

AI-Based Learning Tools and EFL Students' Engagement, Motivation, Enjoyment

Lina Ardiyanti ✉

Ikip PGRI Bojonegoro, Indonesia

✉ ardilina94@gmail.com

Abstract

This study aims to examine whether learning with artificial intelligence (AI) can enhance students' motivation, enjoyment, and engagement compared to traditional learning methods. The participants were 49 first-year undergraduate students majoring in Information Technology Education at a private university in Indonesia. They were divided into two groups: 24 students in the experimental group (EG), who learned with AI-based learning tools, and 25 students in the control group (CG), who received conventional instruction. During a ten-week intervention, all participants were assessed using three affective scales at both the beginning and the end of the study period. To control for initial score differences between groups, multiple analytical techniques were applied, including response matching, outlier identification, aggregation analysis, and ANCOVA. The results revealed

significant improvements in all three affective variables in the experimental group. Motivation increased significantly ($F = 10.574$, $p = 0.002$, $\eta^2 = 0.186$), enjoyment showed a strong increase ($F = 35.366$, $p < 0.001$, $\eta^2 = 0.435$), and engagement also improved significantly ($F = 29.451$, $p < 0.001$, $\eta^2 = 0.390$). These findings suggest a consistent positive effect of AI-based learning tools, indicating that AI may be more effective than traditional teaching methods in enhancing learners' affective outcomes in language learning. The findings imply that educators and higher education institutions may consider integrating AI-supported learning environments to foster students' motivation, enjoyment, and engagement in EFL classrooms.

Keywords

Problem-Based Learning; Blookit; Critical Thinking Skills; Economics Education

I. Introduction

Many problems still exist when someone learns English as a second language, like not feeling driven, involved, or happy for most students (Amoah & Yeboah, 2021; Astuti et al., 2022; Sabboor Hussain et al., 2020). This issue is clearer when learning is boring and normal, and does not use tech that can make learning active and able to change. When wanting to learn and being involved goes down, doing well learning the language is harder; so, a way of teaching that can make students feel good is needed (J. Wan get al., 2022; X. Zhao & Wang, 2025; Y. Zhao, 2024). The progress of computers that can think like people offers great possibilities in learning (Yuskovych-Zhukovska et al., 2022), (Andewi et al., 2025). New research shows that computers can make learning better by quickly telling students how they are doing, changing materials to suit what they need, and making a

more exciting place to learn (Alam & Windiarti, 2025; Vieri & Petrea, 2025). A study by (Y. Wang & Xue, 2024) showed that Using AI chatbots really helped English as a Foreign Language learners become more interested and excited about learning. Similar findings were reported by (Zaman & Akhter, 2023), (Vo, 2025; L. Yang et al., 2025), Someone noticed that adding a smart computer learning tool could make language students want to learn and participate more. Furthermore, (Sajja et al., 2024) confirmed that When AI tools for learning can automatically check progress, students are more likely to have a good time learning since they feel like they have help and direction. New research shows that artificial intelligence could really improve how people feel about learning, like making them more interested, happy, and involved. (Al Harrasi et al., 2025), (Delello et al., 2025; Zhou & Peng, 2025). But, a lot of studies now look at skill in language or what people learn in their minds, and we still do not know how AI will change feelings in the area of EFL (García-López et al., 2025; Garzón et al., 2025; Zaim et al., 2025). Many research projects have only checked one thing, such as wanting to do something, without also thinking about being involved and having fun (Sun & Wang, 2024). Also, some study results do not match because information collected before and after tests is not always present. In the context of English as a Foreign Language (EFL) learning at the tertiary level, several empirical problems have been observed among first-year university students. Many students demonstrate low participation during classroom activities, limited enthusiasm for completing learning tasks, and a lack of confidence when using English in academic settings. Traditional instructional approaches often rely heavily on teacher-centered practices,

providing limited opportunities for interaction, personalized feedback, and active engagement. Preliminary classroom observations and informal discussions with students also indicated that many learners perceived English learning activities as monotonous, resulting in decreased motivation and enjoyment. These challenges may negatively affect students' engagement and overall learning experiences, highlighting the need for innovative instructional approaches that can better support students' affective development. This study was designed to fill the information gap regarding the impact of AI use on students' psychological well-being. The primary focus was to compare students' motivation and happiness levels before and after using an AI program in English classes. By accurately tracking these changes in feelings, we can obtain concrete evidence of the effectiveness of AI in improving the quality of learning. The research questions formulated to guide the study's focus are as follows:

RQ1. Do AI tools significantly influence EFL students' motivation?

