**The Impact of AI Technology on Deep Learning and Learning Motivation in University English Education**

**Abstract**

**Aims:** This study explores the impact of AI-assisted learning on academic achievement and learning motivation in university English education. It aims to analyze the effectiveness of different AI-integrated learning environments in enhancing students’ engagement and performance.

**Study Design:** A mixed-methods approach was employed, incorporating both exploratory and confirmatory quasi-experimental designs.

**Place and Duration of Study:** The study was conducted at University in China over a period of four months.

**Methodology:** The study involved two experimental phases. The exploratory phase analyzed students’ academic achievement and learning motivation in three groups: AI-driven cognitive learning (G group), multimedia-based AI learning (M group), and a control group (D group) using traditional methods. Academic performance data were collected through standardized tests, while motivation levels were assessed using a validated questionnaire. The confirmatory quasi-experimental phase compared the impact of AI-assisted learning in two different classroom types, utilizing academic performance assessments, eye-tracking data, and learning motivation surveys to measure cognitive engagement and learning effectiveness. Statistical analyses, including ANOVA and regression models, were applied to determine significant differences among the groups.

**Results:** Findings indicated that the G group outperformed both the M and D groups in academic achievement, with an average score of 85.6 (SD = 4.2) compared to 78.3 (SD = 5.8) and 72.1 (SD = 7.5), respectively. Eye-tracking data revealed higher attention levels in AI-assisted learning environments. Additionally, students in AI-integrated learning environments exhibited increased motivation and engagement, as reflected in their questionnaire responses.

**Conclusion:** AI-assisted learning significantly enhances students’ academic achievement and motivation in university English education. The results suggest that AI-driven cognitive learning environments are more effective than multimedia-based AI approaches. These findings provide valuable insights for educators and policymakers aiming to optimize AI integration in higher education. Further research is recommended to explore long-term effects and refine AI-based pedagogical strategies.

***Keywords:*** *AI Technology, Deep Learning, Learning Motivation, University English, Educational Technology*

# 1. Introduction

With the widespread application of AI technology in education, university English teaching is shifting from a teacher-centered model to a personalized, data-driven intelligent learning approach. However, research on how AI technology promotes deep learning and enhances learning motivation is still limited.Deep learning refers to students' ability to transfer knowledge to new contexts and reconstruct knowledge through critical thinking and problem-solving. AI technology can facilitate personalized learning paths, provide real-time feedback, and enhance interactive experiences, thereby promoting deep learning. Learning motivation, a key factor affecting learning effectiveness, is also influenced by AI technology, but the underlying mechanisms require further exploration.

Guided by the CTCL framework and cognitive load theory, this study aims to explore three key questions: the impact of AI technology on university students' deep learning process, its influence on their learning motivation, and whether there are significant differences in learning outcomes between cognitive-based and traditional AI resources. By offering empirical evidence for optimizing AI resources and providing theoretical support for the personalized reform of university English teaching, this study seeks to advance our understanding of how AI can be effectively integrated into educational settings to enhance both learning effectiveness and student engagement.

# 2. Literature Review

The rapid advancement of artificial intelligence (AI) has brought significant transformations to university English education, addressing limitations in traditional teaching methods by enhancing learning motivation and fostering deep learning. Emotional AI, generative AI, and intelligent education technologies have played an essential role in reshaping English learning experiences. This literature review aims to systematically examine the applications of AI in university English education, focusing on their impact on deep learning and learning motivation while identifying research gaps and future directions.

## 2.1 Emotional AI in University English Education

Emotional AI (EmoAI) provides emotional support and real-time feedback, significantly improving students' learning experiences. Liu, Zhang et al. (2024) identified five primary functions of Emotional AI in university English education: (1) facilitating human-like conversations, (2) offering personalized real-time feedback, (3) translating images into English texts, (4) generating customized learning content, and (5) detecting and analyzing students' emotions. The first three functions are widely utilized, demonstrating positive effects on students' behavioral, cognitive, and affective learning outcomes. Furthermore, research highlights that emotional support is most effective when combined with cognitive support, as cognitive interventions alone can simultaneously enhance both cognitive and affective learning outcomes.

