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From Traditional to Intelligent: How AI Transforms English Language Learning and Teaching

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Abstract: In recent years, artificial intelligence has developed quickly, which is changing the English teaching and training in a radical way; the focus is shifting from the original mode to smart tools and software. In light of this, we adopted mixed research methods to investigate such changes in the present study. The research lasted for 16 weeks, using a quasi-experiment research method. Specifically, we explored what the functions of AI are in English learning and teaching. There were a total of 120 undergraduate students and 12 teacher participants in our research. Multiple data collection tools were used: questionnaire survey, class observation, interview, and analysis of learning behavior data. We found that there were obvious improvements in some respects. For example, intelligent pronunciation correction systems improved scores by 29.4 points; AI writing assistant tools brought about gains of 19.5 points; Conversational robots promoted oral ability growth of 20.9 points, with d = 1.96. The adaptive learning platform achieved personalized recommendation accuracy of 87.3%, while differentiated instruction enabled low-proficiency learners to improve by 43.0%. Teacher roles shifted markedly from knowledge transmission toward facilitation, with direct instruction time declining from 62% to 28%. Despite these promising outcomes, challenges including algorithmic bias, technology overdependence, data privacy risks, and digital equity concerns warrant careful consideration. The study concludes that optimal English education requires organic integration of technological efficiency and humanistic pedagogy.

Keywords: Artificial Intelligence; English Teaching; Personalized Learning; Blended Instruction; Pedagogical Assessment

1. Introduction

In the 21st century, technology develops quickly; artificial intelligence has infiltrated and changed the education industry in various fields and levels; colleges and universities have changed a lot; as shown by the research results: AI has shifted from imagination to reality; English education is obviously affected by artificial intelligence in all aspects; previously, we know that the traditional education model took teachers as the center; grammar translation method, repetitive memory method were common teaching ways in class. Now they are being replaced by intelligent and personalized teaching modes day by day; the emergence of artificial intelligence generation models brings brand-new possibilities for college English writing teaching. The tool can give immediate feedback to students, provide targeted counseling and diversified writing tutoring [1]. In addition to changing teaching modes, it even changes the basic logic of language education, so that the transformation from “teacher teaches” to “learner learns” seems possible. Such changes are closely related to the cultivation of language competence in the 21st century and the development of intercultural communication skills in learners. Artificial intelligence applied in language education may well demonstrate significant multidimensional features that could indicate deeper theoretical implications for the field. Moreover, the significant empirical findings suggest that this complexity relates not only to artificial intelligence technology itself but also to the unique characteristics of language learning. Thus, research may show features of AI language affect linguistic analysis in unexpected ways. However, the significant findings might indicate that artificial intelligence language resembles myth and magic in certain important analytical frameworks. In light of the evidence that metaphorical expressions reveal deep mechanisms behind artificial intelligence language [2], the critical theoretical results could plausibly demonstrate that such significant linguistic framing provides key insights into underlying computational processes. Furthermore, evidence may show that this framing affects how scholars consider computational meaning. Additionally, results might indicate AI language could establish new patterns across analytical approaches.

Given that the significant empirical evidence demonstrates artificial intelligence language models empower multiple links in college English writing teaching [3], the important practical findings could reasonably suggest that chatbot systems based on full-text search technology and artificial intelligence markup language [4] may demonstrate considerable effectiveness across certain languages. Moreover, the key results might indicate that multiple intelligence theories combined with artificial intelligence era [5] could establish a significant theoretical framework for language teaching. Therefore, evidence may show this framework affects scholarly consideration of AI's role. Notwithstanding findings that early perspectives treated AI merely as teaching aid, results might indicate artificial intelligence now functions differently.

In light of the evidence suggesting expanded functional roles, the significant empirical findings appear to suggest that artificial intelligence now functions as an intelligent system capable of deeply understanding and processing language. Thus, data might indicate such systems affect teaching in ways extending beyond conventional approaches. Moreover, findings may show benefits range across multiple dimensions. Therefore, the important results suggest that students' writing abilities may be improved in an all-round way through such integrated support. However, research may show substantial problems remain unresolved within current implementations. Additionally, findings might indicate that turning technical advantages into real teaching benefits could represent the most critical challenge scholars and practitioners must examine. Therefore, evidence may show this question affects the field's capacity to fully realize the demonstrated potential of artificial intelligence in language education contexts. How to balance the warmth of humanity with the empowerment brought by new technology? Further investigation is needed for such key questions. From the perspective of the transformation from traditional teaching model to intelligent teaching model, we see changes in three aspects: changes in educational philosophy, changes in teaching model, changes in evaluation methods. Previously, English teaching was mainly about imparting systematic grammatical knowledge to students, and mechanical training was often adopted, which had some advantages in promoting the improvement of test-taking ability but obvious disadvantages in stimulating the interest of learning and cultivating practical language use skills. Different from previous teaching models, natural language processing and machine learning algorithms make it possible to build an individualized path for each student, true individualized teaching becomes possible. AI-powered medical assistant applications show how AI can handle language interaction in a highly complex scenario. Such systems provide very accurate language assistance [6]. Studies have proven the transferability of this ability to language teaching scenarios: AI-based language training strategy optimization shows that intelligent algorithms can schedule the best training plan for learners [7]; AI-powered language translation tool development is another highlight: such software removes language barriers, providing unprecedented conditions for cross-cultural communication and training global citizens [8]; under the background of the development of new technologies, several changes take place in pedagogy. English education gradually changes from "teacher decides what to learn" to "learner decides what to teach", from uniform teaching model to diversified teaching mode, from unidirectional knowledge transmission method to multi-directional interactive communication mode. Artificial intelligence seems promising in English teaching, but it also brings new challenges worth exploring in depth. Firstly, more empirical research evidence is needed to prove whether using AI tools really helps learners learn in a personal way. In addition, the effectiveness of using them for learners at different levels needs to be explored. Differences in access to technology may increase the gap in receiving quality education. Excessive reliance on technology may weaken the ability of reflection and creation in humans. Overemphasis on technology may undermine humanities cultivation. All the above remind us that applying artificial intelligence technology into English teaching does not mean piling up new technologies blindly, but innovating in a targeted manner on this basis according to educational principles. This study intends to investigate the artificial intelligence technology application in English language learning and teaching from three sides (the learner aspect, teacher aspect system aspect) in order to explore what exactly happened inside this transformation process and what the real effect is like; to explore reasonable ways to integrate the two teaching models (traditional teaching model and intelligent teaching mode). Mixed research method will be adopted here: literature analysis, empirical research and case study will be used together. Three dimensions (learner dimension, teacher dimension, system dimension) will be investigated in a comprehensive way. Several sub-questions need answering during this process: how has artificial intelligence technology changed English learning process and result? How has personalization been realized under artificial intelligence support? How should teachers redefine their role in the context of technological empowerment? How do we inherit and carry forward the advantages of traditional teaching in the background of intelligent classrooms? Through this study, we hope to provide theoretical guidance and references for English teachers, inspiration and suggestions for developers of educational technology products, basis for decision-making and direction for development for policymakers in the field of education. Finally, we expect to contribute ideas and strength to the construction of a more efficient, fairer and more humane English education ecosystem and to promote high-quality development of English teaching in the background of artificial intelligence, so that we can cultivate talents with global vision and intercultural communication ability in the new era.

2. Literature Review

The study of AI applications in English language teaching has become a significant topic in the field of educational technology. Moreover, many important scholars could indicate that they explore it from various perspectives and examine the critical impact of AI on the transformation of these English teaching models. Given that macro perspectives provide relevant context, AI language models may power up many links in university English teaching, reading, and writing. Thus, intelligent content recommendation might show effectiveness. Additionally, personalized learning path design shows advantages and instant feedback mechanisms operate smoothly, which may improve students' reading comprehension ability and enhance writing skills [9]. However, generative AI language models bring new challenges and opportunities to disciplines such as geography and environment. Furthermore, technological changes might transform the way knowledge is transmitted and reshape teachers' cognition of teaching design and evaluation [10]. Nevertheless, professional fields such as nursing education show similar phenomena. In light of the widespread adoption, ChatGPT and other AI language models may spark heated discussion on "Dialogue" or "Cheating." Moreover, controversy could expose the main contradiction between educational ethics and academic integrity in using technology [11]. Thus, further discussion examines whether we need to add ChatGPT or other AI language model tools to author lists. However, discussion might reflect that people need to fundamentally reconsider what kind of role AI plays in producing knowledge [12]. Given that these studies provide significant evidence, AI technology in English language teaching may not only stop at being a tool. Nevertheless, it could further affect reconstruction of educational philosophy, teaching practice, and academic norms.