RQ2. Do AI tools significantly influence EFL students' enjoyment?

RQ3. Do AI tools significantly influence EFL students' engagement?

This study makes a significant contribution by presenting a comprehensive analysis of the influence of affective aspects in the use of AI in language learning contexts. The primary focus of this research lies in the variables of student motivation, enjoyment, and engagement—crucial elements that determine the success of

English as a Foreign Language (EFL) instruction. Through these findings, stakeholders such as education practitioners and technology developers can design more responsive and student-oriented learning ecosystems. Furthermore, this research enriches the literature on AI in education and provides a strategic foundation for technology integration that can optimize learning outcomes.

II. Method

Participants

The participants of this study were 49 first-year undergraduate students enrolled in the Information Technology Education program at IKIP PGRI Bojonegoro, Indonesia. The participants were between 18 and 21 years old and had similar educational backgrounds as first-year university students taking compulsory English courses. To ensure effective participation in the AI-supported learning activities, all students had access to digital devices and internet connectivity and possessed basic digital literacy skills.

The participants were divided into two groups. The Experimental Group (EG) consisted of 24 students (15 males and 9 females) who received AI-supported English instruction, while the Control Group (CG) consisted of 25 students (14 males and 11 females) who received conventional English instruction. Participants were selected using convenience sampling because they were enrolled in the same academic program and course during the study period. The relatively similar demographic and academic characteristics of both groups helped ensure comparability in evaluating the effects of AI-based learning on students' motivation, enjoyment, and engagement.. Since all the

people taking part were at the same school level and in the same class, the spread of their features was very similar. The fact that the people answering were alike helps to show that the comparison of how much AI help and normal learning change things is correct. Table 1 summarizes details regarding the research subjects and the grouping of participants involved in this study.

Table 1

Demographic features of the participants.

Feature	EX Group		CT Group	
	N	Percent	N	Percent
Male	15	62.50%	14	56.00%
Female	9	37.50%	11	44.00%
Age Group	24	100%	25	100%
Education	24	100%	25	100%
Total	24	100%	25	100%

Instrument

Student motivation scale

The Academic Motivation Scale (AMS) created by (Kotera et al., 2022; Lim et al., 2022; Mojahed et al., 2021) served as the model for the Student Motivation Scale employed in this study. The original Academic Motivation Scale (AMS) instrument consist of 28 items that assess various determinants of learning motivation. However, this study adapted a more concise version with ten items to examine key factors in learning English as a foreign language (EFL) in depth. The AMS scale encompasses three main motivational dimensions: intrinsic motivation, extrinsic motivation, and amotivation (Algharaibeh, 2021; Chow & Wong, 2020; Sousa & Silva, 2021). Each item was estimated using a 5-point Likert scale, with 1 indicating “strongly disagree” and 5 indicating “strongly agree.” With a reliability value of 0.91, the updated scale demonstrated good internal consistency, making

it a valuable tool for evaluating students' enthusiasm for learning English. As a measurement tool with high validity, the AMS has become a primary choice for educational researchers to assess levels of learning motivation. The adaptation of the AMS in this study facilitated meaningful comparisons with previous findings in the EFL context. Every item is evaluated using a 5-point Likert scale, with 1 denoting "strongly disagree" and 5 denoting "strongly agree." With a reliability value of 0.91, the updated scale demonstrated good internal consistency, making it a valuable tool for evaluating students' enthusiasm to learn English. The AMS remains one of the most trusted and commonly utilized tools for measuring motivation in educational research. The adaptation of the AMS in this study facilitates meaningful comparisons with prior findings in EFL settings,

Enjoyment scale

The Enjoyment Scale in this study was adapted from the Foreign Language Enjoyment Scale (FLES) developed by (Güneş & Uysal Gürdal, 2025). The FLES includes 21 categories that map positive affective dimension associated with foreign language learning. To narrow down the crucial variable of satisfaction, this study used a modified version consisting of eight features. Key factors, including the classroom environment, instructor assistance, students' perceptions of their personal development, and their overall satisfaction with engaging in English learning activities, were evaluated using an adapted FLES measures. A 5-point Likert scale was used to evaluate each item, resulting in a reliability coefficient of 0.88, indicating the instrument's suitability for assessing students' enjoyment of English learning. The FLES is a widely recognized instrument that has been used previously in EFL research; its adaptation allows for relevant

comparisons with previous studies while offering a greater understanding of learners' emotional experiences (Çobanoğulları et al., 2025).

