

Exploring Interdisciplinary Innovation Mechanisms: The “English + Language Intelligence” Model at STEM-focused Universities Under the New Liberal Arts Initiative

Yiran Liu^{1*}, Le Gao^{2*}

^{1,2} School of Foreign Languages, Wuhan University of Technology, Wuhan 430070, China

¹Corresponding author. Email: lyr0312@whut.edu.cn

ABSTRACT

Driven by the integration of the New Liberal Arts strategy and language intelligence technology, the interdisciplinary transformation of English majors in science and engineering universities has become essential. Focusing on the “Language Intelligence and Data Science” micro-major at Wuhan University of Technology, this study surveyed 24 students from the initial cohort using a questionnaire. Through reliability testing, descriptive statistics, cross-tabulation analysis, and Pearson correlation analysis, this study evaluated the curriculum effectiveness and student learning experiences. Findings indicate that while the curriculum generally aligns with the requirements of the New Liberal Arts, issues persist, including the insufficient contextualization of technical courses and a lack of tiered difficulty levels. Student learning is characterized by practical motivation, positive experiences, and differentiated skill levels. Furthermore, students with varying computer proficiencies and academic standings exhibit significantly different learning needs and challenges. A shortage of practical resources and an underdeveloped guidance system were identified as primary obstacles to program implementation. Based on these findings, this study proposes an integrated interdisciplinary innovation mechanism comprising four dimensions: curriculum, resources, guidance, and incentives. This framework provides an empirical reference for developing similar micro-majors and advancing the interdisciplinary transformation of English programs in science and engineering institutions.

Keywords: *New liberal arts, Science and engineering universities, English + language intelligence, Interdisciplinary education, Micro-major.*

1. INTRODUCTION

1.1 Research Significance

The rapid advancement of language intelligence, coupled with national policy directives, has jointly propelled the interdisciplinary transformation of English majors. Key policy documents—namely, *the Notice of the General Office of the Ministry of Education on Recommending New Liberal Arts Research and Reform Practice Projects and the Plan for the Adjustment, Optimization and Reform of Disciplinary and Major Settings in General Higher Education*—explicitly advocate breaking

down disciplinary barriers, deepening interdisciplinary integration, and exploring the “major + foreign language” model. Together, these documents provide robust policy support for the construction of micro-majors. Adhering to the principle of “strengthening liberal arts through science and engineering advantages,” the micro-major program at Wuhan University of Technology is characterized by its small scale, rapid responsiveness, and operational flexibility. It represents a significant pathway through which English majors can adapt to contemporary demands and cultivate interdisciplinary talent. In response to the transformative impact of artificial intelligence, it is imperative to leverage advanced technologies to reconstruct new spaces for foreign language

*These authors contributed equally to this work.

teaching and research. Taking curriculum system development as the point of departure, this effort seeks to explore novel organizational forms and management mechanisms for teaching and research, and to establish a foreign language learner community featuring constructive interaction among individual students, student learning groups, faculty teams, and technical support groups—a community that embraces innovation as its guiding ethos and enhanced efficiency as its benchmark[7].

1.2 Overview of the University’s “English + Language Intelligence” Micro-major

Guided by the principle of “strengthening the liberal arts through science and engineering advantages,” the university’s “Language Intelligence and Data Science” micro-major integrates knowledge from computer science, big data analytics, and linguistics. Addressing the societal demand for language data processing, the program cultivates interdisciplinary talent equipped with both a solid linguistic foundation and robust data processing skills. This approach facilitates the development of an interdisciplinary knowledge framework encompassing “basic programming, big data, and large language models.” The primary educational objective is to prepare students for the era of digital intelligence by ensuring they master theoretical frameworks and practical methodologies in fields such as linguistics and generative artificial intelligence. Jointly established by the School of Foreign Languages and the School of Computer Science and Artificial Intelligence, the program integrates multidisciplinary resources and places a strong emphasis on practical skill development. Consequently, graduates are well-prepared to secure employment in relevant sectors or pursue advanced academic studies.

