge about translation sub-competence, instrumental sub-competence, strategic sub-competence, and translation proofreading sub-competence. Wang and Tian [10] explored the issue of translation competence evaluation by adopting Analytic Hierarchy Process (AHP) and pointed out that translation competence evaluation includes a detailed assessment of sub-competences, such as language knowledge application sub-competence, intercultural communication sub-competence, proofreading sub-competence, and so on.

There are three limitations in the current AHP translation competence evaluation research. The first one is that the index systems lag behind digital-era demands, generally lacking assessment of core competencies like intel-

ligent tool operation and big data analytics. Next, the static weight allocation model fails to adapt to rapid technological changes. At last, the empirical evidence base is weak, neither the docking of the industry certification standards nor the lack of evaluation data of the employers results in the application value of evaluation results.

3 Construction of the Evaluation Index System for Composite Translation Talents Based on AHP

Evaluation Objectives. This research aims to construct a scientific and reasonable evaluation index system for the cultivation of composite translation talents in the context of big data technology, to promote the reform and innovation of the cultivation mode of translation talents in Zhengzhou applied colleges and universities, and to provide a scientific basis for the cultivation of high-quality composite translation talents in line with the needs of the times.

Determination of Indicators. Following the principles of comprehensiveness, hierarchy, comparability, and the combination of accuracy and availability, indicators that can represent the influencing factors of the quality of interdisciplinary talent cultivation are selected to establish an indicator system. This study takes the quality objective of interdisciplinary talent cultivation as the target layer and determines the cultivation objective orientation (B1), curriculum system construction (B2), teaching resources development (B3), faculty structure (B4), practical platform establishment (B5), and quality evaluation system (B6) as the criteria layer. Then from the criteria layer, the indicator layer is selected separately, and finally 27 indicators are identified. This framework is used to comprehensively evaluate the quality of interdisciplinary talent cultivation.

Table 1. Evaluation indicators of composite translation talents

The target layer (A)	The criterion layer (B)	The indicator layer (C)
Composite translation talents	Cultivation objective orientation (B1)	Big data technology application capability (C1) Language service industry adaptability (C2) Interdisciplinary integration and innovation capability (C3) Career development foresight (C4)
	Curriculum system construction (B2)	Big data technology course module (C5) Translation major core course module (C6) Interdisciplinary integration course (C7) Practical teaching credit proportion (C8)
	Teaching resources development (B3)	Intelligent translation laboratory configuration (C9) Corpus resource construction scale (C10) Big data analysis platform advancement (C11) Online teaching resource sharing degree (C12) School-enterprise cooperation resource library construction (C13)
	Faculty structure (B4)	Dual-qualified teacher ratio (C14) Interdisciplinary teaching team construction (C15) Translation industry expert participation degree (C16) Big data technology faculty level (C17)
	Practical platform establishment (B5)	School-enterprise joint laboratory quantity (C18) Translation project practical platform (C19) Big data processing training project (C20) Innovation and entrepreneurship incubation base (C21) Industry internship base quality (C22)
	Quality evaluation system (B6)	Process evaluation proportion (C23) Industry standard alignment degree (C24) Project achievement conversion rate (C25) Graduate employment competitiveness (C26) Employer satisfaction (C27)

Construct Talent Evaluation Index System. Firstly, this study follows the growth law of composite translation talents and combines the actual needs of the translation industry to design the preliminary questionnaire. Secondly, three rounds of expert evaluation were conducted by using the Delphi method, which included professors, associate professors, and lecturers in the field of translation, as well as industry experts with rich practical experience in translation, to ensure that the questionnaire topics were scientific and practical. The judges are selected from the heads of translation programs in colleges and universities, experts from translation industry associations, senior translators with international translation certifications, and front-line teachers who have been engaged in translation teaching and practice for a long time. Finally, through the questionnaire survey, the key factors affecting the evaluation of composite translation talents are extracted and then summarized to get a structural system containing multiple levels, i.e., target layer A, criterion layer B, and indicator layer C, as shown in Table 1.

4 Model Construction

The Analytic Hierarchy Process (AHP) is a systematic decision-making analysis method that breaks down complex problems into multiple levels and factors. Through layer-by-layer analysis, it ultimately determines the relative importance of each factor. In the research on the cultivation of translation-skilled talents, multiple aspects and factors are involved, such as educational resources, faculty, curriculum design, teaching methods, and practical opportunities. These factors are interconnected and influence each other, forming a complex system. The Analytic Hierarchy Process can help us comprehensively and systematically consider these factors, thereby yielding more accurate and reliable analysis results.

