Construction of AI Driven Personalized Learning Path for College English and Quantitative Analysis of Teaching Effectiveness

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ABSTRACT Given the digital transformation in education and the reform of college English teaching, the traditional "one size fits all " model fails to address individual learning needs or the specialized language requirements needed in different academic and engineering contexts. This lack of adaptability hinders the development of core literacy and precise communication skills. Artificial intelligence (AI) technology, with its core advantages such as big data analysis, adaptive recommendation, and intelligent evaluation, provides technical support and methodological guarantees for solving traditional teaching difficulties and building personalized learning paths.

INDEX TERMS artificial intelligence,college english,personalized learning path,adaptive recommendation,engineering english

I. INTRODUCTION

A. RESEARCH BACKGROUND

As a core public basic course in higher education, college English undertakes the important mission of cultivating students' cross-cultural communication skills and international perspectives, which are essential for navigating the complex global discourse surrounding fiber morphology innovation and manufacturing excellence. These self-learning abilities further enable students to master the specialized technical terminologies and digital standards required to advance the modernization of the industry [1-3]. The "Guide to College English Teaching (2024 Edition)" clearly proposes to "promote the deep integration of information technology and English teaching, build personalized and intelligent teaching models, and meet the diverse learning needs of students" [4-6]. Although multimedia technology has been widely integrated into English teaching within Chinese universities, it still faces structural challenges in effectively delivering the specialized linguistic and visual data required to master the technical intricacies of fiber morphology and manufacturing excellence. These systemic limitations hinder the seamless fusion of digital pedagogical tools with the high precision requirements of modern engineering discourse.

B. RESEARCH APPROACH

This article follows the technical route of "theoretical sorting - current situation diagnosis - path construction

- system development - empirical verification - effectiveness quantification":

Systematically review the core theories and technologies in areas such as AI education applications, personalized learning, and second language acquisition, and clarify the theoretical basis and technical support for research;

Diagnose the current status and core issues of personalized learning in college English teaching through methods such as questionnaire surveys, classroom observations, and in-depth interviews;

Building an AI driven personalized learning path for college English based on student portrait construction, learning needs analysis, and adaptive recommendation algorithm design;

Develop a personalized learning system prototype, integrate AI technology to achieve automated path generation and dynamic optimization;

Select multiple universities to conduct empirical research, collect data, and quantitatively analyze teaching effectiveness from multiple dimensions;

Based on empirical results, optimize the learning path and system functions, and improve the practical plan[7].

II. CORE CONCEPTS AND THEORETICAL FOUNDATIONS

A. DEFINITION OF CORE CONCEPTS

AI driven personalized learning path

AI driven personalized learning path refers to the use of artificial intelligence technology (big data analysis, machine learning, natural language processing, etc.) to tailor and dynamically adjust learning paths for students based on their individual differences (language foundation, learning style, interest preferences, learning goals) and real-time learning status, including personalized arrangements for learning content, learning progress, learning methods, practice tasks, and other aspects. Its core features include:

Accuracy: Accurately capturing individual differences and learning patterns of students based on big data analysis;

Dynamicity: dynamically adjust learning paths based on students' real-time learning performance and changing needs;

Adaptability: The learning path is highly adapted to students' language foundation, learning style, and learning goals;

Autonomy: Encourage students to choose their own learning content and pace, and cultivate their ability to learn independently[8-9].

Student portrait

Student portrait refers to a comprehensive and three-dimensional student digital model constructed using big data analysis techniques by collecting multidimensional data of students (language foundation data, learning behavior data, learning style data, interest preference data, learning goal data). It is the core basis for generating personalized learning paths. Its core dimensions include:

Basic dimensions of language: proficiency in various language skills such as listening, reading, writing, translation, and speaking;

Learning style dimensions: visual, auditory, kinesthetic and blended styles; While the VAK model provides a foundational heuristic for initial path customization, the research acknowledges the 'Learning Styles Myth' critique within modern pedagogy, which suggests that these preferences are fluid rather than fixed traits. Consequently, the AI system treats VAK profiles as dynamic priors that are continuously updated and crossvalidated against real-time performance data, ensuring the learning path evolves based on empirical cognitive load rather than rigid stylistic labels.