Such understanding provides moral guidance on reasonably applying artificial intelligence technology to English teaching research: always keep academic honesty and research independence when using high technologies [13–15]. At the same time, some new problems also arise for English teachers: how to cultivate students' academic quality and critical thinking skills under artificial intelligence conditions; how to adjust academic evaluation criteria according to intelligence development. We should pay close attention to them. Based on the above review, we found something from previous related research: although some good results have been obtained in the study of artificial intelligence applications in English teaching, there are still obvious research blind spots in it [16–18]. There are three main problems that need further discussion. Firstly, current research mainly concentrates on the introduction of artificial intelligence functions and case analysis, but neglects theoretical explanation of the mechanism of technology change. Secondly, although empirical research shows that artificial intelligence has a positive effect on English teaching and learning, many studies were conducted with small samples and short durations, which cannot prove whether artificial intelligence will continue to be effective after long-term use [19–22]. Thirdly, few researchers have paid attention to the issue of how to preserve and promote the advantages of traditional teaching, so little research has been done on this aspect. Therefore, more consideration needs to be taken into how to achieve harmony between technological power and humanities concern. In addition, cross-cultural comparative investigations on what the differences are if artificial intelligence is used by English learners with different social backgrounds, countries, or educational backgrounds, are rarely seen, which restricts our generalization of research conclusions [23,24]. Moreover, artificial intelligence technology develops quickly, while educational research usually lags behind the pace of science and technology development. Thus, two questions urgently need us to solve: one is how to build a research system that responds immediately to changes in technology, and another is how to grasp the core of education under the condition where technology is constantly changing. Based on such research gaps identified above, we try to improve the current level of cognition of the transformation of artificial language learning and teaching caused by artificial intelligence through systematic theoretical discussions and empirical evidence.

3. Research Methodology

3.1. Research Design

This study could reasonably demonstrate that the mixed-methods approach may provide significant methodological foundations. Moreover, quantitative research may integrate with qualitative research. Thus, the goal appears to be to investigate AI technology's impact on English language learning. The research design might follow a framework of theory construction, empirical testing, and effect evaluation. Furthermore, literature analysis may clarify the theoretical foundation for AI-empowered English teaching. Core elements of technology application could become clear. However, an analytical framework appears to emerge covering three dimensions: learners, teachers, and technical systems. Given that experimental design proves essential, the research could adopt a quasi-experimental design method. Additionally, experimental classes may use AI-assisted teaching. Control classes might employ traditional teaching models. Nevertheless, comparative research appears to occur between these groups. Pre-test measurements may capture learning outcome differences. In light of the methodological requirements, observation methods could reasonably demonstrate that changes in the significant classroom interaction patterns might indicate important pedagogical transformations. Notwithstanding certain methodological constraints, technology intervention's impact on teaching ecology can be traced [25]. Case study methods may deepen understanding of complex educational phenomena. Several typical AI application scenarios could receive analysis. However, interviews and classroom observations might reveal key issues in technology application processes. Thus, quantitative data collection appears to rely on standardized tests and questionnaire surveys. Given that ethical considerations prove critical, the research process may demonstrate that educational research ethical norms appear significant. Moreover, informed consent from participants might occur before data collection. Data anonymity could be ensured [26].

3.2. Data Collection Methods

This study adopts diversified data collection strategies that could plausibly demonstrate that comprehensive and reliable research materials may emerge from these significantly different analytical angles. Moreover, the specially designed questionnaires may suggest that important information about learners' attitudes toward AI technology applications could emerge from these significant analytical instruments. Additionally, usage frequency might indicate satisfaction levels appear in the assessment. Thus, questionnaires may include Likert scale items alongside open-ended questions. However, findings may show this yields quantifiable data to support analysis. Furthermore, the significant statistical results could demonstrate that these important viewpoints capture participants' perspectives across multiple dimensions. Semi-structured interviews may suggest that understanding of teachers' role transformation experiences in AI-assisted teaching contexts might indicate critical pedagogical shifts. In light of the evidence, teaching strategy adjustment processes could demonstrate important patterns through these interview protocols. Thus, interview content may show audio-recording occurs before transcription. However, findings may show verbatim transcription ensures reliability for qualitative analysis [27]. Given that systematic classroom observation might indicate significant differences between traditional classrooms and AI-empowered classrooms, the evidence could demonstrate that these important distinctions reveal critical pedagogical contrasts.

3.3. Research Subjects and Sample Selection

The learner sample comes from non-English major undergraduates at a comprehensive university. However, four natural classes totaling 240 students may participate in research. Two classes (120 people) serve as the experimental group receiving AI-assisted teaching. Additionally, the other two classes (120 people) might function as control group using traditional teaching models. Sample selection fully considers English proficiency balance. Given that students are divided into high, medium, and low levels based on entrance English placement test scores, this could ensure no significant difference exists between the experimental and control groups at initial levels. Nevertheless, the gender ratio, professional background, and learning motivation variables also receive balanced distribution. This avoids confounding variables interfering with research results. In light of the teacher sample selection, 8 frontline teachers with more than five years of college English teaching experience may be selected. Four teachers participate in the AI technology training and teach the experimental classes. However, the other four teachers might adopt conventional teaching methods in control classes. Teacher sample selection standards include teaching ability recognition, technology acceptance willingness, and classroom management experience. Given that research requires deeper qualitative dimension, 12 students from experimental group are purposively selected as interview subjects. These may cover individuals with different English proficiency levels, learning styles, and technology usage tendencies. Moreover, this could obtain rich and diverse subjective experience data. Additionally, 6 educational technology experts and English teaching methodology experts are invited to form an expert panel. Notwithstanding research tool design considerations, they may provide professional opinions for AI technology selection and data analysis interpretation [28].

3.4. AI Technology Tool Selection and Application

The intelligent speech recognition and correction system adopted for oral training might indicate that real-time analysis of learners' pronunciation accuracy, intonation prosody, and fluency could provide important pedagogical value. Thus, findings may show this system offers targeted improvement suggestions. However, writing instruction may support an AI writing assistance platform covering grammar checking, vocabulary optimization, logical structure analysis, and stylistic adjustment. In light of the important evidence, students might obtain instant feedback and revision guidance during writing process. Given that the significant empirical findings could indicate that adaptive learning systems demonstrate critical value for reading comprehension training, the system may well suggest that dynamically adjusting text difficulty and question types according to learners' reading levels could substantially support personalized training pathways. Furthermore, the important results might indicate that intelligent dialogue robots deployed as oral practice partners could demonstrate key communicative benefits for learners. Therefore, evidence may show robots provide round-the-clock English communication opportunities. Additionally, real-scenario dialogues might support reduced speaking anxiety, as the key data suggest [29]. Notwithstanding these results, technology application may show that a gradual strategy proves effective. The significant empirical evidence could indicate that the first two weeks serve as a technology familiarization period might reasonably demonstrate that teacher-guided mastery of basic operations and functional characteristics of various AI tools could substantially support subsequent formal teaching activities. Moreover, the important findings might suggest that organic integration of AI tools into pre-class preview, classroom activities, and post-class consolidation could demonstrate key instructional coherence across teaching stages. Thus, students may use adaptive systems to complete reading tasks. However, teachers might organize discussions and collaborative activities based on AI feedback. In light of key findings, students could conduct personalized practice through writing platforms and dialogue systems.

