Enhancing Deep Learning and Motivation in University English Education through AI Technology: A Quasi-Experimental Study

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. Twenty-four students (six from each group) are selected for eye-tracking.

**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

Motivation is a key driver of academic achievement, and strategies to enhance student motivation have been widely studied. Odanga (2018) identified effective strategies such as goal setting, time management, autonomy, and the integration of extrinsic and intrinsic motivational factors. These strategies align with SDT principles and are increasingly implemented through AI. For instance, AI systems can support goal orientation by providing clear objectives, tracking progress, and delivering personalized content, thus fostering students’ sense of competence and relatedness, which are crucial for sustained motivation and deep engagement.

Self-Determination Theory (SDT), proposed by Deci and Ryan, posits that motivation arises from the fulfillment of three basic psychological needs: competence, autonomy, and relatedness (Deci & Ryan, 2000). In educational contexts, intrinsic motivation flourishes when students feel competent and autonomous. AI technologies can support these needs by creating autonomy-supportive environments, facilitating personalized learning, and providing real-time feedback. For example, adaptive learning platforms and intelligent tutoring systems allow learners to control their own learning paths, thereby enhancing engagement and persistence in English learning.

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

The Technology Acceptance Model (TAM), developed by Davis (1989), emphasizes two core determinants of technology adoption: perceived usefulness and perceived ease of use. In college English education, students are more likely to use AI-driven tools when they find them intuitive and beneficial for language learning. Empirical research has confirmed that learners who believe AI technologies can improve academic performance exhibit greater willingness to use them (Davis, 1989; Waluyo & Kusumastuti, 2024). However, addressing perceived barriers such as complexity, ethical concerns, or lack of relevance is essential for successful integration.

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.

The integration of artificial intelligence (AI) into college English education is reshaping the role of educators, positioning them as facilitators, innovators, and ethical guides in the learning process. Recent studies highlight the critical role educators play in leveraging AI tools such as ChatGPT to enhance student engagement and learning outcomes. Yeh (2024) demonstrated that AI technologies empower teachers to design interactive and adaptive learning materials, fostering a more dynamic and student-centered learning environment. Hossain and Younus (2024) underscored educators’ perspectives on ChatGPT’s potential to support writing instruction through immediate feedback and idea generation, while also cautioning against overreliance and ethical concerns. Odanga (2018) further highlighted the importance of fostering self-motivation among students—a skill that educators can cultivate by integrating AI tools that promote autonomy and goal orientation. Songsiengchai (2025) provided empirical evidence that AI-driven platforms significantly improve English proficiency among Thai students by offering personalized learning experiences and real-time feedback. Collectively, these studies advocate for a balanced approach in which educators strategically incorporate AI to complement traditional teaching methods, ensuring that AI serves as a tool for enhancement rather than replacement. Future research should focus on the longitudinal impacts of AI integration and equitable access to AI tools, ensuring that all students benefit from these technological advancements.

In summary, AI technologies are profoundly transforming university English education by enhancing learning motivation and fostering deep learning. Emotional and generative AI offer personalized support, real-time feedback, diverse learning materials, and promote intercultural communication, creating more engaging environments. Grounded in insights from SDT and TAM, empirical studies highlight AI’s potential to boost academic achievement. However, successful integration requires addressing challenges related to ethics, data privacy, training, and cultural sensitivity. Future research should explore the effectiveness of AI across educational contexts, optimize AI-assisted learning system designs, and strengthen training and support for both educators and students. With continued development, AI holds great promise for advancing holistic student development in college English education.

3. Methodology

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.

Table 1 illustrates the overall research design and group allocation in this study. The research consists of two phases: the first phase is an exploratory experiment involving three English classes at a university, with a total of 105 students. Based on their pre-test scores, the students were divided into three groups: excellent (G), good (M), and general (D). The second phase is a confirmatory experiment conducted across four classes at two other universities. In this phase, the experimental groups (S1 and S2) were taught by younger teachers who had received AI teaching training, while the control groups (C1 and C2) were instructed by experienced senior teachers with 15–20 years of teaching experience.

**Table 1: The two phases of this study and the corresponding group distributions in both the exploratory and confirmatory experiments**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Phase | Institution(s) | Group(s) | Instructor Profile | Description |
| Phase 1: Exploratory | University A | G (Excellent), M (Good), D (General) | Mixed levels; pre-test-based grouping | 105 students from three English classes; grouped based on English Writing & Translation performance |
| Phase 2: Confirmatory | University B and University C | S1, S2 (Experimental), C1, C2 (Control) | S: Young teachers with AI training; C: Senior teachers | Four English classes; variable control with focus on teaching strategy, content, and motivation |

This study incorporates two distinct types of AI technologies—multimedia-based AI and cognitive process-based AI—each serving a specific function within the research design.