2. LITERATURE REVIEW

2.1 Researches in China

Following the launch of ChatGPT in 2022, domestic generative large language models (LLMs) have undergone rapid development, establishing a robust technical foundation for the application of language intelligence in educational contexts.

Consequently, domestic universities have actively engaged in interdisciplinary initiatives. For example, Shanghai International Studies University established the Institute of Linguistic Sciences to facilitate corpus construction and cultivate

professionals in language intelligence. Similarly, the Key Laboratory of Artificial Intelligence and Human Language at Beijing Foreign Studies University focuses on integrating intelligent technologies with language education. These pioneering efforts provide valuable reference points for the interdisciplinary development of the “English + Language Intelligence” model, thereby promoting the transformation and advancement of foreign language education within the context of the New Liberal Arts initiative.

Furthermore, typical applications of artificial intelligence in language teaching currently encompass automated error correction, real-time feedback, rapid image recognition and content analysis, natural language question-answering systems, and personalized pedagogical support[1].

2.2 Researches in Foreign Countries

In response to contemporary advancements, traditional universities in Europe and North America have transitioned away from purely humanities-dominated educational models. Instead, they have introduced new academic curricula and disciplinary directions, gradually exhibiting a trend toward diversified development[6].

For instance, the Massachusetts Institute of Technology (MIT) offers a micro-major in “Computation and Humanities,” the University of Edinburgh provides a master’s program in “Language Data Science,” and Carnegie Mellon University has launched a dual-degree program in “Computational Linguistics and Communication.” Regarding curriculum structure, the “micro-credential” programs at the Technical University of Munich and the “skill modularization” courses at the National University of Singapore — both centered on modularity and personalized learning—serve as significant reference models for establishing micro-majors at science and engineering institutions. Within the international academic community, interdisciplinary research predominantly focuses on the application of artificial intelligence in language learning[2], analyzing the efficacy of AI in enhancing reading comprehension[5], and evaluating the educational impacts of conversational AI agents[3]. Ultimately, both domestic and international research have established a practical foundation for interdisciplinary education in language intelligence, thereby supporting this study in exploring

innovative pathways that leverage the engineering strengths of STEM-focused universities.

3. RESEARCH DESIGN

3.1 Research Objectives and Core Questions

Setting within the context of the New Liberal Arts initiative and utilizing the “English + Language Intelligence” micro-major at Wuhan University of Technology as a case study, this research aims to achieve two primary objectives. First, it systematically examines the current state of the program’s curriculum structure, pedagogical models, and resource allocation. Second, it integrates students’ learning experiences and needs to delineate an optimization pathway for interdisciplinary innovation mechanisms[4]. Specifically, the study seeks to address three core research questions:

- 1.What is the underlying logic of interdisciplinary integration between English language studies and language intelligence technologies at STEM-focused universities?
- 2.What characterize the students’ learning motivations, evaluations of their experiences, and perceptions of skill enhancement within the micro-major?
- 3.Based on the empirical survey data, how can an integrated interdisciplinary

innovation mechanism—encompassing “curriculum, resources, guidance, and incentives”—be constructed to serve as a reference model for similar micro-majors at other STEM-focused universities?

3.2 Research Participants and Methodology

This study employed purposive sampling to select the inaugural cohort of students enrolled in the micro-major as survey participants. The data collection process yielded 24 valid questionnaires, representing a 100% effective response rate. Although the sample size is relatively small, it encompasses all registered students in the inaugural cohort of this micro-major. As an exploratory case study, the data remains highly representative. The survey encompasses six dimensions (e.g., students’ demographic information, learning motivations, and curriculum evaluations) and consists of 6 single-choice items, 3 multiple-choice items, 19 five-point Likert scale items, and 2 open-ended questions.