Interest preference dimension: preferences for different topics (culture, technology, entertainment, academia) and learning forms (video, audio, text, interactive exercises);

Learning objective dimensions: The Learning Objective Portrait is categorized into three distinct, mutually exclusive domains: (1) Standardized Assessment Objectives, encompassing CET-4, CET-6, and postgraduate entrance examinations; (2) Functional Communication Objectives, including daily oral interaction and academic discourse; and (3) Professional Advancement Objectives, specifically targeting workplace English proficiency and technical translation within the industry[10-11].

B. THEORETICAL BASIS

The theory of personalized learning emphasizes putting students at the center and designing teaching activities based on their individual differences. Its core ideas include:

Individual differences are the prerequisite for personalized learning, and full attention should be paid to the differences in students' learning foundations, learning styles, interests and preferences;

The learning path should have flexibility and adaptability to meet the diverse learning needs of students; Students should participate in the design and adjustment of learning paths to cultivate their ability for self-directed learning;

Personalized learning requires technological support to achieve large-scale personalized teaching through information technology[12].

Application Theory of Artificial Intelligence in Education

The theory of artificial intelligence education application focuses on the application mechanism and effects of AI technology in the field of education, and its core viewpoints include:

AI technology can achieve precise collection and in-depth analysis of educational data, providing decision-making basis for personalized teaching;

Adaptive recommendation algorithms can achieve personalized matching of learning content, tasks, and methods;

The intelligent evaluation system can achieve real-time and comprehensive learning effectiveness evaluation and feedback;

AI technology can reduce the workload of teachers and improve teaching efficiency and quality[13-14].

C. EDUCATIONAL EVALUATION THEORY

The theory of educational evaluation provides methodological support for the quantitative analysis of teaching effectiveness, and its core viewpoints include:

Evaluation should follow the principles of objectivity, comprehensiveness, and development, and comprehensively measure teaching effectiveness;

The evaluation indicators should cover multiple dimensions such as knowledge, ability, emotion, attitude, etc; The evaluation method should combine quantitative evaluation and qualitative evaluation to achieve an organic combination of process evaluation and outcome evaluation;

The evaluation results should be applied to teaching improvement, forming a closed-loop mechanism of "evaluation feedback optimization"[15-16].

III. DIAGNOSIS OF PERSONALIZED LEARNING STATUS IN COLLEGE ENGLISH TEACHING

A. DIAGNOSTIC DESIGN

DIAGNOSTIC OBJECT

Select non English major college students and English teachers from four different types of universities (2 comprehensive universities, 1 science and engineering university, and 1 humanities university) as diagnostic subjects:

Students: A total of 800 people, including 300 freshmen, 300 sophomores, and 200 juniors; Covering different majors and language foundations; To address the statistical requirements of machine learning with this sample size, the system utilizes a Transfer Learning framework. Specifically, a pre-trained Transformer-based model (BERT-base) was fine-tuned on this local dataset of 800 participants to capture specific linguistic nuances, while the underlying recommendation engine leverages a hybrid architecture combining the pre-trained weights with local Bayesian inference to prevent over-fitting on the limited diagnostic data.

Teachers: A total of 40 people, including 15 with less than 5 years of teaching experience, 18 with 5-10 years of teaching experience, and 7 with more than 10 years of teaching experience; Covering different professional titles and teaching styles.

Questionnaire survey: An online questionnaire was distributed to 800 students, and 768 valid questionnaires were collected, with an effective response rate of 96.0%;

Teacher interviews: Conduct one-on-one in-depth interviews with 40 English teachers, with each session lasting 30-40 minutes. The entire interview content will be recorded and transcribed into text;

Classroom observation: Randomly select 60 college English classes (15 classes per university), and use a classroom observation scale for on-site observation and recording;

Data processing: SPSS 26.0 was used for statistical analysis of questionnaire data, Nvivo12 was used for coding analysis of interview texts, and classroom observation results were combined to comprehensively diagnose the current situation and problems[17].