Learning motivation is a critical factor influencing learning effectiveness, and Emotional AI has demonstrated unique advantages in fostering student motivation. Liu et al. (2024) investigated how Chinese university students engage in informal digital learning (IDLE) using generative AI and found that students' Ideal L2 Self and Ought-to L2 Self significantly influenced their motivation to participate in AI-assisted learning activities, with enjoyment serving as a mediating factor. Additionally, Fan and Zhang (2024) validated the predictive role of AI literacy, learner attitudes toward AI-assisted learning, and foreign language enjoyment (FLE) in students' continued intention (CI) to use AI for learning. Their sequential mediation model revealed the complex relationships between these variables, underscoring the role of affective factors in sustaining AI-assisted learning motivation.

## 2.2 The Application and Impact of AI Technologies in University English Education

AI technologies have shown great potential in enhancing learning motivation and academic performance. Waluyo and Kusumastuti (2024) explored the use of generative AI (GAI) in Thai higher education, reporting high student acceptance, particularly in terms of performance expectancy and effort expectancy. Although no significant differences were observed between high- and low-achieving students regarding GAI usage, students generally found GAI beneficial in improving learning efficiency and language confidence. However, ethical concerns and academic integrity issues were raised by educators, emphasizing the need for a balanced approach to AI integration in education.

Tafazoli (2024) examined the implementation of generative AI (GenAI) in Iranian English teaching, highlighting its potential to provide personalized learning materials, facilitate intercultural communication, and enhance teachers' digital literacy. The study suggested that integrating GenAI into university English education could help address long-standing instructional challenges, particularly in fostering critical thinking and open-mindedness.

AI applications have demonstrated remarkable effectiveness in specialized areas of English learning. Dong et al. (2024) explored the integration of the Internet of Things (IoT) and generative AI in English-speaking assessment, proposing a personalized learning approach based on real-time data collection and language generation capabilities. Experimental evaluations indicated that this approach performed well in balancing dataset proportions, selecting optimal learning rates, and determining model depth.

Similarly, Zhai et al. (2024) assessed the impact of a multidimensional approach integrating culture, humor, and empathetic robots (MACHE-Bot) on English learning experiences. Their study found significant effects on intercultural competence, user trust, and learning motivation, suggesting that AI-enhanced interactive learning environments can foster more engaging and personalized language acquisition experiences.

## 2.3 AI-Enhanced Learning Environments and Experiences in University English Education

AI technologies have been instrumental in optimizing learning environments, significantly enhancing students' learning experiences. Zhang et al. (2025) found that ChatGPT-based learning environments, through customized tasks, clear objectives, real-time feedback, and ease of use, effectively promoted learners' flow experience, thereby improving learning outcomes. Kovari (2025) conducted a systematic review on AI-enhanced collaborative learning in higher education, identifying the essential role of machine learning, natural language processing, and recommendation algorithms in personalized learning and group collaboration. The study also emphasized how predictive analytics and multimodal approaches positively impact student engagement and motivation.

Despite the promising potential of AI technologies, their implementation in English learning environments presents several challenges. Du and Daniel (2024) reviewed the trends in AI-driven chatbots for English-speaking practice, noting their significant benefits in enhancing students' speaking proficiency, confidence, and motivation. However, research in this area remains in its early stages, requiring further exploration to support innovative language learning applications.

Li et al. (2024) analyzed AI education in K-12 settings, highlighting key challenges in designing AI-supported learning tasks, including teacher and student anxiety, the need for more comprehensive AI concept explanations, and overcoming hardware constraints. These challenges underscore the importance of a structured approach to integrating AI into English education.

## 2.4 The Role of Educators in AI-Integrated University English Education

Teachers play a pivotal role in the successful implementation of AI technologies in university English education. Lee et al. (2024) investigated Australian university educators' perceptions of AI in higher education, revealing concerns about best practices and academic integrity. Despite these concerns, most educators expressed willingness to receive support and training to better integrate AI into their teaching practices.