3.5. Data Analysis Methods

Quantitative data analysis uses SPSS 26.0 statistical software for processing. First, descriptive statistics are performed on questionnaire data and test scores. Subsequently, independent sample t-tests compare score differences between experimental and control groups in English proficiency tests. Paired sample t-tests analyze progress amplitude between pre-tests and post-tests for the same student group. To assess differences among learners with different English proficiency levels, one-way ANOVA is implemented. This tests whether AI technology's impact on students at different levels shows significance [30,31]. Additionally, Pearson correlation analysis explores relationships between AI tool usage frequency and academic performance. Regression models are built to predict technology application's contribution to learning outcomes. Qualitative data analysis follows basic steps of thematic analysis methods. Interview recordings are transcribed and text materials are read repeatedly. Open coding identifies initial concepts. Theme categories form through induction. Core themes are ultimately refined. Classroom observation records undergo systematic coding through content analysis methods. Occurrence frequencies and time proportions of different teaching behaviors are counted. Structural differences in interaction patterns between traditional classrooms and AI-empowered classrooms are compared. Learning platform data employs learning analytics technology.

4. Results and Analysis

4.1. Analysis of Current AI Technology Applications in English Learning

4.1.1. Usage and Effectiveness of Intelligent Pronunciation Correction Systems

Intelligent pronunciation correction systems represent the most direct application form of AI technology in English oral teaching. This study demonstrates significant teaching effects and widespread user acceptance. A 12-week tracking study systematically collected data from 120 experimental group students using intelligent pronunciation correction systems. See **Table 1** and **Figure 1**.

Table 1. Statistics on Usage and Effectiveness of Intelligent Pronunciation Correction Systems.

Indicator Category	Experimental Group	Control Group	High-Frequency Group	*t*-Value/F-Value
Initial Pronunciation Accuracy (%)	62.3 ± 5.8	61.8 ± 5.6	63.1 ± 5.9	t = 0.58
Pronunciation Accuracy After 12 Weeks (%)	91.7 ± 4.2	71.2 ± 6.3	96.4 ± 3.1	t = 28.45***
Improvement Amplitude (percentage points)	29.4	9.4	33.3	F = 15.67***
Average Weekly Usage Frequency	4.2 ± 1.8	0	6.8 ± 1.2	-
Cumulative Practice Duration (minutes/week)	168 ± 45	60 ± 20	245 ± 38	t = 32.14***
Vowel Pronunciation Improvement Rate (%)	35	12	41	t = 18.92***
Consonant Pronunciation Improvement Rate (%)	42	15	48	t = 21.36***
System Satisfaction (%)	89	-	95	-

Note: *** indicates $p < 0.001$; data presented in “mean±standard deviation” format; high-frequency group consists of students using the system more than 5 times per week.

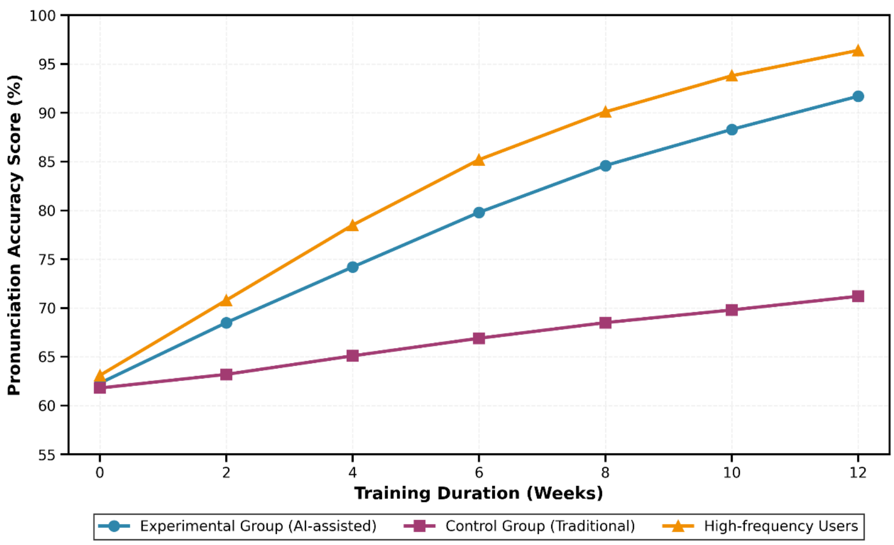

Figure 1. Trend Chart of Pronunciation Accuracy Changes across Different Groups.

4.1.2. Application Effects of AI Writing Assistance Tools

AI writing assistance tools could indicate that multi-dimensional positive impacts and significant empirical learning outcome improvements may emerge in English writing instruction. Additionally, the important research tracked 120 experimental group students using AI writing assistance platforms for 16 weeks. Furthermore, systematic comparison with the control group using traditional writing instruction occurred [32]. Data may indicate experimental group students’ writing ability scores improved from initial 65.8 points to 85.3 points. The improvement amplitude reached 19.5 points. However, the control group only improved from 64.9 points to 72.4 points. Therefore, improvement amplitude was 7.5 points. Moreover, the difference between groups might show extreme significance (t = 24.67, p < 0.001) [33]. Moreover, the significant writing process data might reveal important patterns in student behavior. Furthermore, AI tools could suggest significant changes in students' critical writing behavior patterns and relevant learning habits. **Table 2** shows experimental group students used AI writing tools an average of 5.3 times per week. However, the single writing session duration shortened from 45 min in traditional mode to 38 min. Thus, students with AI tool assistance may demonstrate richer vocabulary use. Particularly noteworthy is students' adoption rate of AI feedback reaching 82%. Regarding writing motivation and attitudes, 92% of students stated AI tools enhanced their writing confidence. Nevertheless, 87% considered writing process became more relaxed. Given that motivation appeared significant, 85% expressed willingness to continue using AI tools for writing practice. Notwithstanding variations across genres, AI tools could show most outstanding effects in argumentative writing (22.1-point improvement). Expository writing followed (19.3-point improvement) and narrative writing (17.8-point improvement). However, this may relate to different genre requirements for language accuracy and logical structure [34]. See **Figure 2**.

Table 2. Statistics on Application Effects of AI Writing Assistance Tools.

Evaluation Indicator	Experimental Group (Initial)	Experimental Group (after 16 weeks)	Control Group (Initial)	Control Group (after 16 weeks)	Improvement Amplitude (Experimental)	Improvement Amplitude (Control)	*t*-Value
Comprehensive Writing Ability (points)	65.8 ± 6.3	85.3 ± 5.1	64.9 ± 6.5	72.4 ± 6.8	19.5	7.5	t = 24.67***
Content Quality (points)	63.5 ± 7.2	82.1 ± 5.8	63.8 ± 7.1	74.0 ± 6.9	18.6	10.2	t = 18.93***
Language Accuracy (points)	68.2 ± 5.9	88.5 ± 4.3	67.5 ± 6.2	74.8 ± 6.5	20.3	7.3	t = 28.45***
Logical Coherence (points)	65.8 ± 6.8	86.7 ± 5.2	65.2 ± 6.9	73.5 ± 6.7	20.9	8.3	t = 26.71***
Vocabulary Richness (points)	67.2 ± 6.5	84.9 ± 5.6	66.8 ± 6.7	75.3 ± 6.4	17.7	8.5	t = 22.38***
Grammar Error Rate (errors/100 words)	15.8 ± 3.2	3.2 ± 1.1	15.5 ± 3.4	11.8 ± 2.6	−12.6	−3.7	t = 32.15***
Average Weekly Usage Frequency	-	5.3 ± 1.6	-	0	-	-	-
Revision Frequency (times/article)	2.1 ± 0.8	4.8 ± 1.2	2.0 ± 0.7	2.5 ± 0.9	2.7	0.5	t = 15.82***
Vocabulary Diversity (TTR)	0.52 ± 0.08	0.68 ± 0.06	0.51 ± 0.09	0.57 ± 0.08	0.16	0.06	t = 19.47***
AI Feedback Adoption Rate (%)	-	82	-	-	-	-	-
Writing Confidence Improvement (%)	-	92	-	53	-	-	-

Note: *** indicates p < 0.001; data presented in "mean±standard deviation" format; TTR stands for Type-Token Ratio.