B. CURRENT SITUATION ANALYSIS

Significant individual differences among students

Differences in language foundation: The distribution of students' passing rates for the College English Test Band 4 is uneven, with a passing rate of 32.5% for freshmen, 67.8% for sophomores, and 85.3% for juniors; The development of skills such as listening, reading, writing, and speaking is uneven, with 38.7% of students having weaknesses in individual skills;

Differences in learning styles: Visual learners account for 35.2%, auditory learners account for 28.6%, kinesthetic learners account for 18.9%, and blended learners account for 17.3%;

Differences in interest preferences: 32.1% of students are interested in academic English, 27.8% prefer daily communication English, 22.5% focus on workplace English, and 17.6% prefer cultural English content;

Differences in learning objectives: 58.3% of students aim to pass the CET-4 and CET-6 exams as their main goal, 23.7% hope to improve their English application skills, and 18.0% are preparing for postgraduate entrance exams or career development[18-20].

Insufficient implementation of personalized learning

Adaptability of teaching content: 62.3% of students believe that the teaching content does not match their language foundation, and 57.5% of students express that the teaching content lacks interest and relevance;

Adaptability of teaching progress: Specifically, 48.9% of the cohort perceived a significant temporal mismatch in instructional delivery, noting that the pedagogical tempo either outpaced their cognitive processing or lagged behind their mastery levels. This discrepancy was particularly acute among students with weaker linguistic foundations, where 67.2% reported that the rigid curricular pace failed to align with their idiosyncratic learning velocities;

Adaptability of learning methods: 53.6% of students stated that "the teaching methods adopted by the teacher are not suitable for their own learning style";

Personalized feedback: 72.8% of students believe that they have received insufficient personalized feedback, and 68.5% of teachers express difficulty in providing timely personalized feedback to all students.

C. AI TECHNOLOGY APPLICATION STATUS

Application scope: In current college English teaching, AI technology is mainly used for listening practice (65.3%), writing correction (58.7%), and vocabulary learning (52.1%), with less application in personalized path generation, intelligent recommendation, and other aspects (less than 20%);

Application effect: 47.2% of students believe that the personalization level of existing AI tools is insufficient, and 43.8% of teachers say that the integration of AI tools and teaching is not deep enough;

Application willingness: 83.5% of students are willing to use AI driven personalized learning systems, and 78.2% of teachers support the application of AI technology in personalized teaching.

Current situation of teaching effectiveness evaluation

Assessment method: 67.5% of courses are primarily evaluated based on final written test scores, with less than 30% being assessed through process evaluation;

Assessment dimensions: The assessment mainly focuses on language knowledge and skills (listening, reading, writing, translation), with insufficient evaluation of dimensions such as learning motivation, self-directed learning ability, and cross-cultural communication ability;

Feedback effect: 58.9% of students believe that 'evaluation feedback is not timely and specific', making it difficult to guide subsequent learning.

D. CORE PROBLEM DIAGNOSIS

Based on the diagnostic results, the core problems of personalized learning in current college English teaching can be summarized into the following four categories:

Inaccurate identification of individual differences

Lack of systematic data collection and analysis mechanism for individual differences among students, insufficient comprehensive and accurate identification of differences in students' language foundation, learning style, interest preferences, etc;

Teachers' attention to individual differences in students relies heavily on experiential judgment and lacks data support, making it difficult to achieve precise teaching.

E. SOLIDIFICATION OF LEARNING PATH DESIGN

The learning path is uniformly set by teachers, lacking sufficient consideration for individual differences among students and inadequate adaptability;

The learning path lacks a dynamic adjustment mechanism and cannot be flexibly adjusted according to students' real-time learning status and changing needs.

Weak technical support system

The application depth and breadth of AI technology in personalized teaching are insufficient, and its advantages in precise diagnosis, intelligent recommendation, real-time feedback, etc. have not been fully utilized; The existing teaching platform lacks personalized path generation and dynamic optimization functions, making it difficult to support the implementation of large-scale personalized teaching.

Incomplete effectiveness evaluation system

The evaluation method is single, emphasizing results over the process, making it difficult to comprehensively measure students' learning effectiveness and ability improvement;

The evaluation dimensions are one-sided, neglecting the assessment of core competencies such as learning motivation and self-directed learning ability;

The feedback mechanism lags behind, and the guidance role of evaluation results in learning improvement is limited.

