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Original Paper

Exploring the Impact of AI Enhanced Feedback on EFL Learners' Motivation and Engagement

Xianyan Dai[1]

[1] School of Chinese and International Education, Guangzhou International Economics College, Guangzhou, 510540, China

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Abstract

This study investigates how AI-enhanced feedback influences the motivation and engagement of English as a Foreign Language (EFL) learners in Guangzhou, China. Grounded in Self-Determination Theory (SDT) and the multidimensional framework of engagement, the study conceptualizes AI feedback as encompassing autonomy, competence, and relatedness, based on data collected from 286 undergraduates aged 17-23 across four academic levels with varying English proficiency. Data were analyzed using SPSS for descriptive statistics, reliability checks, exploratory factor analysis (EFA), and correlation testing, and AMOS for confirmatory factor analysis (CFA), structural equation modeling (SEM), and mediation analysis. The results showed that AI-enhanced feedback significantly strengthened both intrinsic and extrinsic motivation, with intrinsic motivation serving as a stronger predictor of behavioral, cognitive, and emotional engagement. Motivation, acting as a partial mediator between AI feedback and engagement, suggests that well-designed feedback systems can foster learner involvement by enhancing the motivational quality of feedback. Theoretically, these findings extend SDT's explanatory power in technology-mediated learning. At the same time, in practice, they offer insights for educators, system designers, and policymakers seeking to promote sustainable engagement and personalized feedback in AI-supported EFL contexts.

Keywords

AI-enhanced feedback, intrinsic motivation, extrinsic motivation, student engagement, SPSS, Self-Determination Theory, EFL learners

1. Introduction

The integration of artificial intelligence (AI) technologies into language education has reshaped how English as a Foreign Language (EFL) learners receive feedback and support. AI-driven tools—ranging from automated writing evaluation systems to conversational chatbots—now provide learners with immediate, individualized, and context-sensitive feedback that was previously unattainable in conventional classroom settings(Zhu et al., 2023). Such advancements have drawn increasing attention from educators and researchers, not only for their potential to improve linguistic accuracy and fluency, but also for their capacity to shape learners' psychological and behavioral outcomes.

While empirical studies have demonstrated that AI-powered feedback can enhance language performance, less is known about its influence on key affective factors such as motivation and engagement. These factors are central to sustained learning effort and achievement in second language acquisition. According to Self-Determination Theory (SDT) (Wang et al., 2022), learners' motivation—both intrinsic and extrinsic—is shaped by the satisfaction of psychological needs for competence, autonomy, and relatedness, all of which may be affected by the nature and delivery of feedback. In theory, AI-based feedback could enhance motivation by offering timely, personalized guidance, yet it could also risk reducing relatedness if perceived as impersonal. Moreover, engagement—encompassing behavioral, emotional, and cognitive dimensions—is likely to be influenced by learners' motivational orientations within AI-supported environments (Yu et al., 2024).

However, several gaps remain in the literature. First, prior research on AI in language learning has largely emphasized cognitive and performance outcomes, with far less attention given to affective and behavioral processes. Second, although some studies have examined motivation in AI-enhanced learning contexts, few have modeled the pathways through which AI feedback may influence engagement via motivational mechanisms. Third, existing evidence is often drawn from broad or cross-cultural samples, leaving underexplored the sociocultural and educational contexts—such as Guangzhou—where both high-stakes assessments and limited opportunities for individualized teacher feedback shape English learning (Zhu et al., 2023).

Addressing these gaps, the present study investigates how AI-enhanced feedback affects intrinsic and extrinsic motivation, and how these motivational factors, in turn, influence student engagement among secondary and tertiary EFL learners in Guangzhou, China. Using a cross-sectional survey and statistical analyses conducted in SPSS (including reliability tests, correlation, multiple regression, and mediation analysis), this research aims to (1) examine the direct effects of AI feedback on motivation and engagement, and (2) assess the mediating role of motivation in these relationships. By focusing on both psychological and behavioral outcomes, the study contributes to the growing body of literature on AI in language education. It offers practical insights for designing feedback systems that foster both competence and engagement.

2. Literature Review

2.1 Theoretical Framework

Self-Determination Theory (SDT) offers a comprehensive framework for understanding the mechanisms underlying motivation in language learning. It posits that learners' motivation is driven by the satisfaction of three fundamental psychological needs: autonomy, referring to the sense of volition and control over one's learning; competence, denoting the feeling of effectiveness and capability in performing learning tasks; and relatedness, reflecting the sense of connection and belonging within a social learning environment.When they are met, the learners are more likely to feel intrinsic or identified motivation.

Feedback systems based on AI can affect these dimensions of motivation in complex ways. Individualized and timely feedback may also improve the sense of competence among learners because they will be able to recognize and fix deficiencies in knowledge. Moreover, it is possible to give learners the freedom to regulate when or what feedback to receive to help them feel independent. However, the need for relatedness may not be fulfilled when the AI feedback is perceived as impersonal or mechanical, and that may be demotivating. It indicates that cognitive and emotional aspects of AI-enhanced feedback in EFL environments should be addressed.