Engagement scale

The Engagement Scale in this study was adapted from the Student Engagement Scale developed by (Li et al., 2023). The initial scale consisted of twenty items designed to assess behavioral, emotional, and cognitive dimensions of engagement. This study focused on engagement factors most relevant to the context of foreign language acquisition, using a shorter version consisting of eight items. The revised items measure key aspects such as student participation in classroom activities, emotional involvement in learning English, and effort to understand and complete learning tasks. This tool is ideal for assessing student enthusiasm for learning English, as it has a 4-point Likert scale for each item and has a reliability of 0.90.

Procedure

This research included 49 undergraduate students, separated into two groups: 25 in the Control group (CT) and 24 in the Experimental group (EX). The research process involved the following steps:

1. Three emotional scale instruments were administered to all participants to measure their motivation, enjoyment and engagement during English learning.
2. A pre-test was administered to all participants as a preliminary step to collect data parameters before the start of the treatment or intervention.
3. All participants were classified into two groups: the Control (CT) group and the Experimental (EX) group.
4. The EX group received instruction supported by an AL system for ten weeks.

5. The CT group received instruction through conventional learning methods without the integration of artificial intelligence.
6. After the ten-week intervention period ended, all participants took a post-test using instruments identical to those used in the initial test.
7. Data obtained from the pre-test and post-test were synchronized for each participant, and the validity test were conducted to ensure the accuracy of the data.

The structured process of analysis process that came after the data collection included data validation, comparing pre-test and post-test responses, outlier detection using Z- scores, and scoring for total (motivation enjoyment), & engagement. S schematic diagram of research flow is shown in figure 1, which outlines a procedure for stepwise and systematic anlaysi appliedin the present analysis.

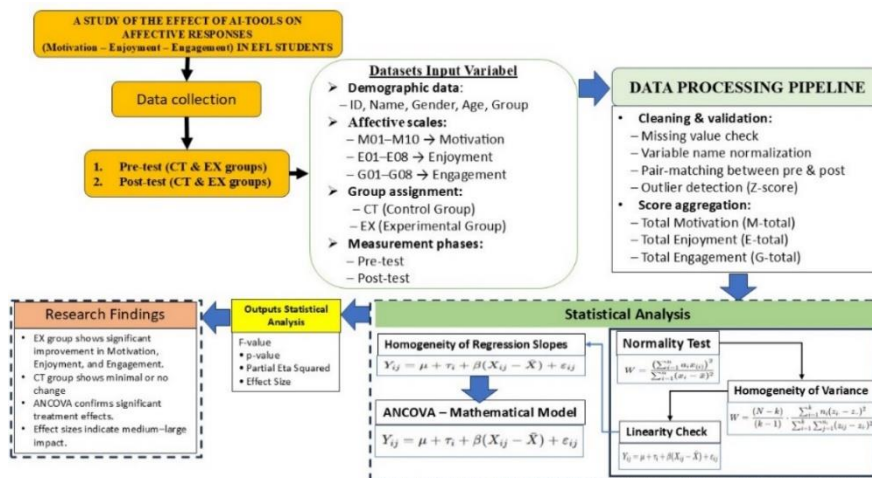


Figure 1. Research Placement Diagram

Post-test scores of the two groups were compared with analysis of covariance (ANCOVA) considering pre-test score as covariate. After controlling for differences in subjects' initial

parameters, the same methodology was applied to provide more valid estimates of the variance in learning gains.

III. Result and Discussion

Research Findings

The fundamental aim for this research is to investigate the effects of smart techonology integration on different levels of motivation, engagement, and enjoyment. A pre-test and post-test analysis was conducted on all 49 participants as presented. Prior to further analysis, a pre-requisite test was conducted on the dataset to ensure data quality. All data were within the valid parameter range, according to data distribution checks including skewness analysis, outlier identification, and normality testing therefore ther were no mising values. Descriptive statistics for every variable in the pre-test and post-test for the experimental (EX) and control (CT) groups are shown in Table 2.