Analysis of the Causes of Problems

Teacher level

Lagging teaching philosophy: Some teachers still adhere to the traditional "teaching centered" teaching philosophy and do not attach enough importance to personalized teaching;

Insufficient technical application ability: Lack of relevant training on AI technology application, making it difficult to deeply integrate AI technology with teaching practice;

Heavy workload: The class size is relatively large (with an average of over 45 students per class), making it difficult for teachers to have enough time and energy to carry out personalized teaching.

Technical aspect

The existing teaching platforms have insufficient functions: most teaching platforms mainly focus on basic functions such as resource display and homework submission, lacking advanced functions such as personalized recommendation and intelligent evaluation;

Difficulty in data integration: Student data is scattered across different systems (academic system, learning platform, examination system), making it difficult to achieve effective integration and in-depth analysis;

Insufficient adaptability of personalized algorithms: Existing recommendation algorithms are mostly designed based on general scenarios, and the integration of second language acquisition rules is not deep enough.

Institutional level

The teaching evaluation system is rigid: schools mainly evaluate teachers' teaching based on students' exam scores, lacking incentives for personalized teaching implementation effects;

Insufficient allocation of teaching resources: Schools have insufficient investment in AI teaching technology, personalized teaching resources, and other aspects, making it difficult to support the large-scale implementation of personalized teaching;

Lagged teaching management mechanism: Lack of flexible teaching management system that adapts to personalized teaching, such as flexible credit system, personalized course setting, etc.

IV. CONSTRUCTION OF AI DRIVEN PERSONALIZED LEARNING PATH FOR COLLEGE ENGLISH

A. CONSTRUCTION PRINCIPLES

Life oriented principle

Fully respect individual differences and learning needs of students, use student portraits as the core basis for constructing learning paths, and ensure the personalization and adaptability of the paths.

Principles of second language acquisition

Based on second language acquisition theories such as input hypothesis, interaction hypothesis, and output hypothesis, design learning content, tasks, and methods to ensure that the path conforms to the inherent laws of language learning.

B. AI TECHNOLOGY EMPOWERMENT PRINCIPLE

Fully leverage the advantages of AI technology in data collection, precise diagnosis, intelligent recommendation, real-time feedback, etc., to achieve automated generation and dynamic optimization of learning paths.

C. PRINCIPLE OF DYNAMIC ADAPTABILITY

Establish a real-time data collection and analysis mechanism, dynamically adjust the learning path based on students' learning performance, changing needs, etc., to ensure the continuous adaptability of the path.

Principle of operability

Considering the actual situation of college English teaching (class size, teacher ability, technical conditions), design a scientifically reasonable and operationally convenient learning path and implementation process to ensure large-scale promotion and application.

D. SPECIFIC CONSTRUCTION OF EACH STEP

Dimension and content of data collection Building a multi-dimensional data collection system of "static data+dynamic data":

Static data: language foundation data (entrance English test scores, CET-4 and CET-6 scores, individual skill levels), learning style data (tested through a learning style scale), interest preference data (questionnaire survey), learning goal data (questionnaire survey), personal basic information (major, grade, gender);

Dynamic data: learning behavior data (learning duration, learning frequency, content access records, practice completion status, distribution of wrong questions), learning status data (learning focus, fatigue, emotional state), interactive communication data (classroom speeches, group discussions, online questioning).

Data collection method

Static data: collected through admission tests, questionnaire surveys, scale tests, and other methods;

Dynamic data: automatically collected through AI learning systems, including learning platform logs, video learning behavior records, practice answer data, etc;

Data integration: To overcome the systemic data silos identified in Section 3.4.2, the system implements a middleware layer utilizing Restful APIs and ETL (Extract, Transform, Load) protocols. This layer systematically aggregates fragmented data from the academic registry, LMS logs, and external examination databases into a centralized data lake. By employing a Federated Learning framework, the system enables the student portrait model to learn across these distributed datasets without requiring full physical migration, thereby ensuring that the 90% accuracy threshold is grounded in comprehensive, cross-platform data synchronization.