Data were analyzed using SPSS software. Given the small sample size, the analysis primarily relied on descriptive statistics, supplemented by cross-tabulation and scale reliability testing to ensure analytical rigor. The specific analytical methods and their respective applications are detailed in the “Table 1” below:

Table 1. Data analysis methods and applicable scenarios of questionnaire survey

| Analysis Method | Applicable Scenarios | Core Function |
|--------------------------------------|---|---|
| Descriptive Statistics | Distribution of basic information, proportion of learning motivation, scores of scale questions | Present sample characteristics and overall situation of core survey indicators |
| Cross-analysis | Correlation between grade/computer foundation and curriculum satisfaction, ability improvement | Explore the potential impact of background variables on learning effect |
| Cronbach’s α Reliability Test | 19 scale questions (learning engagement, curriculum evaluation, ability improvement) | Verify the internal consistency of scale items and ensure data reliability |
| Pearson Correlation Analysis | Analysis of the relationship among core indicators such as learning engagement, curriculum setting, learning experience and ability improvement | Analyze the linear correlation between variables and identify key factors affecting ability improvement |

4. ANALYSIS OF QUESTIONNAIRE DATA

4.1 Reliability Analysis of the Measurement Scale

The 19 Likert scale items in this survey encompass four core dimensions, including learning engagement and curriculum evaluation.

Cronbach’s alpha (α) coefficient was employed to assess the reliability, thereby verifying the rationality of the items and the internal consistency of the data. The results indicate an overall Cronbach’s α of 0.943, with the α coefficients for all individual dimensions exceeding 0.79. These values surpass the threshold for high reliability, demonstrating excellent internal consistency among the scale items. Consequently, the collected data is

highly reliable and provides a valid empirical foundation for subsequent analysis. ("Table 2")

Table 2. Scale reliability test results

| Scale Dimension | Number of Items | Cronbach's α Coefficient | Standardized Cronbach's α Coefficient | Reliability Judgment |
|-----------------------|-----------------|---------------------------------|--|----------------------|
| Learning Evaluation | Engagement 4 | 0.797 | 0.802 | Good |
| Curriculum Evaluation | Setting 5 | 0.917 | 0.921 | Excellent |
| Learning Evaluation | Experience 5 | 0.903 | 0.908 | Excellent |
| Ability Evaluation | Improvement 5 | 0.912 | 0.916 | Excellent |
| Overall Scale | 19 | 0.943 | 0.945 | Excellent |

4.2 Descriptive Statistics: Sample Characteristics and Distribution of Core Indicators

The demographic profiles distribution of the survey respondents was categorized into five variables (e.g., academic year, academic major). The specific demographic distribution is detailed in the "Table 3" below:

4.2.1 Distribution of Demographic Variables

Table 3. Distribution of demographic variables of survey samples

| Variable | Grade | Total | Major | Total | Computer Foundation | Total | Career Planning | Total |
|----------------|-----------|------------|------------------|------------|---------------------|-----------|--|--------------|
| Classification | Sophomore | 13(54.17%) | English | 14(58.33%) | None | 4(16.67%) | Shift language intelligence-related fields | to 8(33.33%) |
| | Junior | 8(33.33%) | French | 7(29.17%) | Basic | 18(75%) | Deepen English major | 3(12.5%) |
| | Senior | 3(12.5%) | Japanese/ Others | 2(12.5%) | Proficient | 2(8.33%) | No clear career planning | 13(54.17%) |

4.2.2 Distribution of Learning Motivations

Students' motivations for enrolling in the micro-major exhibit a strong practical orientation. Data from multiple-choice questions reveal that 100% of respondents identified "improving interdisciplinary abilities and enhancing employment competitiveness" as their primary motivation. This is followed by broadening professional horizons (54.17%) and aligning with career planning (50%), all of which center on career development. Conversely, intrinsic interest (41.67%) and policy incentives (4.17%) are less influential, indicating that the micro-major's appeal stems primarily from its inherent interdisciplinary utility.