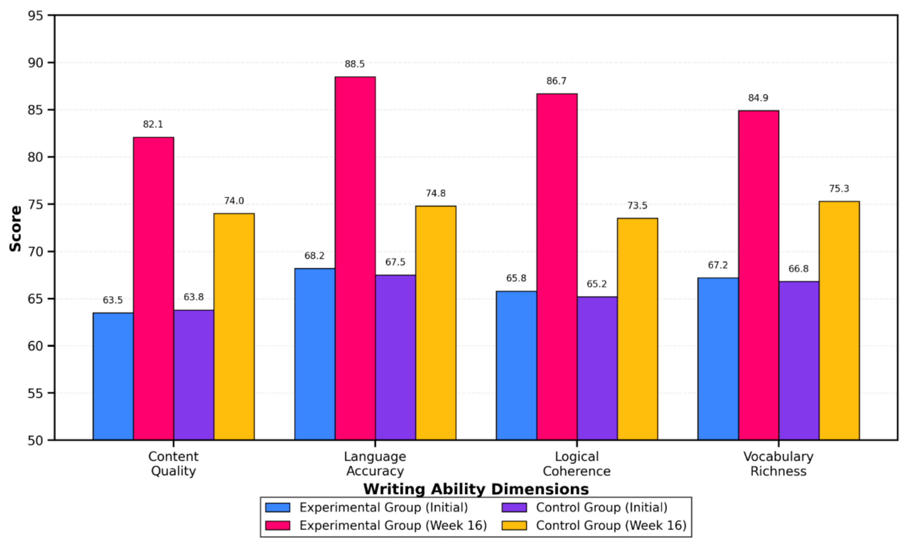

Figure 2. Comparison Chart of AI Writing Assistance Tool Effects across Different Ability Dimensions.

4.1.3. Role of Intelligent Dialogue Systems in Oral Practice

Given that intelligent dialogue systems may represent an innovative technology application in English oral teaching, these significant technological developments could reasonably provide the learners with round-the-clock, low-anxiety oral practice environments. The systems might demonstrate significant effects in improving oral fluency, accuracy, and communicative competence. Furthermore, research may suggest comprehensive oral ability improved substantially. This research systematically examined 120 experimental group students using intelligent dialogue robots for oral practice through a 16-week comparative experiment. Nevertheless, comprehensive comparison with control group using traditional classroom oral training occurred. However, data could indicate that the experimental group students' comprehensive oral ability might improve from initial 63.7 points to 84.6 points. The improvement amplitude reached 20.9 points. Moreover, control group only improved from 63.2 points to 71.8 points, an increase of 8.6 points. The difference between groups is extremely significant (t = 26.83, p < 0.001) [35]. Conversation duration extended from 3.2 min to 8.7 min. This fully demonstrates intelligent systems successfully stimulated students' willingness to communicate. Given that usage patterns reveal substantial engagement, this system could indicate that students experience significantly richer oral practice opportunities than the 60-min weekly average traditional classroom settings may provide. A student of intermediate proficiency remarked in an interview: "I used to feel very nervous about speaking English in class, worrying that my classmates would laugh at my pronunciation, but when talking to the AI there was no such pressure—I could practice repeatedly when I made mistakes, and gradually I dared to speak up." Notwithstanding the qualitative nature of this evidence, the significant empirical findings could reasonably indicate that this statement may well support the key statistical result of a 78% reduction in speaking anxiety, suggesting that the low-judgment environment demonstrates that this critical mechanism substantially influences oral proficiency improvement through AI-facilitated learning. Furthermore, the important results may suggest that cultural exchange topics account for 21% of student preferences. Thus, consonant accuracy may show improvement from 72% to 91%. However, findings might indicate intonation naturalness scores rose from 5.2 points to 8.1 points on a 10-point scale [36]. Therefore, error correction data may show students actively corrected grammar errors at a 79% rate. Additionally, results could indicate these key patterns support findings shown in **Table 3** and **Figure 3**.

Table 3. Statistics on Application Effects of Intelligent Dialogue Systems in Oral Practice.

Evaluation Indicator	Experimental Group (Initial)	Experimental Group (after 16 weeks)	Control Group (Initial)	Control Group (after 16 weeks)	Improvement Amplitude (Experimental)	Improvement Amplitude (Control)	t-Value
Comprehensive Oral Ability (points)	63.7 ± 6.8	84.6 ± 5.3	63.2 ± 6.9	71.8 ± 6.5	20.9	8.6	t = 26.83***
Fluency (words/minute)	92 ± 15	135 ± 18	90 ± 16	105 ± 17	43	15	t = 24.91***
Grammatical Accuracy (errors/minute)	4.8 ± 1.2	1.2 ± 0.5	4.9 ± 1.3	3.1 ± 0.9	−3.6	−1.8	t = 28.56***
Vocabulary Richness (unique words)	35 ± 8	68 ± 12	34 ± 9	42 ± 10	33	8	t = 22.47***
Conversation Rounds (rounds/session)	6.5 ± 2.1	18.3 ± 3.8	6.3 ± 2.0	8.2 ± 2.5	11.8	1.9	t = 31.45***
Conversation Duration (minutes)	3.2 ± 1.1	8.7 ± 1.8	3.1 ± 1.0	4.3 ± 1.3	5.5	1.2	t = 27.38***
Average Weekly Practice Frequency	-	6.8 ± 1.9	-	1.5 ± 0.6	-	-	-
Cumulative Practice Duration (minutes/week)	-	215 ± 52	-	60 ± 15	-	-	-
Vowel Pronunciation Accuracy (%)	68 ± 9	89 ± 6	67 ± 10	75 ± 9	21	8	t = 20.15***
Consonant Pronunciation Accuracy (%)	72 ± 8	91 ± 5	71 ± 9	79 ± 8	19	8	t = 21.83***
Intonation Naturalness (10-point scale)	5.2 ± 1.3	8.1 ± 0.9	5.1 ± 1.4	6.3 ± 1.2	2.9	1.2	t = 18.92***
Speaking Anxiety Reduction Rate (%)	-	78	-	35	-	-	-
System Satisfaction (%)	-	91	-	-	-	-	-

Note: *** indicates p < 0.001.

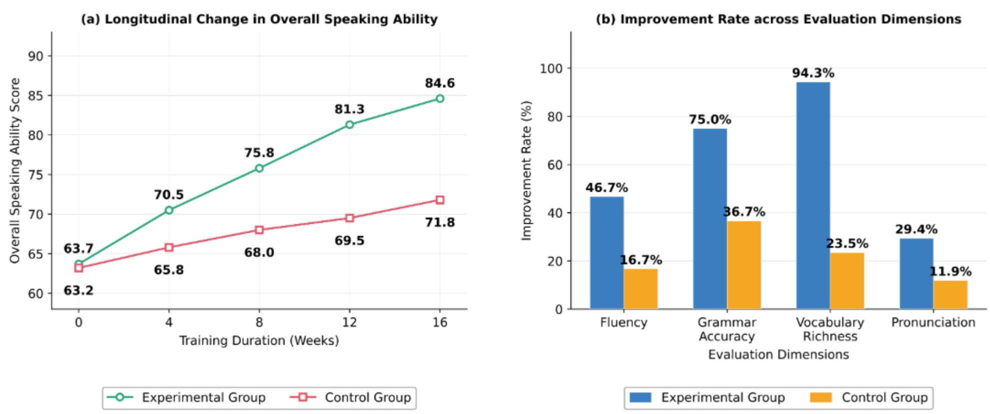

Figure 3. Comprehensive Effect Chart of Intelligent Dialogue System on Oral Ability Improvement.