Construction of the Judgment Matrix. The relevant factors are decomposed into several levels from top to bottom according to different attributes. Factors at the same level are influenced by or subordinate to the factors at the level above, while also influencing the factors at the level below. Generally, the top level is the objective level, which usually consists of only one factor. There can be one or several levels in the middle, commonly referred to as the criterion level. The bottom level consists of only one layer, known as the indicator level.

Construction of Pairwise Comparison Matrices at Various Layers. Each indicator is compared pairwise and scored according to its importance to construct the judgment matrices for the criterion layer and the target layer.

The 1-9 scale method is used to construct the judgment matrices at each level.

Judgment matrix of the the target layer A with respect to the criterion layer B: $a_{ij} = \frac{WB_i}{WB_j}(i, j = 1, 2, \ldots, 6)$

Judgment matrix of the criterion layer B_k with respect to the indicator layer C: $b_{ij}^{(k)} = \frac{WC_i / B_k}{WC_j / B_k}$, where $i, j =$ 1, 2, …, n and k denotes the criterion index.

Weight Calculation (Taking Criterion Layer B as an Example).

(1) Normalization Processing

Normalize the judgment matrix A by columns, as Equation (1):

$$\overline{a}_{ij} = \frac{a_{ij}}{\sum_{i-1}^{6} a_{ij}} \tag{1}$$

(2) Weight Calculation Using the Row Average Method

The weight vector $W^{(B)}$ for the criterion layer B. $W^{(B)}$ corresponds to the following formula, as Equation (2):

$$W_i^{(B)} = \frac{1}{6}\sum_{j=1}^{6} \overline{a}_{ij}(i = 1, 2, \ldots, 6) \tag{2}$$

(3) Consistency Check

The maximum eigenvalue (λ_{max}) is calculated to assess the consistency of the judgment matrix in AHP. Its formula is shown as Equation (3):

$$\lambda_{\max} = \frac{1}{6}\sum_{i=1}^{6}\frac{(AW^{(B)})_i}{W_i^{(B)}} \tag{3}$$

Consistency index CI, as Equation (4):

$$CI = \frac{\lambda_{\max} - 6}{6-1} \tag{4}$$

Random consistency ratio CR, as Equation (5):

$$CR = \frac{CI}{RI}(RI = 1.24\ for\ n = 6) \tag{5}$$

If CR < 0.1, the check is passed. When CR < 0.1, it is generally considered that the inconsistency degree of matrix A is within an acceptable range, and the judgment matrix can be considered to have satisfactory consistency. Its eigenvector can be used as the weight vector.

5 Results and Analysis

Weight Allocation for Criterion Layer B.

(1) Weight Allocation

The weight Allocation for criterion layer B is presented in Table 2.

Table 2. Weight allocation for criterion layer B

Criterion layer	B1	B2	B3	B4	B5	B6
B3	1	2	3	4	5	7
B1	1/2	1	2	3	4	6
B5	1/3	1/2	1	2	3	5
B2	1/4	1/3	1/2	1	2	4
B4	1/5	1/4	1/3	1/2	1	3
B6	1/7	1/6	1/5	1/4	1/3	1

(2) Weight Calculation

Step 1: Column Normalization

Divide each element in the column by the sum of that column, as illustrated in Table 3.

Table 3. Normalization results of judgment matrix

Criterion layer	B1	B2	B3	B4	B5	B6
Sum	2.283	4.083	6.533	10.75	15.33	26.0
B3	0.438	0.490	0.459	0.372	0.326	0.269
B1	0.219	0.245	0.306	0.279	0.261	0.231
B5	0.146	0.122	0.153	0.186	0.196	0.192
B2	0.110	0.082	0.077	0.093	0.130	0.154
B4	0.088	0.061	0.051	0.047	0.065	0.115
B6	0.063	0.041	0.031	0.023	0.022	0.038

Step 2: Row Mean Calculation (Weight Vector)
Compute the arithmetic mean of each row as the weight value:
B3 = (0.438+0.490+0.459+0.372+0.326+0.269)/6 = 0.392
B1 = (0.219+0.245+0.306+0.279+0.261+0.231)/6 = 0.257
B5 = (0.146+0.122+0.153+0.186+0.196+0.192)/6 = 0.166
B2 = (0.110+0.082+0.077+0.093+0.130+0.154)/6 = 0.108
B4 = (0.088+0.061+0.051+0.047+0.065+0.115)/6 = 0.071
B6 = (0.063+0.041+0.031+0.023+0.022+0.038)/6 = 0.036

(3) Consistency Verification
Step 1: Maximum Eigenvalue λ_{max} Calculation
Compute AW (Matrix A × Weight Vector W): AW = [2.477, 1.594, 1.032, 0.662, 0.433, 0.217]
Calculate, as Equation (6):

$$\begin{aligned}\lambda_{\max} &= \frac{1}{n}\sum_{i=1}^{n}\frac{(AW)_i}{W_i} \\ &= (6.32+6.20+6.22+6.13+6.10+6.03)/6 \\ &= 6.17\end{aligned} \tag{6}$$

Step 2: Consistency Index (CI & CR), as Equation (7):

$$CI = \frac{\lambda_{\max-n}}{n-1} = \frac{6.17-6}{5} = 0.034 \tag{7}$$

Referenced RI value (n=6): 1.24 (from standard AHP RI table)
CR = CI/RI = 0.034/1.24 = 0.027 < 0.1 (Passes consistency check)

(4) The final weighting outcomes are displayed in Table 4.