4.2.3 Mean Scores of Core Evaluation Scales (1 = Strongly Disagree/No Improvement, 5 = Strongly Agree/Great Improvement)

The mean scores across all four dimensions indicate moderate to high levels of satisfaction, each displaying distinct characteristics. The learning experience dimension received the highest rating $M=4.06$, driven by excellent scores in classroom atmosphere $M=4.29$ and instructional clarity $M=4.04$. For curriculum evaluation $M=3.87$, students highly rated the cutting-edge nature of the content $M=4.04$ and its practicality $M=4.00$, though integration with the core English curriculum $M=3.75$ requires optimization. Regarding skill

enhancement $M=3.76$, the most significant perceived improvement was in the comprehension of interdisciplinary knowledge $M=4.00$, whereas the application of technology and employment competitiveness scored comparatively lower. Finally, in learning engagement $M=3.59$, while self-reported time investment was robust $M=3.71$, course interest and the willingness to pursue continuous learning both $M=3.50$ indicate room for improvement.

4.2.4 Analysis of Resource Demands and Existing Challenges

The demand for teaching resources is predominantly focused on practical applications. Specifically, 87.5% of students desire increased access to industry corpora and datasets, 75% require complimentary cloud computing platforms or software accounts, and 66.67% express a need for offline practical laboratories. Conversely, the demand for additional teacher guidance is notably low. The primary challenges identified by students pertain to practical application components, with 58.33% reporting a lack of practical opportunities and 41.67% noting a shortage of resources. Secondary challenges include insufficient integration between the micro-major courses and the core English curriculum, as well as a steep learning curve (both cited by 33.33%). Workload and scheduling constraints appear to have a minimal impact (cited by < 25% of respondents).

4.3 Cross-tabulation Analysis of Background Variables and Their Impact on Learning Outcomes

Using foundational computer skills as the primary grouping variable and academic year as the secondary grouping variable, a cross-tabulation analysis was conducted to explore the impact of student backgrounds on curriculum satisfaction and skill enhancement. The findings are as follows:

4.3.1 The Significant Impact of Foundational Computer Skills on Learning Outcomes

Students with stronger foundational computer skills reported significantly higher scores in data analysis skill enhancement $M = 4.20$ and satisfaction with curriculum practicality $M = 4.32$ compared to those with weaker foundational skills

($M = 2.94$ and $M = 3.85$, respectively). Furthermore, 68.4% of students with weaker skills reported a steep learning curve and insufficient guidance, a proportion substantially higher than that of their more skilled peers (20%). This indicates that disparities in technical backgrounds lead to divergent learning outcomes, highlighting an urgent need for targeted support for students with weaker foundational skills.

4.3.2 The Differential Impact of Academic Year on Learning Outcomes

Students across different academic years exhibited distinct, stage-specific characteristics regarding their learning outcomes and needs. Third-year students (juniors) reported the highest levels of curriculum satisfaction $M = 3.92$ and skill enhancement $M = 3.81$; however, 53.3% of this group cited scheduling conflicts and heavy academic workloads. Second-year students (sophomores) demonstrated high learning engagement $M = 3.65$ but lower perceptions of the curriculum's cutting-edge nature and practicality $M = 3.78$, expressing a pressing need for foundational technical guidance. Conversely, fourth-year students (seniors) provided the lowest overall evaluations $M = 3.67$, as their primary focus shifted toward practical applications and relevance to future employment.

4.4 Pearson Correlation Analysis of Core Indicators in the Micro-Major

4.4.1 Analytical Methodology

Drawing upon the learning experience survey data from the Language Intelligence and Data Science micro-major, this study establishes a core analytical framework comprising independent and dependent variables. All indicators were standardized using a 5-point scale to ensure data comparability and analytical validity. Pearson correlation analysis was conducted using Python 3.9 to quantify the linear relationships among the core indicators. The strength of these correlations was measured using the correlation coefficient (r), while statistical significance was verified via the p -value.