Table 2. Descriptive Statistics

Group	Test	Variable	N	Mini mum	Maxi mum	Mean	Std	Skewness
CT Group	Pretest	Motivation	25	26	30	26.68	0.9	2.0698
		Enjoyment	25	21	22	21.4	0.5	0.40825
		Engagement	25	20	22	21.08	0.4 1.9	0.70806
	Posttest	Motivation	25	30	37	33.28	9 1.2	0.08968
		Enjoyment	25	24	28	25.6	91 0.8	0.54549
		Engagement	25	24	27	24.92	62	0.94851
EX Group	Pretest	Motivation	24	28	31	29.83 33 23.37	0.9 17 0.6	-0.3586
		Enjoyment	24	22	24	5 23.62	47 0.6	-0.5076
		Engagement	24	22	24	5 37.70	47 1.2	-1.4612
	Posttest	Motivation	24	36	40	83 30.16	68 1.1	0.17299
		Enjoyment	24	28	32	67 29.91	67 1.3	0.1738
		Engagement	24	28	32	67 16	16	-0.0785

Table 2 demonstrates that the EX group had marginally higher pre-test results than the CT group. While the CT group

scored 26.68, 21.40, and 21.08, the EX group's average motivation, enjoyment, and engagement scores were 29.83, 23.38, and 23.63, respectively. With post-test scores of motivation of 37.71, enjoyment of 30.17, and engagement of 29.92 following the AI-based intervention, the EX group showed more progress. The CT group also improved, although to a lesser level, with motivation of 33.28, enjoyment of 25.60, and involvement of 24.92. Skewness scores were generally within the usual range (± 1.96), including pre-test EX motivation of -0.36 and pre-test EX enjoyment of -0.51 . One value surpassing the limit was detected in pre-test CT motivation (2.07) and should be treated with caution. The main analysis employed ANCOVA to compare post-test scores by adjusting for pre-test values. The assumption test revealed that the regression slopes' linearity and homogeneity were satisfied, and the pre-test $\times$ group interaction's significant value was greater than 0.05 (motivation $p = 0.875$, enjoyment $p = 0.692$, engagement $p = 0.801$). A scatterplot of the link between pre-test and post-test scores was used to verify linearity, as seen in Figure 1.

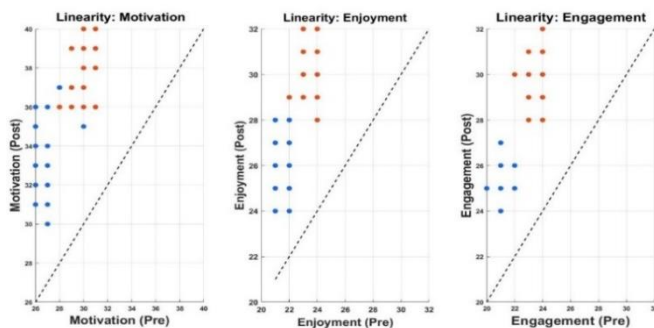


Figure 2. Scatterplot of the relationship between dependent variables and covariates

Figure 1 depicts a linear pattern with no sign of a curved link. This linear trend coincides with the findings of the interaction test, which provided p-values over 0.05 for all factors (motivation $p = 0.875$, enjoyment $p = 0.692$, engagement $p = 0.801$), demonstrating that the linearity assumption is met. The full test findings for the three variables—motivation, enjoyment, and engagement—are shown in Table 3.

Table 3
Homogeneity of regression slopes

	Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Motivation	Corrected Model	865.77	53	16.335	6.488	.000
	Intercept	372.12	48	7.753	—	—
	Group	246.86	3	82.285	29.560	.000
	Motivation1	246.79	2	123.39	44.327	.000
	Group * Motivation1	0.069	1	0.069	.025	.875
	Error	125.27	45	2.784		
	Total	1116.4	144			
	Corrected Total	991.03	98			
Enjoyment	Corrected Model	838.46	53	15.820	10.209	.000
	Intercept	326.69	48	6.806	—	—
	Group	256.01	3	85.337	54.328	.000
	Enjoyment1	255.76	2	127.88	81.413	.000
	Group * Enjoyment1	0.249	1	0.249	.159	.692
	Error	70.684	45	1.571		
	Total	980.08	144			
	Corrected Total	909.15	98			
Engagement	Corrected Model	975.76	53	18.411	14.027	.000
	Intercept	363.39	48	7.571	—	—
	Group	306.23	3	102.080	80.360	.000
	Engagement1	306.15	2	153.070	120.510	.000
	Group * Engagement1	0.081	1	0.081	.064	.801
	Error	57.161	45	1.270		
	Total	1090.2	144			
	Corrected Total	1032.9	98			