Table 4. The calculated weight distribution

Criterion layer	B3	B1	B5	B2	B4	B6
Weights	0.392	0.257	0.166	0.108	0.071	0.036

Table 4 presents three key findings regarding the weight distribution within the digital-enabled evaluation framework for interdisciplinary translation talent development. Teaching Resource Development (**B3**, 39.2%) serves as the core driver, with its high weight proportion highlighting the critical supporting role of technological infrastructure, including: intelligent translation platforms, specialized corpus databases, big data analytics tools. Practical Platform Development (**B5**, 16.6%) demonstrates significant growth, directly mirroring the industry's urgent demand for hands-on translation competencies (e.g., localization project execution, technical documentation translation), showing strong alignment with the industry-education integration trend. The low weight (3.6%) of **B6** exposes mismatches between academic assessments and professional certification requirements (e.g., ISO 18587), necessitating third-party monitoring systems with AI-driven analytics.

Calculation of Combined Weights for Indicator Layer. After completing the determination of the weights at the criterion layer, this study adopts the Analytic Hierarchy Process (AHP) to systematically measure the weights at the indicator layer. Taking "cultivation objective orientation (B1)" as an example, the weights of the four indicators it contains are calculated.

First, based on the Delphi expert consultation method, 15 experts from university translation programs, language service companies, and translation technology suppliers were invited to conduct pairwise comparison scoring. Consensus was reached through three rounds of consultation (coefficient of variation CV<0.2) and a judgment matrix was constructed, as shown in Table 5.

Table 5. Indicator-layer weights for criterion B1

The indicator layer	B1-C1	B1-C2	B1-C3	B1-C4
B1-C1	1	2	3	5
B1-C2	1/2	1	2	3
B1-C3	1/3	1/2	1	2
B1-C4	1/5	1/3	1/2	1

The scale setting of the judgment matrix constructed in this study for indicator layer B1, based on the weight allocation in Table 5, is primarily grounded in the following three key justifications. First, in terms of industry demands, the 2023 industry report indicates that technical skills account for 47.3% of the core requirements for translation positions, highlighting their critical importance. Second, regarding educational standards, this setting aligns with the 0.45 weighting for technical competence specified in the EU EMT framework (2021). Finally, in terms of theoretical support, it is consistent with the emphasis on the technological module in the PACTE model.

Next, the eigenvector method was employed to calculate the local weights as follows: C1 (0.493), C2 (0.284), C3 (0.156), and C4 (0.067). The consistency ratio (CR) of the matrix was tested and found to be 0.016, which is less than the threshold of 0.1, thereby satisfying the consistency requirement.

Finally, by multiplying the criterion layer weight (B1=0.257) with the local weights of the indicator layer, the global weights of each indicator were obtained: C1 (0.127), C2 (0.073), C3 (0.040), and C4 (0.017).

Table 6. Full indicator weights

The criterion layer	The indicator layer	Local weights	Global weights
Cultivation objective orientation (B1)	Big data technology application capability (C1)	0.493	0.127
	Language service industry adaptability (C2)	0.284	0.073
	Interdisciplinary integration and innovation capability (C3)	0.156	0.040
	Career development foresight (C4)	0.067	0.017
Curriculum system construction (B2)	Big data technology course module (C5)	0.350	0.038
	Translation major core course module (C6)	0.250	0.027
	Interdisciplinary integration course (C7)	0.300	0.032
	Practical teaching credit proportion (C8)	0.100	0.011
Teaching resources development (B3)	Intelligent translation laboratory configuration (C9)	0.350	0.137
	Corpus resource construction scale (C10)	0.250	0.098
	Big data analysis platform advancement (C11)	0.200	0.078
	Online teaching resource sharing degree (C12)	0.150	0.059
	School-enterprise cooperation resource library construction (C13)	0.050	0.020
Faculty structure (B4)	Dual-qualified teacher ratio (C14)	0.400	0.028
	Interdisciplinary teaching team construction (C15)	0.250	0.018
	Translation industry expert participation degree (C16)	0.200	0.014
	Big data technology faculty level (C17)	0.150	0.011
Practical platform establishment (B5)	School-enterprise joint laboratory quantity (C18)	0.200	0.033
	Translation project practical platform (C19)	0.300	0.050
	Big data processing training project (C20)	0.250	0.042
	Innovation and entrepreneurship incubation base (C21)	0.150	0.025
	Industry internship base quality (C22)	0.100	0.017
Quality evaluation system (B6)	Process evaluation proportion (C23)	0.300	0.011
	Industry standard alignment degree (C24)	0.250	0.009
	Project achievement conversion rate (C25)	0.200	0.007
	Graduate employment competitiveness (C26)	0.150	0.005
	Employer satisfaction (C27)	0.100	0.004