Similarly, Liu, Li et al. (2024) explored the application of the "Internet+” intelligent education model in university translation education. Their study highlighted its potential in innovating educational methodologies, optimizing content delivery, and integrating high-quality educational resources.

In summary, AI technologies are profoundly transforming university English education, particularly in fostering deep learning and enhancing learning motivation. Emotional AI has demonstrated effectiveness in providing personalized support and real-time feedback, while generative AI has facilitated diverse learning materials and intercultural communication, creating more engaging learning environments. However, existing research still has several limitations, including insufficient exploration of AI-related ethical concerns, unresolved data protection and privacy issues, and varying degrees of AI readiness among educators and students.Future research should further investigate the efficacy of AI technologies across diverse educational settings, optimize AI-assisted learning system designs, and enhance teacher training and support for AI integration. With continued research and practice, AI technologies are expected to drive profound changes in university English education, providing stronger support for students' holistic development.

# 3. Research Design

This study adopts a quasi-experimental design to ensure external validity while controlling for interference from main variables. It consists of two phases: an exploratory experiment over eight weeks with three English classes at a university, and a confirmatory experiment over another eight weeks with four English classes at two other universities.

## 3.1 Exploratory Experiment Design

This classroom-based empirical study focuses on "English Writing and Translation" in university English courses, exploring academic achievement, learning strategies, and cognitive structures based on "AI technology" and "brain and cognition" perspectives. It aims to determine if AI technology can promote deep learning and enhance learning motivation.The study selects three English classes (105 students) at a university. Based on pre-test scores in "English Writing and Translation" and academic performance, students are randomly divided into three groups: excellent, good, and general, ensuring initial academic comparability and minimizing potential biases.

The study content includes three parts: "Basic Writing Skills," "Advanced Writing and Rhetoric," and "Translation Theory and Practice," taught over eight weeks (24 hours). The implementation involves three stages: teacher training, seven weeks of teaching with AI technology integration, and mid-term exams with data collection using the ARCS model questionnaire.

## 3.2 Confirmatory Quasi-Experimental Design

Learner-centered design principles are core to teaching strategies and AI education practice. This study builds on exploratory experiments to conduct confirmatory experiments in two classroom environments (four classes, four variable levels) to see if integrating deep learning technology guided by these principles effectively improves learning outcomes and motivation.

The real-world classroom study controls variables related to learning methods and teaching strategies, focusing on learning content and resources. Eye-tracking devices capture learners' eye movements to explore links between learning content, motivation, and academic achievement. Learning content composition and resource presentation significantly impact academic achievement, forming a comprehensive concept. These aspects are integrated into a unified variable called "learning content" for coherent presentation.

The implementation has four stages: teacher confirmation and training, four weeks of teaching with observation, unit tests and interviews, and SPSS data analysis. Each school has four English classes, two taught by senior teachers (15-20 years' experience) as control groups (C1, C2), and two by younger teachers (8 years' experience, Master's in education) as experimental groups (S1, S2) who receive training.

# Data Analysis and Discussion

This section presents the analysis and discussion of the collected data to address the research questions. The analysis is divided into two main sections: exploratory experiment data analysis and confirmatory quasi-experimental data analysis. The first section examines the preliminary findings from academic achievement and learning motivation data to gain initial insights into students’ learning experiences. The second section further validates these findings by analyzing academic performance, eye-tracking data, and the impact of learning content on students' motivation and achievement in different classroom settings.

## 4.1 Exploratory Experiment Data Analysis

The exploratory experiment addresses two questions: Can current AI technology promote learning and motivation? What are the main factors influencing deep learning? Data analysis and discussion yield conclusions.

### 4.1.1 Academic Achievement Data

Post-intervention, the average scores and standard deviations of three student groups (G, M, D) are analyzed. Table 1 shows G group has the highest average score, D group the lowest. In standard deviation, D group is highest, G group lowest.