The independent variables focus on the core input elements of the learning process, encompassing four key factors: learner engagement, curriculum design, perceived learning experience,

and resource support. These variables were selected to identify potential drivers affecting learning outcomes. Conversely, the dependent variables focus on the core outcomes of the micro-major. An outcome evaluation framework was constructed across three dimensions—skill enhancement, knowledge application, and career relevance—to quantify the program’s actual value and impact on learners.

4.4.2 Analysis Results

The Pearson correlation coefficient matrix and the corresponding significance matrix for the seven core indicators were computed using Python. To

visualize the correlation patterns among the indicators, a heatmap was generated using the Seaborn library, as depicted in the figure below. In this heatmap, red denotes a positive correlation, blue denotes a negative correlation, and color intensity corresponds to the strength of the correlation. Asterisks (*) indicate statistical significance at the $p < 0.05$ level. Overall, varying degrees of linear correlation exist among the dimensions. Notably, learning experience, curriculum design, and skill enhancement exhibited the most prominent positive correlations. Conversely, resource accessibility, knowledge application, and skill enhancement demonstrated significant negative correlations. (“Figure 1”)

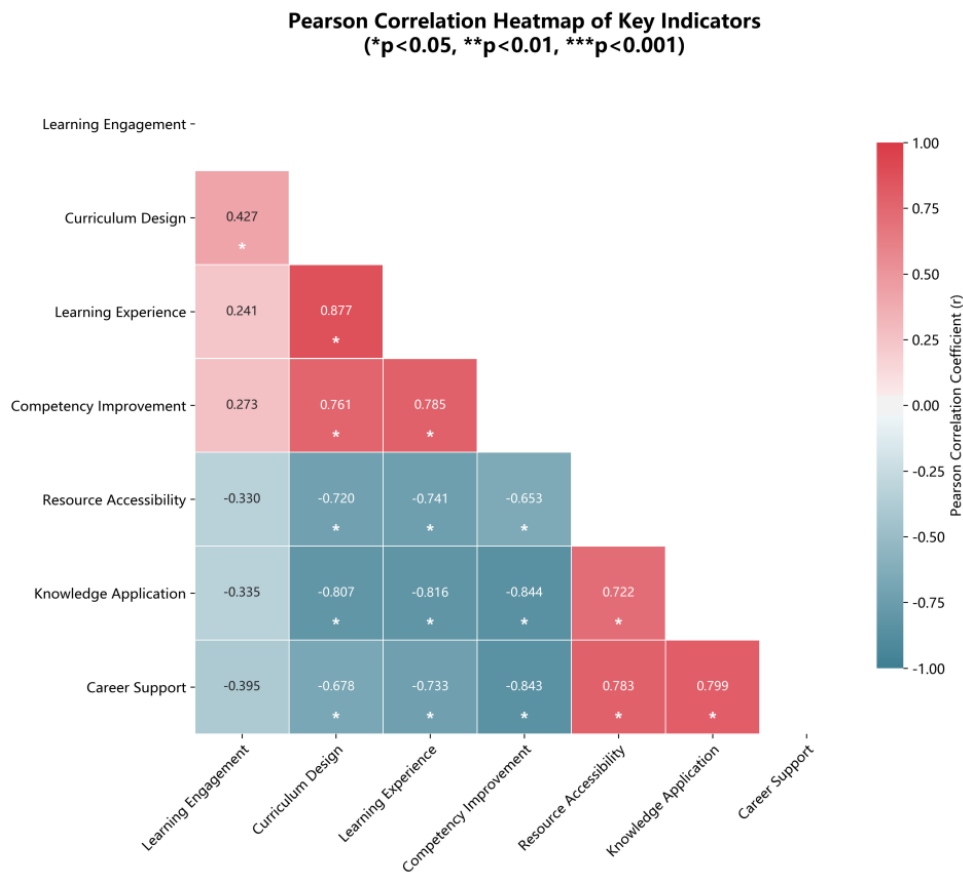


Figure 1 Heatmap of correlation among core indicators of the language intelligence micro-major.