Table 3 demonstrates that the interaction between group and pre-test scores for the three variables of motivation, enjoyment, and engagement is above the significance threshold ($p > 0.05$). The assumption of homogeneity of regression slopes is satisfied, according to the statistical test findings for the three variables. The findings of comparing error variances using Levene's test are displayed in Table 4.

Table 4
Equality of error variances

Variable	F	df ₁	df ₂	Sig.
Motivation	4.823	1	47	0.033
Enjoyment	0.112	1	47	0.74
Engagement	4.259	1	47	0.045

Table 4 demonstrates that the error variances for motivation ($p = 0.033$) and engagement ($p = 0.045$) differed significantly between groups ($p < 0.05$). The condition of homogeneity of variance was satisfied because the only variable that did not exhibit a difference in error variance was the satisfaction variable ($p = 0.740$). Violation of the assumption in two of the three dependent variables caused the researcher to select a more cautious significance level, namely $\alpha = 0.01$. An ANCOVA analysis was performed following the verification of all assumptions, as indicated in Table 5.

Table 5. ANCOVAs: tests of between-subjects effects.

	Source	Type III Sum of Squares	df	Mean Square	F	Sig
Motivation	Corrected					
	Model	865.8	53	16.3	6.49	0
	Intercept	372.1	48	7.75		
	Group	246.9	3	82.3	29.6	0
	Motivation1	246.8	2	123	44.3	0
	Group *					
	Motivation1	0.069	1	0.07	0.02	0.88
	Error	125.3	45	2.78		
	Total	1116	144			
Enjoyment	Corrected Total	991	98			
	Corrected					
	Model	838.5	53	15.8	10.2	0
	Intercept	326.7	48	6.81		
	Group	256	3	85.3	54.3	0
	Enjoyment1	255.8	2	128	81.4	0
	Group *					
	Enjoyment1	0.249	1	0.25	0.16	0.69
	Error	70.68	45	1.57		
Engagement	Total	980.1	144			
	Corrected Total	909.1	98			
	Corrected					
	Model	975.8	53	18.4	14	0
	Intercept	363.4	48	7.57		
	Group	306.2	3	102	80.4	0
	Engagement1	306.1	2	153	121	0
	Group *					
	Engagement1	0.081	1	0.08	0.06	0.8
Engagement	Error	57.16	45	1.27		
	Total	1090	144			
	Corrected Total	1033	98			

The ANCOVA analysis revealed that, adjusting with the effect of pre-test scores. That post-test mean scores of the experimental and control groups for all three variables (motivation, enjoyment, engagement) were significantly different. There were significant effects of the group factor for the motivation variables ($F = 29.60$, $p < 0.01$), indicating that the introduction of AI-driven technology contributed to increased student motivation. Moreover, the covariate MOtivation resulted in a non- significant interaction ($F= 0.02$, $p =0.88$) and significant effect ($F = 44.30$, $p <.01$). Enjoyment A second match was

observed for the enjoyment variable. The group effect was substantial ($F = 54.30, p < 0.01$) and the covariate Enjoyment was a robust predictor of post-test scores ($F = 81.40, p < 0.01$), whereas the interaction value remained insignificant ($F = 0.16, p = 0.69$). For the engagement variable, the group effect was likewise significant ($F = 80.40, p < 0.01$), and the covariate Engagement1 made a very high contribution ($F = 121.00, p < 0.01$). The non-significant interaction term ($F = 0.06, p = 0.80$) implies that the association between pre-test and post-test scores was consistent across both groups.

Comprehensively, these findings confirm that the use of AI-based learning resources significantly enhances students' engagement, motivation, and enjoyment. The non-significant interaction term demonstrates that the assumption of homogeneity of regression slopes is met.