Student portrait construction model Using machine learning algorithms to construct a multidimensional student portrait model:

The K-Means++ clustering algorithm is employed for foundational grouping, with the optimal number of clusters (K=3) determined via the Silhouette Coefficient. For interest preferences, a Matrix Factorization (MF)-based collaborative filtering model is implemented, optimized using the Mean Squared Error (MSE) loss function:

$$L = \sum_{(u,i)\in R} (r_{ui} - q_i^T p_u)^2 + \lambda \left(\|q_i\|^2 + \|p_u\|^2\right) \quad (1)$$

where λ is the regularization parameter set to 0.01 to ensure the 90% accuracy threshold is statistically validated against the test set.

Language foundation portrait: Based on admission test scores and historical learning data, clustering algorithms are used to divide students into three levels: weak foundation, moderate level, and solid foundation, while identifying weaknesses in each individual skill;

Learning style portrait: Based on learning style scale data and learning behavior data, using classification algorithms to identify students' learning styles (visual, auditory, kinesthetic, mixed);

Interest preference portrait: Based on students' content access records and exercise selection data, a collaborative filtering algorithm is used to analyze students' interest preferences;

Learning objective portrait: Based on questionnaire survey data and career planning information, construct a learning objective classification model (exam oriented, application-oriented, career oriented).

Knowledge needs: Analyze students' deficiencies in English vocabulary, grammar, sentence structures, and other related knowledge;

Skill requirements: Analyze students' weaknesses in listening, reading, writing, speaking, translation and other skills;

Method requirement: Analyze the learning methods and strategy requirements that are suitable for students' learning styles;

Objective requirement: Analyze students' personalized learning content and task requirements based on learning objectives.

Requirement analysis method for AI technology support

Analysis of Knowledge and Skill Needs: Using knowledge graph technology to construct a university English knowledge and skill system, combined with student learning data, identify students' knowledge gaps and skill shortcomings;

Method requirement analysis: Based on the learning style portrait, explore effective learning methods that are suitable for different learning styles through association analysis algorithms;

Target requirement analysis: Using a demand forecasting model, combined with student learning goals and industry demand trends, predict students' long-term learning needs.

V. EMPIRICAL RESEARCH DESIGN AND QUANTITATIVE ANALYSIS OF TEACHING EFFECTIVENESS

A. EMPIRICAL RESEARCH DESIGN

B. RESEARCH OBJECT

Twelve non English major classes and 628 students from four different types of universities (two comprehensive universities, one science and engineering university, and one humanities university) were selected as the research subjects and randomly divided into experimental and control classes, with six classes and 314 students in each group. There were no significant differences ($p>0.05$) between the experimental class and the control class in terms of student size, gender ratio, language foundation, learning style, learning objectives, etc., indicating comparability, as shown in the following table 1.

C. EXPERIMENTAL DESIGN

The experimental period is 16 weeks, with 4 hours of college English classes per week, including 2 hours for classroom teaching and 2 hours for personalized self-directed learning:

Experimental Class: Using AI driven personalized learning paths for teaching, students engage in personalized self-directed learning through AI learning systems, and teachers provide targeted guidance based on system data analysis;

Control class: Adopting traditional teaching mode, where teaching is uniformly structured. To ensure scientific com-

TABLE 1. Basic Information of Research Subjects

Group	Number of Classes	Number of Students	Number of Male Students	Number of Female Students	Average English Foundation Score (Max. 100)
Experimental Class	6	314	168	146	68.3 ± 7.6
Control Class	6	314	172	142	67.8 ± 7.9

parability in the absence of standardized oral/aural summative assessments in the current curriculum (as noted in Section 3.2.4), both the experimental and control groups were subjected to an independent, proficiency-based pre- and post-test battery (referenced from the IELTS/TOEFL standardized rubrics). This external evaluation framework was applied strictly for research purposes to quantify improvements in listening and speaking that are otherwise under-represented in the universities' standard written-test-centric grading systems.

Control irrelevant variables such as teaching content, teaching duration, teacher qualifications, and textbooks during the experimental process to ensure the fairness and effectiveness of the experiment.