Designating the “mean score for skill enhancement” as the primary outcome indicator for the micro-major, the specific impact of each independent variable on this metric was analyzed in detail. The results are presented in Table 4. Based on the threshold criteria of $r \geq 0.4$ and $p < 0.05$, two key influential factors were identified: the mean score for learning experience and the mean score for curriculum design.

Table 4. Correlation analysis results of influencing factors of average score of ability improvement

| Influencing Factor | Correlation Coefficient r | Significance p Value | Significance Level | Correlation Strength | Key Factor |
|--------------------------------------|---------------------------|----------------------|-----------------------------------|------------------------------|------------|
| Average Score of Learning Experience | 0.785 | 0 | Extremely Significant (**p<0.001) | Strong Correlation | Yes |
| Average Score of Curriculum Setting | 0.761 | 0 | Extremely Significant (**p<0.001) | Strong Correlation | Yes |
| Average Score of Learning Engagement | 0.273 | 0.197 | Not Significant (ns p≥0.05) | Weak Correlation | No |
| Resource Convenience | -0.653 | 0.001 | Significant (**p<0.01) | Strong Correlation | No |
| Employment Help Degree | -0.843 | 0 | Extremely Significant (**p<0.001) | Extremely Strong Correlation | No |
| Knowledge Application Degree | -0.844 | 0 | Extremely Significant (**p<0.001) | Extremely Strong Correlation | No |

The data presented in the preceding “Table 4” reveal the following:

- (1) A strong positive correlation $r = 0.785, p < 0.001$ exists between the mean scores for learning experience and skill enhancement. This suggests that a superior classroom experience—characterized by instructional clarity, adequate resources, and a high perceived value—is closely associated with greater skill enhancement. Consequently, the learning experience emerges as the primary factor influencing students’ skill enhancement. (Note: The original text incorrectly interpreted the correlation coefficient r as a regression slope. Correlation describes the strength of an association, not a 1:1 unit increase.)
- (2) A strong positive correlation is also observed between the mean scores for curriculum design and skill enhancement $r = 0.761, p < 0.001$. Specifically, higher ratings for the curriculum’s cutting-edge content, disciplinary integration, and practicality correspond to more significant improvements in learners’ skills. This makes curriculum design the second most critical influencing factor, following the learning experience.
- (3) The correlation between learning engagement and skill enhancement is weak and statistically insignificant $r = 0.273, p = 0.197$. This indicates that, at the current stage, the extent of learners’

engagement (e.g., time investment, proactive research) does not significantly correlate with perceived skill enhancement. This lack of significance may stem from insufficient instructional scaffolding within the curriculum design.

- (4) Interestingly, resource accessibility, the extent of knowledge application, and perceived career utility exhibit significant negative correlations with skill enhancement. This anomalous finding may be attributed to a perceptual bias within the sample; specifically, learners’ assessments of “skill enhancement” rely more heavily on subjective feelings, whereas evaluations of objective conditions like “resource accessibility” are based on actual provision. This hypothesis requires further validation, triangulated with qualitative feedback from the open-ended survey questions.

5. CONCLUSION

Drawing upon the 24 valid survey responses from the micro-major cohort, this chapter has established the analytical rigor of the data through reliability analysis, descriptive statistics, and cross-tabulation analysis. It has examined the current state of the micro-major, the characteristics of students’ learning experiences, and the impact of demographic variables. By addressing the three core research questions, this chapter provides empirical support for the construction of an interdisciplinary innovation mechanism. The primary findings are summarized as follows:

5.1 Clear Interdisciplinary Logic but Room for Curriculum Optimization

The logic underpinning the interdisciplinary integration of the “English + Language Intelligence” model at STEM-focused universities is clear, and the overall curriculum design aligns well with the objectives of the New Liberal Arts initiative. However, further optimization is required. Certain purely technical courses lack integration with English language contexts, and the curriculum would benefit from tiered difficulty levels to better accommodate students with varying technical backgrounds.