Multimedia-based AI refers to AI tools that support teaching and learning through the analysis and delivery of multimodal content, such as video lectures, audio-enhanced writing tutorials, and intelligent feedback systems. These tools were used during instruction to adapt content to students’ language proficiency levels, generate automated suggestions for writing improvements, and provide tailored rhetorical explanations. Such applications are valuable for enhancing student engagement, delivering personalized learning materials, and supporting formative assessment in real time.

In contrast, cognitive process-based AI focuses on capturing and interpreting learners’ internal cognitive and behavioral processes. In this study, eye-tracking devices were employed to record students’ visual attention during reading and writing tasks, enabling the researchers to examine correlations between gaze patterns, motivation, and learning outcomes. Additionally, behavior prediction models were used to detect potential disengagement or surface learning strategies, contributing to a deeper understanding of learning behavior in AI-enhanced environments.

By combining these two AI approaches, the study not only evaluated instructional effectiveness through output metrics (e.g., writing quality and test scores) but also gained insights into the underlying cognitive mechanisms that influence learning. This dual perspective enabled a more comprehensive analysis of how AI integration affects both teaching practices and learner development.

## 3.3 Ethical Considerations

This study adhered strictly to ethical standards concerning the use of AI technologies in educational research. Prior to data collection, all participants were provided with detailed information regarding the study’s purpose, procedures, and potential risks, and gave written informed consent. Participants were made aware of how AI tools (such as adaptive writing platforms and eye-tracking software) would be used, and how their data would be collected, stored, and analyzed.

To protect student privacy, all personally identifiable information was anonymized, and data were stored securely in encrypted formats accessible only to the research team. Ethical approval was obtained from the institutional review board, and all research activities complied with national guidelines on research integrity and data protection. Special attention was paid to ensuring that the AI tools employed did not exert undue influence on student decision-making or academic performance, aligning with the principle of fairness in educational technology.

4. Findings

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 2 shows G group has the highest average score, D group the lowest. In standard deviation, D group is highest, G group lowest.

**Table 2: 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 3: 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 |

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

**Table 4: 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 5: 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 6: 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 7. 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 8. 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. Discussion

This study demonstrates the significant impact of AI technologies on student academic achievement, engagement, and motivation. By examining the results of the confirmatory experiment, we can observe important differences in learning outcomes between the two types of AI technologies implemented: cognitive process-based AI (e.g., eye-tracking and behavior prediction) and multimedia-based AI (e.g., video/audio analysis and personalized learning content). This comparison provides deeper insights into how these two forms of AI contribute to learning and highlight their respective strengths and limitations in educational contexts.

### 5.1 Cognitive Process-Based AI: Enhancing Cognitive Engagement

One of the most notable findings in this study is the substantial effect of cognitive process-based AI on student engagement. The eye-tracking data, as shown in Table 5, reveal that the S2 group—which experienced AI-driven, behavior-oriented teaching—demonstrated the longest fixation durations, largest pupil diameters, and longest scan paths. These indicators suggest that cognitive engagement was significantly higher in the S2 group compared to the S1, C1, and C2 groups. Such higher engagement is a key factor for promoting deep learning and critical thinking, as longer fixation durations and larger pupil diameters are often associated with increased attentiveness and cognitive load (Duchowski, 2007).

Furthermore, the S2 group's stronger academic performance (Table 4) aligns with these cognitive engagement findings. This suggests that when students are more cognitively engaged, they tend to perform better academically, as their learning is not only more focused but also more thoughtful and reflective. The use of cognitive process-based AI, such as eye-tracking and behavior prediction, allows educators to track and adjust to individual students' cognitive engagement in real-time, offering personalized interventions that can significantly improve learning outcomes.

### 5.2 Traditional Multimedia-Enhanced AI: Promoting Content Engagement

In contrast, the multimedia-based AI employed in the S1, C2, and C1 groups facilitated the delivery of content and interaction through video, audio, and personalized feedback. While these methods have been proven effective in maintaining engagement and providing a variety of content formats, they do not directly measure or adapt to cognitive engagement in the same way as cognitive process-based AI. The results from Table 5 show that the S1 and C2 groups, who received multimedia-based AI instruction, had shorter fixation durations and smaller pupil diameters than the S2 group. This suggests that while multimedia-based AI may engage students with dynamic content, it does not fully capture or adapt to the cognitive processes underlying deep learning.