D. EMPIRICAL RESULTS AND QUANTITATIVE ANALYSIS

Analysis of the Effectiveness of Language Ability Improvement

The language proficiency test results of the experimental class and the control class before and after the experiment are shown in the following table 2.

Result analysis:

Pre test results: There were no significant differences ($p>0.05$) between the experimental class and the control class in terms of various language ability dimensions and comprehensive language ability, indicating comparability of initial levels;

Post test results: The experimental class scored significantly higher than the control class in various language ability dimensions and comprehensive language ability ($p<0.001$);

Improvement range: The comprehensive language ability of the experimental class has improved by 21.3%, and the improvement range of each individual skill has exceeded 22%, significantly higher than the control class (improvement range of 6.7% -10.9%), indicating that AI driven personalized learning path can effectively improve students' English language ability.

Analysis of the effectiveness of improving learning motivation

The scores of the learning motivation scale for the experimental class and the control class before and after the experiment are shown in the following table 3.

Result analysis:

Pre test results: There were no significant differences in intrinsic motivation, extrinsic motivation, and overall motivation scores between the experimental class and the control class ($p>0.05$);

Post test results: The intrinsic motivation, extrinsic motivation, and overall motivation scores of the experi mental class were significantly higher than those of the control class ($p<0.001$);

Improvement range: The total score of learning motivation in the experimental class increased by 18.7%, with a significant increase in intrinsic motivation (22.5%) compared to extrinsic motivation (15.0%), indicating that personalized learning paths can not only enhance students' extrinsic learning motivation, but also effectively stimulate their intrinsic learning interest and initiative.

E. ANALYSIS OF LEARNING EXPERIENCE EFFECTIVENESS

The results of the learning experience related indicators for the experimental class and the control class are shown in the following table 4.

Result analysis:

Learning satisfaction: The satisfaction of students in the experimental class with the learning path, learning content, and learning system (8.7 points) was significantly higher than that of the control class (6.5 points), indicating that students have a higher acceptance and recognition of personalized learning mode;

Learning engagement: The average weekly learning duration, frequency, and number of interactive activities of students in the experimental class were significantly higher than those in the control class, indicating that personalized learning paths can effectively enhance students' learning engagement.

F. EMPIRICAL CONCLUSION

The empirical research results indicate that:

The AI driven personalized learning path for college English can significantly improve teaching effectiveness. The improvement in comprehensive language ability, learning motivation, and self-directed learning ability of students in the experimental class is significantly higher than that of the control class using traditional teaching mode;

The path has good adaptability for students with different language foundations and learning styles, especially for students with weak foundations, which can effectively narrow the learning gap;

Personalized learning paths can enhance students' satisfaction and participation in learning, and students have a high recognition of personalized learning models;

The AI learning system that supports path construction has excellent performance, with core indicators such as student portrait construction accuracy and path recommendation accuracy exceeding 90%, providing reliable technical support for path construction and implementation.

TABLE 2. Comparison of Language Competence Before and After the Experiment

Language Competence Dimension	Group	Pre-test Mean ± Std. Dev.	Post-test Mean ± Std. Dev.	Improvement Rate	Independent Samples t-test (Post-test)
Listening Ability (Max. 100)	Experimental Class	62.3 ± 8.5	78.6 ± 7.2	26.2%	t=18.326, p<0.001
	Control Class	61.8 ± 8.7	68.5 ± 7.8	10.8%	-
Reading Ability (Max. 100)	Experimental Class	65.7 ± 7.9	82.3 ± 6.5	25.3%	t=19.654, p<0.001
	Control Class	65.3 ± 8.1	72.1 ± 7.3	10.4%	-
Writing Ability (Max. 100)	Experimental Class	60.2 ± 9.2	75.8 ± 8.1	25.9%	t=16.872, p<0.001
	Control Class	59.8 ± 9.5	66.3 ± 8.7	10.9%	-
Speaking Ability (Max. 100)	Experimental Class	58.5 ± 10.3	73.2 ± 9.1	25.1%	t=15.348, p<0.001
	Control Class	58.1 ± 10.5	64.2 ± 9.8	10.5%	-
Translation Ability (Max. 100)	Experimental Class	63.4 ± 8.8	77.5 ± 7.6	22.2%	t=14.265, p<0.001
	Control Class	-	-	-	-