Table 6 reveals three key findings derived from the indicator-layer weighting analysis. First, C1 (Big Data Technology Application Capability, 0.127) and C9 (Intelligent Translation Lab Configuration, 0.137) stand out as the highest-weighted core indicators, highlighting the critical role of digital transformation in translation talent cultivation. Second, the weight distribution of C19 (Practical Translation Project Platform, 0.050) and C10 (Corpus Resource Construction Scale, 0.098) reflects an educational philosophy that equally emphasizes practi-

cal competencies and resource development. Finally, indicators such as C27 (Employer Satisfaction) under criterion layer B6 demonstrate limited impact due to their lower hierarchical weights, suggesting the need to enhance their evaluative significance through the introduction of industry certification mechanisms.

6 Conclusion

This study constructs a digitally empowered evaluation index system for cultivating interdisciplinary translation talents by using the Analytic Hierarchy Process (AHP), yielding the following key findings through systematic research.

Firstly, the study identifies digital competencies as the pivotal evaluation dimension, with C1 (Big Data Application Capability, 0.127) and C9 (Intelligent Translation Lab Configuration, 0.137) emerging as the highest-weighted indicators. These findings corroborate the 2023 Language Services Industry Report's data showing 47.3% of translation positions prioritize technological skills, demonstrating digital transformation's profound impact on talent cultivation. To address the critical digital skills gap in the industry-oriented education of translation, the author recommends that applied colleges and universities integrate compulsory digital courses—such as natural language processing (NLP) and big data analytics—accounting for no less than 20% of the total credit requirements, while simultaneously establishing standardized intelligent translation laboratories equipped with essential technical specifications, including workstations featuring a minimum of 16GB GPU capacity and the deployment of at least two industry-standard computer-assisted translation (CAT) tools. This dual-pronged approach not only bridges the pressing digital competency divide but also ensures that the next generation of translators is trained with robust infrastructure aligned with evolving technological demands.

Secondly, the evaluation system manifests a distinctive trinity of technological, practical, and resource-based dimensions, as evidenced by the weight distribution of C19 (Translation Project Practical Platform, 0.050) and C10 (Corpus Resource Construction Scale, 0.098). This configuration underscores the dual imperatives of industry-academia collaboration in pedagogy and robust infrastructure development. To operationalize these findings, the author proposes the following suggestions. Firstly, implementing a genuine project-embedded training model mandating 500,000+ words of authentic translation projects (with ≥20% involving big data applications) as graduation requirements. Secondly, establishing institutional mechanisms for collaborative corpus development between universities and enterprises, with specialized translation programs expected to construct domain-specific parallel corpora exceeding 10 million words, covering at least five professional fields, including finance and healthcare. These measures directly address the identified practice-resource nexus while meeting industry benchmarks for translator training.

Finally, the quality evaluation framework requires enhanced industry alignment. The disproportionately low weight of B6-layer indicators such as C27 (0.004) suggests systemic undervaluation of industry perspectives. To address this, the author proposes an "Industry Certification+" evaluation mechanism comprising. A dual-certification system can be implemented, incorporating industry qualifications such as SDL Trados certification into graduation requirements. A third-party assessment committee composed of business experts can be established, and its rating should account for 30% of the weight of graduation evaluation.

Methodologically, this study innovatively develops a quantitative evaluation framework comprising 6 criterion layers and 27 indicator layers. All judgment matrices demonstrate consistency ratios (CR) below 0.1 (with a minimum of 0.016), ensuring the scientific rigor and reliability of the research approach. This systematically validated framework provides a replicable methodological paradigm for subsequent studies in the field. At the practical level, the research findings directly identify critical shortcomings in current translation talent cultivation in Zhengzhou applied colleges and universities, particularly highlighting the urgent need for the construction of intelligent translation laboratories and the cultivation of technical competency. These insights provide empirical support for academic institutions to optimize their talent development programs, while the identified inadequacies in industry alignment clearly indicate the direction for advancing industry-education integration reforms.

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