Moreover, while multimedia-based AI was effective in improving S1 and C2 group motivation (Table 6), its impact on academic achievement was less pronounced than that of cognitive process-based AI. As seen in Table 7, the S2 group (which received cognitive process-based AI) significantly outperformed the C1 and C2 groups in academic achievement, with an average score difference of 12.5 points between S2 and C1. This difference highlights the added value of cognitive engagement through AI-driven behavioral tracking and real-time adjustments to instruction, which were not present in the multimedia-based AI groups.

### 5.3 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.

### 5.4 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. Conclusion

The comparison between these two AI approaches underscores an important distinction in educational technology integration: multimedia-based AI excels in content delivery and maintaining surface-level engagement, while cognitive process-based AI fosters deeper cognitive engagement and enhances critical thinking skills, which are vital for academic success. The S2 group, benefiting from AI-driven cognitive analysis, was able to better engage with the content, leading to both higher motivation and greater academic achievement. This suggests that AI technologies designed to track and respond to cognitive and behavioral patterns can significantly improve both the depth of learning and student motivation. However, it is also important to recognize that multimedia-based AI has its own merits in terms of accessibility, scalability, and ease of use. These systems can quickly provide dynamic and engaging content to large groups of students, making them suitable for certain types of instructional contexts, such as initial exposure to new content or reinforcing foundational knowledge. Therefore, a hybrid model that combines both multimedia-based AI for content delivery and cognitive process-based AI for tracking and engaging cognitive behaviors could be an ideal approach for fostering both engagement and deep learning in diverse educational settings.

This study contributes to understanding the differences between multimedia-based and cognitive process-based AI, further research is needed to explore how these AI tools interact with individual differences in learning styles, cultural backgrounds, and prior knowledge. Additionally, the long-term effects of sustained AI integration on student motivation and academic performance remain an area for future investigation. Future studies could examine how these AI-driven approaches influence students' attitudes toward learning and their ability to apply learned skills in real-world contexts.

While this study primarily focused on the short-term outcomes of AI-assisted instruction—such as immediate academic achievement, cognitive engagement, and learning motivation—we recognize the importance of investigating the long-term impacts of AI integration in education. Future longitudinal studies are necessary to explore how AI-driven learning environments influence students’ retention of knowledge, development of higher-order thinking skills such as critical thinking, and cultivation of learner autonomy over extended periods.

Such research could examine whether the improvements in attention and academic performance observed in the short term are sustained over time, and how various types of AI (e.g., cognitive process-based vs. multimedia-enhanced) contribute to self-regulated learning and independent problem-solving. Tracking students' learning trajectories across semesters or academic years would provide deeper insights into the transformative potential of AI in fostering lifelong learning competencies, especially in rapidly evolving digital learning environments.

Conflict of Interest Statement

The author declares no conflicts of interest.

Informed Consent

The author has obtained informed consent from all participants.

 Disclaimer (Artificial intelligence)

We, the authors, hereby confirm that no generative AI technologies, including but not limited to Large Language Models (e.g., ChatGPT, Copilot) or text-to-image generators, were used in the writing, editing, or preparation of this manuscript. All content was developed solely by the authors based on original research, analysis, and interpretation.

References

Case, R., Liu, L., & Mintz, J. (2025). Integrating AI Technology Into Language Teacher Education: Challenges, Potentials, and Assumptions. Computers in the Schools, 1-7.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340.

Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. Psychological Inquiry, 11(4), 227–268.

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>

Hossain, M. K., & Al Younus, M. A. (2025). Teachers’ perspectives on integrating ChatGPT into EFL writing instruction. TESOL Communications, 4(1), 41-60.

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>

Odanga, J. O. (2018). Strategies for increasing students’ self-motivation. Asian Research Journal of Arts & Social Sciences, 6(4), 1–16. <https://journalarjass.com/index.php/ARJASS/article/view/9>

Songsiengchai, S. (2025). Implementation of Artificial Intelligence (AI): Chat GPT for Effective English Language Learning among Thai Students in Higher Education. International Journal of Education and Literacy Studies, 13(1), 302-312.

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>

Yeh, H. C. (2025). The synergy of generative AI and inquiry-based learning: transforming the landscape of English teaching and learning. Interactive Learning Environments, 33(1), 88-102.

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>