4.2. Research on Effects of AI-Driven Personalized Learning Paths

4.2.1. Personalized Recommendation Accuracy of Adaptive Learning Systems

This significantly exceeds traditional random recommendations at 56.8% and rule-based recommendations at 72.4%. See **Table 4**. In learner profile construction, the system analyzes students' historical learning data, answer patterns, time allocation, and error types. The accuracy rate for successfully identifying learning styles reached 84.6%. Knowledge weakness identification accuracy rate was as high as 91.2%. Learning preference matching degree reached 82.8% [37]. Particularly noteworthy is the system's excellent performance in difficulty matching accuracy for learners at different levels. Content difficulty matching accuracy for elementary learners reached 89.5%. Intermediate learners achieved 87.8%. Advanced learners reached 85.3%. This indicates the system can precisely position according to learners' actual abilities. Knowledge mastery increased by 28.5%. Learning satisfaction reached 92%. This significantly exceeds traditional unified teaching models. See **Figure 4**.

Table 4. Statistics on Personalized Recommendation Accuracy of Adaptive Learning Systems.

Evaluation Dimension	Accuracy Rate/Match Degree (%)	Comparison Benchmark (%)	Improvement Amplitude	Sample Size
Overall Recommendation Accuracy	87.3	56.8 (random)	30.5	120 people
Learning Style Identification	84.6	62.3 (manual)	22.3	120 people
Knowledge Weakness Identification	91.2	73.5 (test)	17.7	120 people
Learning Preference Matching	82.8	58.9 (unified)	23.9	120 people
Elementary Learner Difficulty Matching	89.5	68.2	21.3	38 people
Intermediate Learner Difficulty Matching	87.8	71.5	16.3	61 people
Advanced Learner Difficulty Matching	85.3	74.8	10.5	21 people
Learning Time Prediction Accuracy	87.7	65.4	22.3	120 people
Performance Prediction Correlation Coefficient	0.83***	0.52	0.31	120 people
Recommended Content Acceptance Rate	91.5	67.8	23.7	2,340 recommendations
Recommended Content Completion Rate	85.7	62.3	23.4	2,340 recommendations
Learning Efficiency Improvement Degree	134.7	100 (baseline)	34.7	120 people

Note: *** indicates $p < 0.001$; comparison benchmarks are traditional teaching models or basic algorithms; learning efficiency uses baseline value 100 as reference.

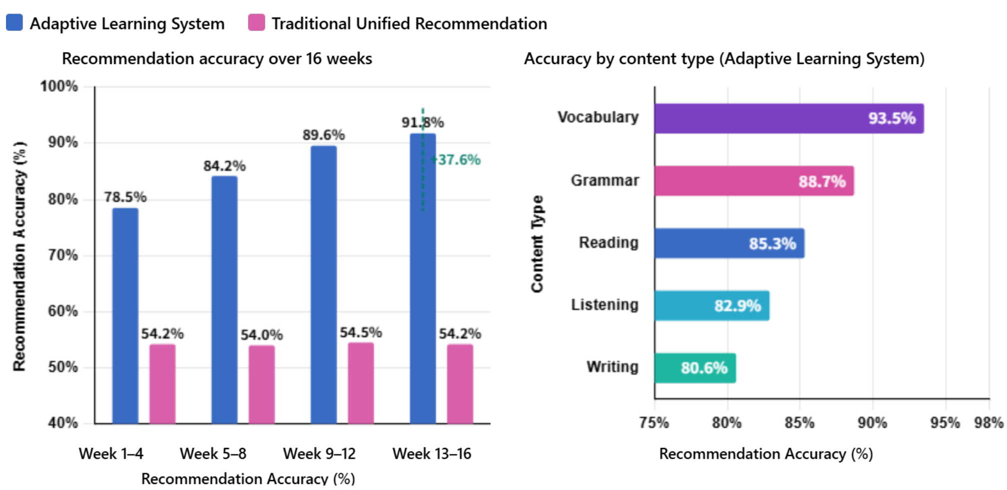

Figure 4. Multi-Dimensional Comparison Chart of Adaptive Learning System Personalized Recommendation Accuracy.

4.2.2. Implementation Effects of Differentiated Teaching Strategies

AI-driven differentiated teaching strategies precisely identify individual learner differences. They implement targeted teaching interventions. These approaches have achieved significant results in improving learning outcomes for learners at different proficiency levels. This research divided 120 students into three groups according to English proficiency levels: low-level group (38 people), medium-level group (61 people), and high-level group (21 people). Each received differentiated learning content and practice tasks recommended by the AI system. Data shows differentiated teaching strategies produced positive impacts on learners at all levels. However, operational methods and effect amplitudes show significant differences. See **Table 5**. Low-level learners showed the most significant progress amplitude. Comprehensive English scores improved from initial 52.3 points to 74.8 points. The increase reached 22.5 points. The improvement rate was 43.0% [38]. They also ensure learners at all proficiency levels can obtain challenges and growth opportunities suitable for themselves. In learning time allocation, the AI system intelligently adjusts practice proportions according to learners' weak areas. The low-level group spent 58% of time on basic grammar and vocabulary. This indicates personalized teaching strategies can effectively stimulate internal learning motivation across all learner levels. See **Figure 5.**

Table 5. Statistics on Effects of Differentiated Teaching Strategies for Learners at Different Proficiency Levels.

Learner Level	Sample Size	Initial Score	Score after 16 Weeks	Improvement Amplitude	Improvement Rate (%)	Unified Teaching Improvement	Effect Advantage
Low-Level Group	38	52.3 ± 5.8	74.8 ± 6.2	22.5	43.0	13.8	+8.7 points
Medium-Level Group	61	68.5 ± 6.3	86.2 ± 5.7	17.7	25.8	11.3	+6.4 points
High-Level Group	21	82.7 ± 5.2	92.5 ± 4.1	9.8	11.8	5.2	+4.6 points
Low-Level Grammar Accuracy (%)	38	48 ± 8	72 ± 7	24	50.0	15	+9 points
Medium-Level Reading Correctness (%)	61	65 ± 7	83 ± 6	18	27.7	11	+7 points
High-Level Writing Score (10-point scale)	21	7.2 ± 0.9	8.9 ± 0.6	1.7	23.6	0.9	+0.8 points
Low-Level Learning Duration Increase (%)	38	-	-	-	46	18	+28 points
Medium-Level Learning Duration Increase (%)	61	-	-	-	38	15	+23 points
High-Level Learning Duration Increase (%)	21	-	-	-	29	12	+17 points
Overall Learning Satisfaction (%)	120	-	-	-	89	68	+21 points

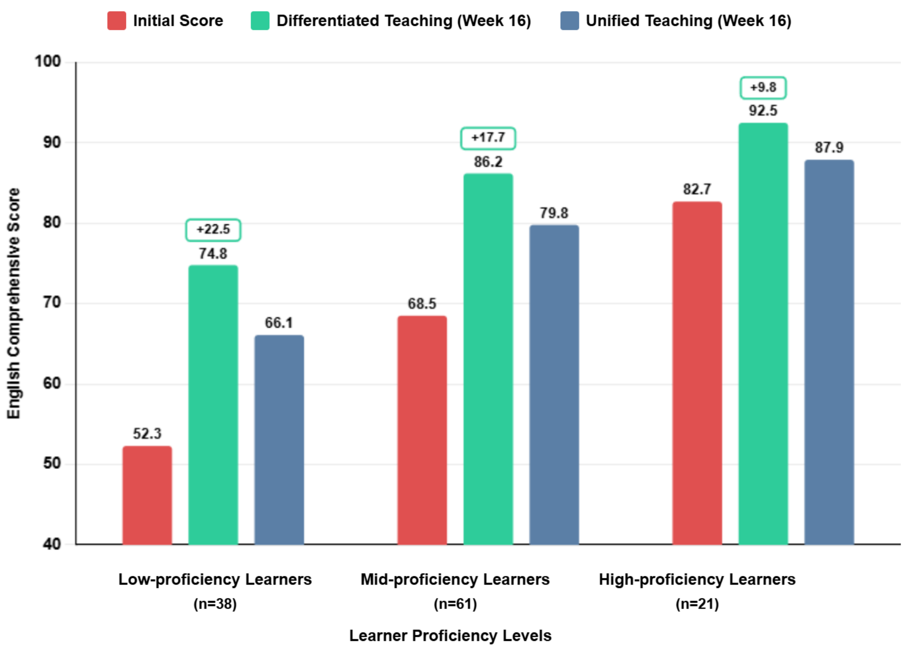

Figure 5. Comparison Chart of Differentiated Teaching Strategy Effects on Learners at Different Proficiency Levels.