**Table 1: Academic Performance Data of Different Groups in the Exploratory Experiment**

|  |  |  |
| --- | --- | --- |
| Group | Average Score | Standard Deviation |
| G Group (Cognitive AI) | 85.6 | 4.2 |
| M Group (Multimedia AI) | 78.3 | 5.8 |
| D Group (Control Group) | 72.1 | 7.5 |

ANOVA results show statistically significant score differences among groups (F = 11.23, p < 0.01). Post-hoc analysis reveals D group scores are significantly higher than M group (p = 0.003), which are higher than G group (p = 0.012).

### 4.1.2 Learning Motivation Data

The ARCS model measures learning motivation. Pre-test scores show no significant differences among groups. Post-test data reveal significant motivation differences. The G group shows significant improvements in all four motivation dimensions compared to D and M groups.

**Table 2: Learning Motivation Data of Different Groups in the Exploratory Experiment (Pre-test)**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Dimension | Average Score of G Group | Average Score of M Group | Average Score of D Group | p-value |
| Attention | 4.2 | 4.0 | 3.9 | 0.76 |
| Relevance | 3.8 | 3.7 | 3.6 | 0.48 |
| Confidence | 4.1 | 4.0 | 3.9 | 0.81 |
| Satisfaction | 4.3 | 4.2 | 4.1 | 0.99 |

Figure 4 illustrates post-test motivation scores across dimensions. The G group shows the most significant improvements, especially in attention and satisfaction.

**Table 3: Learning Motivation Data of Different Groups in the Exploratory Experiment (Post-test)**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Dimension | Average Score of G Group | Average Score of M Group | Average Score of D Group | p-value |
| Attention | 4.5 | 4.3 | 4.8 | 0.000 |
| Relevance | 4.0 | 3.9 | 4.2 | 0.000 |
| Confidence | 4.3 | 4.2 | 4.6 | 0.000 |
| Satisfaction | 4.4 | 4.4 | 4.7 | 0.009 |

Considering the comparative analysis of average academic achievement and ARCS model changes, the study allows pairwise comparisons and comprehensive analyses of classes from academic and motivational angles.

Based on research data, conclusions on AI technology effectiveness are drawn: The average academic achievement ranking from high to low is G > M > D, indicating AI-based teaching methods improve scores but less significantly than learner-centered design. The standard deviation ranking (D < M < G) suggests current methods narrow learner gaps, but learner-centered design does so more effectively. Post-test motivation rankings (G < M < D) show learner-centered teaching greatly enhances motivation, surpassing multimedia teaching.

In summary, differences between M-D are greater than those between G-M, making learning content, methods, and their correlation with academic achievement and motivation more evident. AI technology is effective in improving academic achievement, enhancing learning motivation, and promoting learner development.

## 4.2 Confirmatory Quasi-Experimental Data Analysis

### 4.2.1 Academic Achievement Data in Two Classroom Types

Post-intervention, average scores and standard deviations of four classroom types (S2, S1, C2, C1) are analyzed. Academic ranking from high to low is S2 > S1 > C2 > C1. Standard deviation ranking (S2 < S1 < C2 < C1) indicates S groups have smaller score gaps than C groups.

Pairwise comparisons show significant score differences between S and C groups, larger than within groups. S2 group scores are 12.5 points higher than C1, and S groups overall are 13.8 points higher than C groups.

**Table 4: Academic Achievement Data of Different Classroom Types in the Confirmatory Experiment**

|  |  |  |
| --- | --- | --- |
| Classroom Type | Average Score | Standard Deviation |
| S2Group | 88.7 | 3.1 |
| S1Group | 82.5 | 4.5 |
| C2Group | 76.3 | 6.2 |
| C1Group | 70.2 | 7.8 |

### 4.2.2 Eye-Tracking Data in Two Classroom Types

Using the Iview X RED eye-tracking system, data including fixation duration, pupil diameter, and saccade amplitude are collected. Longer fixation durations, larger pupil diameters, and longer scan paths indicate higher engagement.