5.2 Pragmatic Motivations and Differentiated Learner Needs

Students are primarily driven by practical motivations rather than extrinsic utilitarian factors. While the overall learning experience is positive, there are notable deficiencies in practical guidance and resource accessibility. Students report significant enhancements in cognitive skills, but improvements in technical application and employability remain comparatively weak. Due to insufficient practical training and disparate foundational knowledge, clear interdisciplinary employment advantages have not yet materialized. Furthermore, learner needs are highly differentiated: students with weaker technical foundations require fundamental guidance, whereas those with stronger backgrounds seek advanced practical opportunities. Significant variations in needs also exist across different academic years.

5.3 Learning Experience and Curriculum Design as Primary Drivers

Pearson correlation analysis indicates that learning experience and curriculum design are the principal positive factors driving skill enhancement within the micro-major, with learning experience exerting the most substantial impact. Conversely, learning engagement demonstrates a weak correlation with skill enhancement, a finding likely attributable to insufficient instructional scaffolding within the current curriculum design.

5.4 Four-dimensional Optimization of the Innovation Mechanism

The interdisciplinary innovation mechanism can be optimized across four key dimensions:

- (1) Curriculum: Implementing tiered curriculum design, deepening contextual integration, and emphasizing cutting-edge practical applications.
- (2) Resources: Prioritizing the provision of key practical resources and better integrating existing institutional assets.
- (3) Guidance: Facilitating collaboration among interdisciplinary faculty to support students with weaker foundations and providing tailored guidance based on academic year.
- (4) Incentives: Improving credit recognition systems, establishing platforms for practical competitions, strengthening students' identification with interdisciplinary values, and fostering a sustained willingness for continuous learning.

ACKNOWLEDGMENTS

Funding: This work was supported by the Provincial Innovation and Entrepreneurship Training Program for College Students under Grant No. 20250100234.

REFERENCES

- [1] Gao, T. T., & Guo, J. A review of research on artificial intelligence education applications. *Modern Educational Technology*, (1), 11–17. 2021. Roles and research foci of artificial intelligence in language education: An integrated bibliographic analysis and systematic review approach. *Interactive Learning Environments*, 2019:(7), 4270–4296.
- [2] Liang, J., Hwang, G., Chen, M. & D. Darmawansah. Roles and research foci of artificial intelligence in language education: An integrated bibliographic analysis and systematic review approach[J]. *Interactive Learning Environments*, 2021(7): 4270-4296.
- [3] Smutny, P., & Schreiberova, P. Chatbots for learning: A review of educational chatbots for the Facebook Messenger. *Computers & Education*, (2020). 151, Article 103862. Xu, Z., Wijekumar, K., Ramirez, G. The effectiveness of intelligent tutoring systems on K-12 students' reading comprehension: A meta-analysis. *British Journal of Educational Technology*, 2019:(6), 3119–3137.

- [4] Wang Chao, Feng Ji, Sun Song, et al. Research on the Impact and Implications of Artificial Intelligence Large Language Models on Talent Cultivation in Higher Education [J]. Digital Communication World, 2026 (02): 178-180.
- [5] Xu, Z., Wijekumar, K., Ramirez, G., et al. The effectiveness of intelligent tutoring systems on K-12 students' reading comprehension: A meta-analysis[J]. British Journal of Educational Technology, 2019(6): 3119-3137.
- [6] Yuan, C., Men S. Thoughts on the mixed teaching mode of ideological and political courses in colleges and universities based on the MOOC platform[EB/OL]. 2021.
- [7] Zhang, W., & Wang, S. How to take the key step of "interdisciplinarity" in the construction of university micro-majors. Educator, 2025:(4), 30-31.