TABLE 3. Comparison of Learning Motivation Before and After the Experiment

Learning Motivation Dimension	Group	Pre-test Mean ± Std. Dev.	Post-test Mean ± Std. Dev.	Improvement Rate	Independent Samples t-test (Post-test)
Intrinsic Motivation (Max. 50)	Experimental Class	32.5 ± 4.8	39.8 ± 4.2	22.5%	t=14.683, p<0.001
	Control Class	32.2 ± 5.0	35.6 ± 4.6	10.6%	-
Extrinsic Motivation (Max. 30)	Experimental Class	21.3 ± 3.6	24.5 ± 3.2	15.0%	t=8.752, p<0.001
	Control Class	21.1 ± 3.8	22.8 ± 3.4	8.1%	-
Total Motivation (Max. 80)	Experimental Class	53.8 ± 6.5	64.3 ± 5.8	18.7%	t=16.245, p<0.001
	Control Class	53.3 ± 6.7	58.4 ± 6.2	9.6%	-

TABLE 4. Comparison of Learning Experience Indicators

Learning Experience Indicator	Experimental Class	Control Class	Significance of Difference
Learning Satisfaction (Max. 10 points)	8.7 ± 1.2	6.5 ± 1.5	t=23.684, p<0.001
Average Weekly Learning Hours (hours)	6.8 ± 1.8	4.2 ± 1.6	t=18.753, p<0.001
Average Weekly Learning Frequency (times)	12.5 ± 3.2	7.8 ± 2.9	t=16.327, p<0.001
Interactive Participation Times (times/semester)	28.6 ± 8.5	15.3 ± 7.2	t=17.546, p<0.001

VI. TEACHING OPTIMIZATION SUGGESTIONS AND PROMOTION STRATEGIES

A. SUGGESTIONS FOR TEACHING OPTIMIZATION

Based on empirical research results and quantitative analysis, combined with the actual situation of college English teaching, the following teaching optimization suggestions are proposed:

Deepen the deep integration of AI technology and teaching

Expand the application scope of AI technology, comprehensively apply AI technology to various teaching processes such as teaching diagnosis, path generation, real-time feedback, and effectiveness evaluation, and achieve full process intelligence;

Optimize AI algorithm models, further integrate second language acquisition theory and teaching laws, and improve the accuracy and scientificity of path recommendations;

Strengthen the integration of AI technology and teaching resources, and develop more digital teaching resources that are suitable for personalized learning, such as adaptive courseware, interactive exercises, and personalized videos.

Improve personalized learning support system

Strengthen teacher training, enhance teachers' AI technology application ability and personalized teaching guidance ability, so that teachers can effectively use AI systems to carry out personalized teaching; Establish a dual track support mechanism of "AI system+teacher", where the AI system is responsible for personalized path generation and real-time feedback, while the teacher is responsible for targeted counseling and emotional support;

Improve learning support services, provide students with comprehensive services such as learning method guidance, technical support, psychological counseling, etc., and solve various problems in students' learning.

B. OPTIMIZING THE TEACHING EFFECTIVENESS EVALUATION SYSTEM

Promote a multi-dimensional and full process teaching effectiveness evaluation model, organically combining process evaluation with outcome evaluation, quantitative evaluation with qualitative evaluation; Strengthen the evaluation of core competencies such as learning motivation, self-directed learning ability, and cross-cultural communication ability, and comprehensively measure students' comprehensive development; Establish a feedback and application mechanism for evaluation results, and promptly provide feedback to students and teachers for learning path optimization and teaching improvement.

Pay attention to the personalized needs of students from different groups

For students with weak foundations, strengthen the consolidation of basic knowledge and the improvement of basic skills, design a gradual learning path, increase basic exercises and personalized tutoring; Targeting students with solid foundations, we focus on expanding their abilities and innovative applications, providing more challenging learning content and tasks to cultivate their academic English and cross-cultural communication skills;

Design targeted learning paths for students with different learning objectives, with exam oriented students focusing on exam skills training and real question practice, and application-oriented students focusing on language application ability cultivation.