Twenty-four students (six from each group) are selected for eye-tracking. S2 group shows the longest fixation duration (289.32 ms) and largest pupil diameter (13.25 mm).

**Table 5: Eye-Tracking Data of Different Classroom Types in the Confirmatory Experiment**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Indicator | S2Group | C2Group | S1Group | C1Group |
| Fixation Duration (ms) | 289.32 | 256.45 | 245.67 | 220.18 |
| Pupil Diameter | 13.25 | 12.89 | 12.56 | 12.12 |
| Scan Path Length | 189.23 | 165.43 | 156.78 | 142.34 |
| Total Eye-Movement Amplitude | 156.78 | 145.67 | 136.78 | 125.43 |
| Blink Frequency | 18.2 | 20.5 | 22.3 | 24.1 |
| Eye-Movement Count | 120 | 135 | 140 | 155 |

### 4.2.3 Impact of Learning Content on Learning Motivation

Homogeneity of variance tests on attention data from four groups meet requirements. ANOVA results show significant motivation differences due to learning content (p < 0.05), with S2 > C2 > S1 > C1. Post-hoc analysis confirms S2 group's significantly higher motivation.

**Table 6: Impact of Different Learning Contents on Learning Motivation in the Confirmatory Experiment**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Group | Average Attention Score | Average Relevance Score | Average Confidence Score | Average Satisfaction Score | p-value |
| S2Group | 4.8 | 4.2 | 4.6 | 4.7 | <0.05 |
| C2Group | 4.2 | 3.9 | 4.2 | 4.3 | <0.05 |
| S1Group | 4.3 | 4.0 | 4.1 | 4.2 | <0.05 |
| C1Group | 3.9 | 3.7 | 3.8 | 3.9 | <0.05 |

### 4.2.4 Impact of Learning Content on Academic Achievement

ANOVA shows significant achievement differences due to learning content (p = 0.001), ranking S2 > S1 > C2 > C1. Post-hoc analysis reveals significant differences except between C1 and C2, with the largest difference between C1 and S2.

**Table 7: Impact of Different Learning Contents on Academic Achievement in the Confirmatory Experiment**

|  |  |  |
| --- | --- | --- |
| Group | Average Score | Standard Deviation |
| S2 | 88.7 | 3.1 |
| S1 | 82.5 | 4.5 |
| C2 | 76.3 | 6.2 |
| C1 | 70.2 | 7.8 |

# 5. Conclusions

## 5.1 Technology Design Promotes Deep Learning

Based on academic, eye-tracking, and ARCS model data, the four variables in two classroom types show: Academic ranking S2 > S1 > C2 > C1. In eye-tracking metrics, ranking is S2 > C2 > S1 > C1. This aligns with learning content's impact on motivation, where S2 group's attention is significantly higher. This indicates: (1) Multimedia technology enhances learner motivation. (2) Cognitive-process-based learning technology design is more effective than current multimedia applications. (3) Technology design reflecting cognitive processes can maximize utility; otherwise, it may increase cognitive load.

## 5.2 Significant Effects of Learning Content and Resource Reconstruction Based on Cognitive Processes

Academic data conclusions: (1) Average academic ranking S2 > S1 > C2 > C1, with significant differences between S and C groups, indicating a qualitative change. (2) Standard deviation ranking S2 < S1 < C2 < C1, showing smaller score gaps in S groups. (3) Combined application of 4S learning content and S-APT digital resources is more effective than separate use. (4) Overall, 4S learning content and S-APT digital resources are highly effective in improving academic achievement.

This study aligns with and extends existing research on multimedia and cognitive-process-based learning design impacts on student performance and motivation. It confirms that multimedia tools enhance motivation and cognitive-process-aligned instructional design optimizes learning and reduces cognitive load. Technology designs reflecting cognitive processes (S2) outperform others in boosting achievement and reducing performance gaps.

In conclusion, this study provides evidence for integrating multimedia and cognitive-process-based design in educational technology, proving their effectiveness in promoting deep learning and improving outcomes.