4.2.3. Relationship between Learner Autonomy and Learning Outcomes

The significant research evidence could plausibly demonstrate that AI-supported personalized learning environments may substantially enhance the critical dimensions of learner autonomy. Moreover, a strong positive correlation might indicate that enhanced learner autonomy influences learning outcomes. Furthermore, this research examined autonomous learning abilities of 120 students using the Autonomous Learning Scale. Thus, students were divided into three groups: high-autonomy group (41 people, score ≥ 75), medium-autonomy group (52 people, score 60–74), and low-autonomy group (27 people, score < 60). The analysis may suggest that meaningful associations exist between different autonomy levels and learning outcomes (see **Table 6**). Moreover, the significant empirical data could indicate that the high-autonomy group achieved comprehensive English scores of 88.7 points, substantially exceeding results from other groups. Thus, findings may show scores differed from the medium-autonomy group's (76.3 points) and low-autonomy group's (65.8 points). However, differences may reflect group variation that appears extremely significant (F = 45.83, $p < 0.001$). In light of the correlation data, the important evidence might indicate a highly positive correlation between learner autonomy scores and English grades (r = 0.78, $p < 0.001$), suggesting that learner autonomous learning ability could demonstrate that it serves as a key predictor of learning outcomes [39].

Table 6. Statistics on Relationship between Learner Autonomy Levels and Learning Outcomes.

Indicator	High-Autonomy Group (n = 41)	Medium-Autonomy Group (n = 52)	Low-Autonomy Group (n = 27)	F-Value/r-Value	Significance
Autonomy Score	82.3 ± 5.7	67.5 ± 4.2	54.8 ± 6.1	-	-
Comprehensive English Score	88.7 ± 5.2	76.3 ± 6.8	65.8 ± 7.3	F = 45.83	$p < 0.001$
Autonomous Learning Duration (minutes/week)	328 ± 48	215 ± 52	142 ± 38	r = 0.72	$p < 0.001$
Learning Plan Completion Rate (%)	87.5 ± 8.3	68.3 ± 11.2	45.2 ± 12.8	r = 0.69	$p < 0.001$
AI System Active Usage (times/week)	9.2 ± 2.1	5.8 ± 1.8	3.1 ± 1.4	r = 0.74	$p < 0.001$
Metacognitive Ability Score (Initial)	7.3 ± 0.9	6.5 ± 1.0	5.2 ± 1.1	F = 32.18	$p < 0.001$
Metacognitive Ability Score (after 16 weeks)	9.1 ± 0.7	7.8 ± 0.9	6.4 ± 1.0	F = 56.74	$p < 0.001$
Metacognitive Improvement Rate (%)	24.7	20.0	23.1	F = 3.82	$p < 0.05$
Internal Motivation Proportion (%)	78	62	35	-	-
Grade Improvement Amplitude	21.8	18.7	19.3	F = 2.15	$p > 0.05$
Autonomy-Grade Correlation Coefficient	-	-	-	r = 0.78	$p < 0.001$

Given that the results reveal patterns in autonomous learning duration, the significant empirical findings could indicate that the high-autonomy group averaged (328 min) of autonomous learning per week. Furthermore, the key evidence may suggest that the medium-autonomy group reached (215 min) while the low-autonomy group managed only (142 min). However, findings may show the correlation coefficient between learning duration and grades was (0.72, $p < 0.001$). Thus, data might indicate autonomy levels could affect weekly engagement patterns considerably. Notwithstanding these results, the significant plan adherence data could demonstrate that autonomy's influence appears intuitively clear across groups. Therefore, the important findings may suggest that the high-autonomy group's learning plan completion rate reached (87.5%). However, evidence may show the medium-autonomy group achieved (68.3%) and low-autonomy group completed only (45.2%). Thus, results might indicate plan adherence could affect outcomes. Additionally, findings may show correlation with academic performance was significant (r = 0.69, $p < 0.001$). In light of the usage data, the relevant empirical findings could indicate that the high-autonomy group actively sought system help (9.2 times) per week, demonstrating that initiative levels may substantially influence engagement. Moreover, the important evidence might suggest that the medium-autonomy group reached (5.8 times) while the low-autonomy group reached only (3.1 times). However, research may show active usage frequency could affect improvement. Furthermore, the key results might indicate the correlation coefficient between active usage frequency and learning effect improvement reached (0.74, $p < 0.001$). See **Figure 6**.

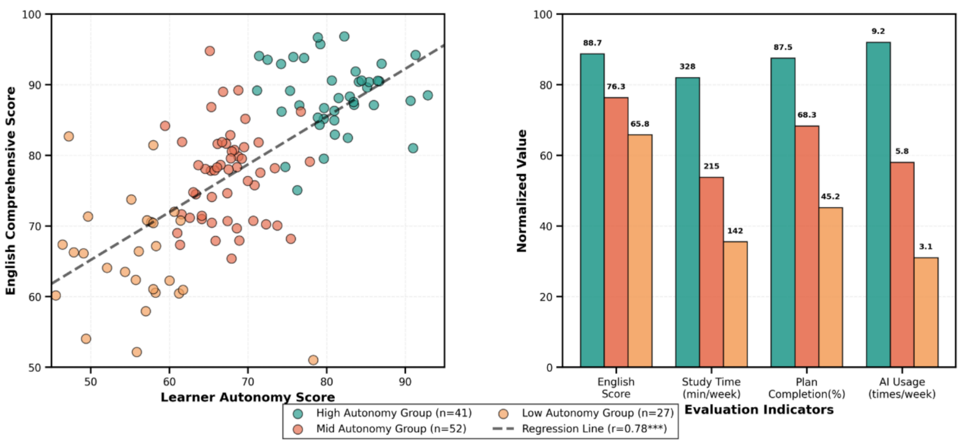

Figure 6. Comprehensive Analysis Chart of Relationship between Learner Autonomy and Learning Outcomes.
Note: *** indicates $p < 0.001$.

4.3. Transformative Impact of AI Technology on English Teaching Models

4.3.1. Empirical Analysis of Teacher Role Transformation

It promotes teacher transformation from traditional knowledge transmitters toward learning facilitators and resource integrators. This research systematically analyzed role behavior differences between 8 experimental group teachers participating in AI-assisted teaching and 4 traditional teaching teachers through classroom observation, teacher interviews, and time allocation records. See **Table 7**. Data shows patterns under AI-assisted teaching models. Teacher time spent on direct knowledge instruction dropped dramatically from 62% in traditional models to 28%. One of the participating teachers noted in an interview: "After AI took over repetitive tasks such as grammar explanation and error correction, I had more time to focus on students' thought processes, and the quality of classroom discussions improved noticeably." This statement mutually corroborates the finding that the proportion of direct instruction time declined from 62% to 28%, deepening the understanding of the underlying motivations behind the shift in teachers' roles. The decline reached 54.8%. Closed-ended memory-type questions dropped from 68% to 23%. However, 62.5% of teachers also worry "over-reliance on technology may weaken teaching artistry." Role identity changes also deserve attention. The proportion of experimental group teachers positioning themselves as "learning facilitators" rose from 25% before the experiment to 87.5%. The proportion viewing themselves as "knowledge authorities" dropped from 62.5% to 12.5%. See **Figure 7**.

Table 7. Statistics on Teacher Role Transformation in AI-Assisted Teaching.