Discussion

The results of this study demonstrate that the usage of artificial intelligence-based learning aids has a good and significant impact on EFL students' motivation, enjoyment, and engagement. All three affective variables considerably improved in the experimental group, despite relatively slight beginning differences in the pre-test. The AI introduction appears to have directly influenced the mediating aspects of students, evidenced by high group effect for motivation, enjoyment and engagement. It seems that AI based features like adaptive feedback, personalized learning, and gamification aspects catered to sustained level of engagement as was indicated by the significant increase of motivation reported by the experimental group. These results are in line with studies by (Zaman & Akhter, 2023) which shown that perceptions of competence and autonomy can be raised through personalised learning in AI platforms. Similar findings were reported by Wang and Xue (2024), who found that AI-powered chatbots increased EFL learners' motivation and willingness to participate in language learning activities. Likewise,

Zaman and Akhter (2023) demonstrated that AI-supported learning environments enhanced students' learning motivation through personalized feedback and immediate instructional support. These studies support the present finding that AI can foster learners' intrinsic motivation by promoting autonomy and competence. These findings also confirm the negative correlation between amotivation and engagement. With students with low motivation tending to display a disinterested attitude toward learning. The significant improvement in the experimental group demonstrates the potential of AI technology as a preventative tool to mitigate low student engagement.

Fun also shot up in a big way thanks to AI learning. The interactive and flexible nature of the AI medium as well as the presence of an appropriate level of difficulty are accountable for higher learning delight among students in experimental group. These findings align with research by (Yang & Rui, 2025), which revealed that AI technology can reduce anxiety and create a more emotionally supportive learning environment. From the perspective of control-value theory, an increase in enjoyment reflects heightened perceptions of value and control factors that are crucial for generating positive emotions during language learning. The most significant improvement was recorded in the aspect of internet engagement, which identified that AI not only increased motivation and positive affect but also encouraged deeper and more active engagement in learning. Students in experimental group demonstrated higher consistency in task completion, utilized feedback as a means of reflection, and demonstrated stronger persistence. These findings align with research by Jiang et al., (2025), which found that AI plays a role in creating learning autonomy through personalized support. Theoretically, this improvement validates control-value theory, where students' active engagement is strongly influenced by their sense of control and assessment of the relevance of the tasks they are working on.

Although several prior studies warned of potential negative implications such as dependency on automated feedback or greater cognitive load (Khan & Suhluli, 2025), the results of this study indicate minimal risks. Students actually noticed enhanced self-confidence and less anxiety. The adaptive capabilities of the AI platform seemed to provide enough scaffolding to avoid misconceptions at the cost of clipping student agency. In doing so, this would corroborate the Control-Value Theory claim that perceptions of competence and support can alleviate negative affect and heighten positive effect. In general, findings of this line of research contribute to the theoretical foundation of CVT and suggest that AI-driven learning aids effect motivation, enjoyment, and engagement by facilitating perceived control and perceived task value. Personalized, interactive and autonomy support AI learning environments have been found to be effective in providing pleasurable emotional learning experiences and sustained engagement.

IV. Conclusion

This research investigated the effect of AI-based learning on students' motivation, perceived enjoyment and engagement in English learning. Based on an ANCOVA, the Experimental group (EX) brought significant benefits in all three affective measures vs Control group (CT) condition. Motivation improved significantly ($F = 10.574$, $p = 0.002$) with a large effect size (partial eta squared = 0.186). enjoyment also received a very strong increase with an F value of 35.366, $p < 0.001$; and a partial eta squared = 0.435, large effect). Engagement also increased dramatically with a F value of 29.451, $p < 0.001$, and a partial eta squared of 0.390, indicating a large effect. This pattern of findings implies that AI-based learning has a more constant and potent influence on students' affective development than traditional

teaching techniques. This research demonstrates that artificial intelligence (AI) can strengthen students' psychological readiness by creating adaptive, interactive, and engaging learning experiences. These findings have strategic implications for educators and higher education institutions. Lecturers can utilize AI to provide instant feedback, adjust the difficulty level of material, and personalize learning instruction. Meanwhile, institutions can integrate this technology to foster active engagement and mitigate students' affective barriers. Further research is recommended to expand the sample size. Implement a longitudinal design, and incorporate other psychological variables such as self-efficacy or anxiety to more comprehensively examine the mechanisms by which AI influences affective development.

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beneficial for readers, educators, and future researchers in the field of English language teaching and educational technology.

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