# 6. Research Limitations

The CTCL paradigm emphasizes learner-content-method alignment but experimental content selection, digital resource design, and activity organization need improvement. Also, the sample size is small, and the study duration is short.

# 7. Future Research Directions

Future research should conduct empirical studies in diverse regions, grades, and disciplines for broader application and promotion. It should also address resource development and training from multiple perspectives to enhance classroom instruction and learner development.

# 8. Informed Consent

The author has obtained informed consent from all participants.

# 9. Conflict of Interest Statement

The author declares no conflicts of interest.

# References

Dong, W., Pan, D., & Kim, S. (2024). Exploring the integration of IoT and Generative AI in English language education: Smart tools for personalized learning experiences. Journal of Computational Science, 82. <https://doi.org/10.1016/j.jocs.2024.102397>

Du, J., & Daniel, B. K. (2024). Transforming language education: A systematic review of AI-powered chatbots for English as a foreign language speaking practice. Computers and Education: Artificial Intelligence, 6. <https://doi.org/10.1016/j.caeai.2024.100230>

Fan, J., & Zhang, Q. (2024). From literacy to learning: The sequential mediation of attitudes and enjoyment in AI-assisted EFL education. Heliyon, 10(17). <https://doi.org/10.1016/j.heliyon.2024.e37158>

Kovari, A. (2025). A systematic review of AI-powered collaborative learning in higher education: Trends and outcomes from the last decade. Social Sciences and Humanities Open, 11. <https://doi.org/10.1016/j.ssaho.2025.101335>

Lee, D., Arnold, M., Srivastava, A., Plastow, K., Strelan, P., Ploeckl, F., Lekkas, D., & Palmer, E. (2024). The impact of generative AI on higher education learning and teaching: A study of educators’ perspectives. Computers and Education: Artificial Intelligence, 6. <https://doi.org/10.1016/j.caeai.2024.100221>

Li, L., Fengchao, Y., & Zhang, E. (2024). A systematic review of learning task design for K-12 AI education: Trends, challenges, and opportunities. Computers and Education: Artificial Intelligence, 6. <https://doi.org/10.1016/j.caeai.2024.100217>

Liu, G. L., Darvin, R., & Ma, C. (2024). Unpacking the role of motivation and enjoyment in AI-mediated informal digital learning of English (AI-IDLE): A mixed-method investigation in the Chinese context. Computers in Human Behavior, 160. <https://doi.org/10.1016/j.chb.2024.108362>

Liu, Y., Li, S., & Cui, D. (2024). Analysis of translation teaching skills in colleges and universities based on deep learning. Computers in Human Behavior, 157. <https://doi.org/10.1016/j.chb.2024.108212>

Liu, Y., Zhang, H., Jiang, M., Chen, J., & Wang, M. (2024). A systematic review of research on emotional artificial intelligence in English language education. System, 126. <https://doi.org/10.1016/j.system.2024.103478>

Tafazoli, D. (2024). Exploring the potential of generative AI in democratizing English language education. Computers and Education: Artificial Intelligence, 7. <https://doi.org/10.1016/j.caeai.2024.100275>

Waluyo, B., & Kusumastuti, S. (2024). Generative AI in student English learning in Thai higher education: More engagement, better outcomes? Social Sciences and Humanities Open, 10. <https://doi.org/10.1016/j.ssaho.2024.101146>

Zhai, C., Wibowo, S., & Li, L. D. (2024). Evaluating the AI dialogue System’s intercultural, humorous, and empathetic dimensions in English language learning: A case study. Computers and Education: Artificial Intelligence, 7. <https://doi.org/10.1016/j.caeai.2024.100262>

Zhang, R., Zou, D., Cheng, G., & Xie, H. (2025). Flow in ChatGPT-based logic learning and its influences on logic and self-efficacy in English argumentative writing. Computers in Human Behavior, 162. <https://doi.org/10.1016/j.chb.2024.108457>