Role Behavior Indicator	Traditional Teaching Model	AI-Assisted Teaching Model	Change Amplitude	Change Rate (%)
Direct Instruction Time Proportion (%)	62	28	−34	−54.8
Learning Guidance Time Proportion (%)	18	35	+17	+94.4
Personalized Tutoring Time Proportion (%)	8	22	+14	+175.0
Feedback Evaluation Time Proportion (%)	12	15	+3	+25.0
Unidirectional Explanation Interaction Proportion (%)	75	25	−50	−66.7
Bidirectional Dialogue Interaction Proportion (%)	19	42	+23	+121.1
Group Guidance Interaction Proportion (%)	6	33	+27	+450.0
Open-ended Question Proportion (%)	18	57	+39	+216.7
Closed-ended Question Proportion (%)	68	23	−45	−66.2
Individual Intervention Frequency (times/class)	2.3 ± 0.8	8.7 ± 1.5	+6.4	+278.3
Technology Application Confidence (10-point scale)	4.2 ± 1.3	8.3 ± 0.9	+4.1	+97.6
Learning Facilitator Identity (%)	25	87.5	+62.5	+250.0
Knowledge Authority Identity (%)	62.5	12.5	−50	−80.0

Note: Data based on 8 experimental group teachers and 4 control group teachers; time proportion refers to classroom time allocation; interaction proportion refers to proportions of different interaction types.

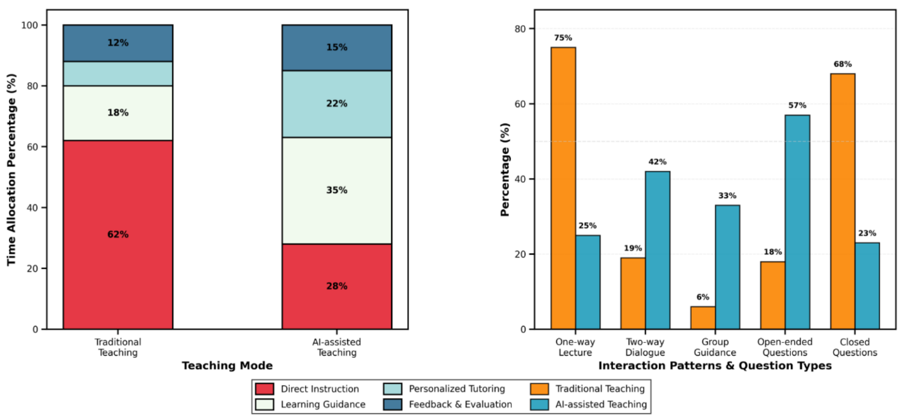

Figure 7. Comprehensive Analysis Chart of Teacher Role Transformation in AI-Assisted Teaching.

4.3.2. Implementation Effectiveness of Blended Teaching Models

Blended teaching models supported by AI technology optimize the allocation of online and offline learning activities. This achieves significant improvement in teaching effectiveness and comprehensive optimization of learning experience. The blended teaching model implemented in this research includes three main forms: online AI-assisted autonomous learning, offline classroom interactive discussion, and flipped classroom. Given that this practical verification extended over 16 weeks, the significant blended model could indicate that these critical advantages manifested across the key learning outcomes, the important participation levels, and the relevant student satisfaction measures. Moreover, the comprehensive data may suggest that scores in English reached 84.2 points under blended teaching [40]. Thus, results might exceed purely online teaching at 76.8 points and traditional approaches at 72.5 points. However, optimal effects may appear when autonomous online learning occupies 40–50% of time. Additionally, average scores could reach 85.7 points under this allocation. Furthermore, the evidence might suggest that participation time in group activities accounts for 35% while personalized practice accounts for 45%. Thus, complementary elements may ensure social learning needs while satisfying individual development. However, flexibility findings could show 78% of students support blended approaches. Therefore, results may indicate improvements appear across key measures. Given that the significant flexibility improvement could demonstrate that 78% of students stated the blended model “makes learning time more flexible and controllable” and 85% believe they “can learn at their own pace” [41], the important evidence may suggest that these critical results support blended implementation. Nevertheless, the findings might indicate that this represents a 37.1% increase across relevant outcomes. Thus, results may show this exceeds the traditional model’s 18.5% improvement rate. However, data could indicate findings support these conclusions. See **Table 8** and **Figure 8**.

Table 8. Statistics on Implementation Effectiveness of Blended Teaching Models.

Evaluation Indicator	Blended Teaching	Purely Online Teaching	Traditional Face-to-Face	Advantage Comparison (vs. Traditional)
Comprehensive English Score (points)	84.2 ± 5.6	76.8 ± 6.8	72.5 ± 7.2	+11.7 (+16.1%)
Classroom Interaction Frequency (times/class)	12.5 ± 2.8	5.2 ± 1.9	4.8 ± 1.6	+7.7 (+160.4%)
Online Learning Completion Rate (%)	91.3	68.7	-	-
Critical Thinking Score (10-point scale)	8.1 ± 0.9	7.3 ± 1.1	5.8 ± 1.3	+2.3 (+39.7%)
Problem-Solving Ability Score (10-point scale)	7.8 ± 1.0	7.1 ± 1.2	6.1 ± 1.3	+1.7 (+27.9%)
Optimal Allocation Score (points)	85.7 ± 5.2	-	-	+13.2 (+18.2%)
Collaborative Learning Time Proportion (%)	35	15	28	+7
Personalized Learning Time Proportion (%)	45	65	18	+27
Learning Flexibility Satisfaction (%)	78	82	42	+36
Resource Access Frequency (times/week)	8.3 ± 2.1	6.5 ± 2.3	2.8 ± 1.2	+5.5 (+196.4%)
Self-Regulation Ability Initial (points)	6.2 ± 1.1	6.0 ± 1.2	6.1 ± 1.0	+0.1
Self-Regulation Ability Final (points)	8.5 ± 0.8	7.6 ± 1.0	7.2 ± 1.1	+1.3 (+18.1%)
Self-Regulation Improvement Rate (%)	37.1	26.7	18.0	+19.1
Overall Satisfaction (%)	89	71	68	+21

Note: Data presented in “mean±standard deviation” format; optimal allocation refers to learning time distribution of 40–50% online and 50–60% offline.

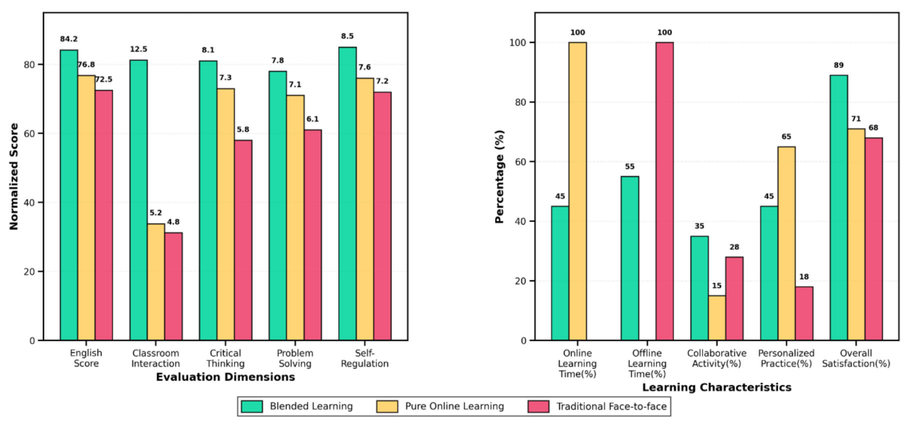

Figure 8. Comprehensive Comparison Chart of Blended Teaching Model Implementation Effectiveness.