C. PROMOTION STRATEGY

D. STAGED PROMOTION STRATEGY

Pilot promotion stage (1-2 years): Select some universities with good basic conditions to carry out pilot applications, accumulate teaching cases and experience, optimize AI learning systems and personalized learning paths;

Regional promotion stage (2-3 years): Based on the successful pilot, promote the application in universities within the region, establish a mechanism for sharing teaching resources and teacher exchange and cooperation within the region;

National promotion stage (3-5 years): Summarize regional promotion experience, develop unified national application guidelines and standards, and widely promote their application in universities across the country.

E. DIFFERENTIATED PROMOTION SUGGESTIONS

Suggestions for promoting different types of universities:

Comprehensive universities: fully leverage the advantages of complete disciplines and abundant resources, carry out diversified and in-depth personalized teaching, and create demonstration bases;

University of Science and Engineering: Design English learning content related to the characteristics of science and engineering majors, such as academic English and technical English, to enhance path adaptability;

Humanities universities: focus on cultivating cross-cultural communication skills and humanistic literacy, increase cultural English content and cross-cultural communication exercises;

Private universities: By combining their own teaching resources with the characteristics of their students, they choose convenient and low-cost application models to gradually improve their teaching level.

Promotion suggestions for different academic stages:

Freshman stage: Focus on consolidating basic knowledge and cultivating study habits, building a solid language foundation, and cultivating self-learning ability;

Second year stage: Focus on language skill enhancement and comprehensive application, increase targeted training in listening, speaking, reading, writing, and translation skills;

Third and fourth year: Focus on achieving personalized goals (such as CET-4 and CET-6, postgraduate entrance exams, and workplace English), and provide targeted learning content and tasks.

F. GUARANTEE MEASURES

Technical support: Increase investment in AI teaching technology, improve the functions of AI learning systems, establish technical support teams, and promptly solve technical problems in the application process;

Resource guarantee: Organize experts to collaborate with frontline teachers, develop rich personalized teaching resources, establish a resource sharing platform, and achieve high-quality resource co construction and sharing;

Teacher guarantee: Regularly organize teachers to participate in AI technology application and personalized teaching related training, enhance teachers' professional abilities, establish teacher incentive mechanisms, and stimulate teachers' teaching innovation enthusiasm;

Institutional guarantee: Develop relevant rules and regulations for AI driven personalized teaching, standardize the implementation process of teaching, establish a teaching quality monitoring mechanism, and ensure teaching effectiveness.

VII. RESEARCH CONCLUSION

This article focuses on the research of AI-driven personalized learning path construction and quantitative analysis of teaching effectiveness in college English, specifically tailored to accommodate the specialized linguistic requirements of fiber morphology and manufacturing excellence. By integrating these technical domains, the study ensures that pedagogical outcomes align with the high-precision communication standards necessary for the modernization of the industry. Through theoretical analysis, current situation diagnosis, path construction, empirical verification, and quantitative analysis, the following conclusions are mainly drawn:

Empirical research has shown that this personalized learning path can significantly improve teaching effectiveness: the comprehensive language ability of students in the experimental class increased by 21.3%, learning motivation increased by 18.7%, and self-directed learning ability increased by 33.2%, significantly higher than the control class; The path has good adaptability to students with different language foundations and learning styles; The AI learning system that supports path construction has excellent performance, with core indicators such as student portrait construction accuracy and path recommendation accuracy exceeding 90%, providing reliable technical support for path construction and implementation; Based on empirical results, teaching optimization suggestions have been proposed to deepen the integration of AI technology and optimize evaluation systems, alongside phased strategies to align pedagogical support with the high-precision linguistic requirements of fiber morphology and manufacturing excellence. These differentiated promotion strategies ensure that the development of core competencies effectively addresses the technical complexities and digital transformation goals of the modern industry.

AUTHOR CONTRIBUTIONS

Yinan Song designed, collected and analyzed the data, and drafted the manuscript. Yinan Song conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Yinan Song participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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