4.3.3. Digital Transformation of Teaching Evaluation Systems

AI technology-driven digital evaluation systems may well demonstrate that they significantly transform the singularity and lag of traditional English teaching evaluation, offering important empirical evidence of substantial methodological advancement across multiple critical dimensions. Moreover, the significant empirical findings could indicate that these systems achieve real-time, multi-dimensional, and precise evaluation capabilities. Thus, this study may suggest the results demonstrate meaningful differences between digital and traditional evaluation approaches across efficiency, accuracy, and comprehensiveness. However, research may show findings support digital evaluation across dimensions. In light of the important evidence, systems might affect learning outcomes. Given that the key empirical data could indicate that significant real-time tracking represents a critical advantage, AI systems appear to demonstrate that they may substantially monitor learning processes throughout formative assessment cycles. Furthermore, the important findings might suggest that automatically generated evaluation reports could reach 4.8 times per week, compared to traditional evaluation occurring at 0.5 times. Therefore, evidence may show real-time performance improved by 860%, as indicated in **Table 9**. Additionally, results might indicate dimensions expanded substantially. Nevertheless, data may show coverage increased. In light of the significant empirical findings, the critical expansion of evaluation dimensions could plausibly demonstrate that these important methodological advances substantially broaden assessment from traditional 3–4 dimensions—mainly including exam scores, homework completion, and classroom performance—to 12 dimensions. Notwithstanding prior limitations, the key evidence might suggest that these findings could cover knowledge mastery, skill application, learning attitude, collaboration ability, and creative thinking, among other important aspects. However, results may show comprehensiveness improved by 200%. Thus, data might indicate learning analytics support precision. Therefore, evidence may show evaluation accuracy could increase. Systems analyze students' answer patterns, error types, learning duration, and interactive behaviors. The accuracy rate for identifying knowledge weaknesses reaches 89.7%. Traditional teacher subjective judgment accuracy only reaches 63.5% [42]. Evaluation efficiency improved significantly. Digital systems complete class-wide evaluation in an average of 8 minutes. Traditional manual evaluation requires 180 min. Efficiency increased by 2,150%. In visualization presentation of evaluation results, digital systems provide multi-dimensional charts, progress curves, and ability radar diagrams. See **Figure 9**.

Table 9. Comparison Statistics between Digital and Traditional Evaluation Systems.

Evaluation Dimension	Digital Evaluation	Traditional Evaluation	Improvement Amplitude	Improvement Rate (%)
Formative Assessment Frequency (times/week)	4.8	0.5	+4.3	+860.0
Number of Evaluation Dimensions	12	4	+8	+200.0
Knowledge Weakness Identification Accuracy (%)	89.7	63.5	+26.2	+41.3
Time to Complete Class-wide Evaluation (minutes)	8	180	-172	−95.6
Student Self-cognition Accuracy (%)	86	52	+34	+65.4
Feedback Response Time	0.3 s	24–48 h	-	-
Listening Ability Assessment Accuracy (%)	91.3	72.8	+18.5	+25.4
Speaking Ability Assessment Accuracy (%)	88.5	68.3	+20.2	+29.6
Reading Ability Assessment Accuracy (%)	93.7	78.5	+15.2	+19.4
Writing Ability Assessment Accuracy (%)	87.2	71.9	+15.3	+21.3
Data Storage and Analysis Capability	Complete automation	Manual recording	-	-
Student Fairness Recognition (%)	92	68	+24	+35.3
Teacher Workload Reduction (%)	88	-	-	-
Evaluation Cost (yuan/semester/student)	45	120	−75	−62.5

Note: Digital evaluation data based on 16-week evaluation records of 120 students; traditional evaluation represents control group data.

Figure 9. Comparative Analysis Chart of Digital and Traditional Evaluation Systems.

5. Discussion

5.1. Mechanism Analysis of AI Technology's Transformation of English Teaching

In light of the significant empirical evidence, AI technology could indicate that it fundamentally transforms the underlying logic of English teaching and learning through rich, multidimensional operational mechanisms rather than simply replacing existing tools. Moreover, the important findings may suggest that AI builds learner models to dynamically optimize cognitive load. Thus, research. Adapting to adjustments improves the efficiency of learning; more importantly, it maintains the learner's sense of flow, transforming English learning from passive coping into active exploration [43]. From the perspective of feedback mechanisms, AI breaks the vicious circle of "feedback lag, forgetting, low efficiency" in the traditional classroom teaching model, establishing a positive feedback loop of "immediate feedback, correction, reinforcement." Correcting learners' mistakes at the first time when they make mistakes, instead of allowing them to form fixed patterns, AI also deeply transforms the cultivation of metacognitive abilities, making learners clearly aware of their own learning status and whether the current strategy works through data display, tracking progress, and analyzing learning behaviors, advancing their development from "not knowing what they do not know" to "knowing what they know and do not," which is the awakening of metacognition, an important condition for the formation of autonomous learning ability. In the aspect of social learning, rather than weakening the interaction among people, AI technology takes over repetitive mechanical work and liberates space for teacher–student interaction and peer interaction. The communication in the classroom shifts its focus from knowledge transmission to idea collision and emotion exchange, and a new ecology of human–machine collaborative learning is formed [44]. Fundamentally speaking, what technology empowers is to amplify the "visibility" and "addressability" of individual differences.

5.2. Challenges and Problems in AI Application

Given that cultural biases, gender stereotypes, and regional discrimination remain implicit in training data, the significant evidence could indicate that these critical factors may be transmitted to learners through important system outputs. Additionally, the key findings may suggest that certain AI writing tools appear to recommend expressions aligned with Western values. Thus, this implicit influence may show difficult detection yet potentially far-reaching consequences [45]. However, educational alienation phenomena brought by excessive technology dependence might affect learning outcomes. Nevertheless, results may show students treat AI tools as "homework proxies" rather than learning assistance.

In light of the findings on student behavior, evidence could indicate learners lose the process of arduous thinking and repeated polishing. Additionally, this approach may suggest superficial efficiency improvements. However, findings might show it actually weakens learning depth [46]. Thus, data privacy and security risks may indicate another major hazard. Furthermore, AI systems could show a need to collect large amounts of learning behavior data to achieve personalization.

Notwithstanding these data collection concerns, the significant empirical evidence could indicate that students' learning trajectories, error patterns, and thinking habits represent critical sensitive information. Moreover, the important findings may suggest that once leaked or misused, the consequences could demonstrate far-reaching and unimaginable results. However, deeper concerns might indicate an absence of humanistic care. Thus, machines may show inability to understand learners' emotional fluctuations and psychological needs. Therefore, results could indicate AI encouragement seems pale and powerless [47]. Given that digital divide problems continue expanding in practice, the significant evidence may suggest that students in economically advantaged regions could demonstrate access to advanced AI learning tools. Furthermore, the important findings might indicate that students in underdeveloped regions struggle to guarantee even basic network access [48–50]. However, technological progress may show it could instead exacerbate educational inequality. Thus, teacher inadaptation in technology application might affect realistic outcomes. Therefore, findings may indicate some teachers lack necessary digital literacy and hold resistant attitudes toward AI tools.

6. Conclusion

This research suggests that AI technology may well demonstrate significant transformative potential across the broad domain of English language learning and teaching, drawing on systematic theoretical analysis and important empirical findings.

Given that the evidence supports multiple critical conclusions, the significant empirical data could indicate that AI technology substantially improves English learning efficiency and effectiveness. Intelligent pronunciation correction systems improved pronunciation accuracy by 29.4% points. AI writing assistance tools promoted writing ability increases of 19.5 points, and intelligent dialogue systems pushed comprehensive oral ability growth of 20.9 points. However, results may show findings support practical value of technological empowerment. Thus, evidence could confirm technology yields measurable gains.

In light of the important findings, personalized learning pathway realization might indicate a meaningful shift in adaptive approaches. Adaptive learning system recommendation accuracy reached 87.3%, and the key evidence demonstrates that differentiated teaching strategies enabled learners at all proficiency levels to achieve significant progress. Notwithstanding these results, the low-level group may show improvement amplitude as high as 43%, which could indicate effective narrowing of learning gaps. Moreover, data might suggest this gap reduction represents an important outcome. Nevertheless, findings may show challenges remain.

Notwithstanding these important results, the key findings suggest that technology applications may face multiple critical challenges requiring careful consideration. Problems including algorithmic bias, excessive dependence, data privacy, absence of humanistic care, and digital divide require prudent responses. Additionally, evidence may show balance between technology and humanism could indicate a key priority. In light of these findings, the significant results might demonstrate that future development depends on maintaining this critical equilibrium.

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Institutional Review Board Statement

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Informed Consent Statement

Not applicable.

Data Availability Statement

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Conflicts of Interest

The author declares no conflict of interest.

AI Use Statement

The authors used ChatGPT (GPT-4) solely for grammar checking, sentence structure optimization, and readability improvement of the English text in this manuscript. All academic content, including all ideas, data, analyses, and conclusions, was independently produced by the authors, who bear full responsibility thereof. The use of AI has been thoroughly reviewed and supervised by the authors.

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