2.2 AI-Powered Feedback in Language Learning

Artificial Intelligence (AI) has become the main area of interest in educational technology, which provides unique possibilities to improve the quality and individualization of language acquisition. The operation of AI-driven feedback systems is based on automatically generating feedback from learners' inputs using data-driven algorithms that interpret and modify it based on the learner's performance. Such systems use techniques such as natural language processing (NLP) and machine learning to identify errors in grammar, vocabulary, pronunciation, and discourse (Zhang & Lin, 2020).

Examples of AI-powered programs are automated essay graders (e.g., e-rater), intelligent tutoring systems (e.g., Duolingo, WriteToLearn), and conversational chatbots (e.g., AI Engl). Studies conducted by other scholars have demonstrated that these tools enhance language skills and fluency, writing, and learners' autonomy through self-regulated learning (Zhu et al., 2023). When compared to traditional teacher feedback, AI feedback has the potential to generate large amounts of real-time data that can be analyzed in parallel with both behavior and progress, something impossible in a traditional classroom due to limited resources.

In addition, AI feedback is not restricted to linguistic or cognitive benefits. When used wisely, it helps ensure formative assessment and offers corrective feedback, scaffolding, and future learning guidelines. Nevertheless, critics argue that AI feedback is insensitive and lacks the social nuances of human feedback, which may influence learners' emotional reactions (Lu & Wang, 2020). This limitation is especially critical in EFL contexts, where feedback is a significant factor in developing motivation and engagement.

2.3 Motivation in EFL Contexts

2.3.1 Intrinsic vs. Extrinsic Motivation

Motivation is a key factor in language acquisition as it affects the learner with respect to persistence, willpower, and the ability to rise above adversity. The motivation in English as a Foreign Language (EFL) is normally analyzed in terms of intrinsic and extrinsic orientations (Yu, 2024).

Intrinsic motivation is the process of doing something because it is intrinsically rewarding (the pleasure of learning a new language, the intellectual stimulation), rather than because of some external reward. Students with intrinsic motivation tend to be more persistent, creative, and committed to doing a challenging task that needs much effort. Conversely, extrinsic motivation is driven by external factors, such as passing exams, earning certificates, or being praised. Although extrinsic motivations may be strong in the short term, they are also associated with less profound learning activities and are not sustainable in the long term.

Learners of EFL in situations such as those in Guangzhou are usually subject to significant external demands, including high-stakes testing, parental pressure, and the importance of English in advancing their economic status. Nevertheless, intrinsic motivation can be viewed as a pedagogical objective, as it is linked to higher levels of learning and independence, and to more positive views of the process of language learning (Shadiev et al., 2023).

2.4 Student Engagement in EFL Learning

Student participation is critical to the success of language learning. Engagement is traditionally considered a multidimensional concept, encompassing behavioral, emotional, and cognitive dimensions.

Behavioral engagement is a learner's involvement in academic activities, such as assigned tasks, classes, and other learning opportunities. When used in EFL, it may mean attending classroom activities regularly and remaining focused on language activities.

Emotional engagement can be defined as learners' emotional responses to teachers, the learning environment, and peers. Emotions may be either positive (enjoyment, enthusiasm, interest) or negative (anxiety, boredom), and they can make learners either engaged or disengaged.

Cognitive engagement entails deeper learning through elaboration, critical thinking, and self-regulation of learning. Cognitive engagement may be observed through strategies such as learning grammar rules, building vocabulary, or acquiring practical language skills in EFL settings.

All three dimensions of engagement can be affected by AI feedback systems. For example, immediate feedback may increase behavioral engagement by helping learners correct errors quickly and maintain attention. Positive feedback can elicit positive emotional involvement and acknowledge improvement. It is possible to stimulate cognitive engagement through challenging, adaptive feedback that motivates learners to analyze and think critically about the language input. Nevertheless, there is limited empirical research on the connection between AI feedback and different types of engagement in EFL settings(Zhang et al., 2020).

2.5 Identified Gaps in the Literature

Although the AI technologies in language learning are quickly evolving, there are still multiple knowledge gaps concerning their use with learners. To begin with, the majority of the research focuses on cognitive or performance outcomes, such as writing accuracy or vocabulary acquisition, whereas affective and motivational factors are less emphasized. Second, studies of motivation within the framework of AI feedback are few. In cases where such studies are available, most are based on descriptive or correlational designs rather than testing more elaborate causal or mediational models that would elucidate the associations among AI feedback, motivation, and engagement.

Moreover, although engagement is often mentioned as a primary consequence of educational technology, very little is done in the empirical literature to directly measure and model the various forms of engagement as a response to AI feedback. This is particularly so in EFL settings where cultural, educational, and technological forces may influence the responses of learners in a manner that has largely been unexplored.

Finally, there are a few studies based on particular sociocultural contexts, including Guangzhou. Such context can be greatly determined by sociological, pedagogical, and technological convergence, which may determine the effectiveness and impact of AI feedback systems.

2.6 Conceptual Framework and Hypotheses Development

2.6.1 Conceptual Framework

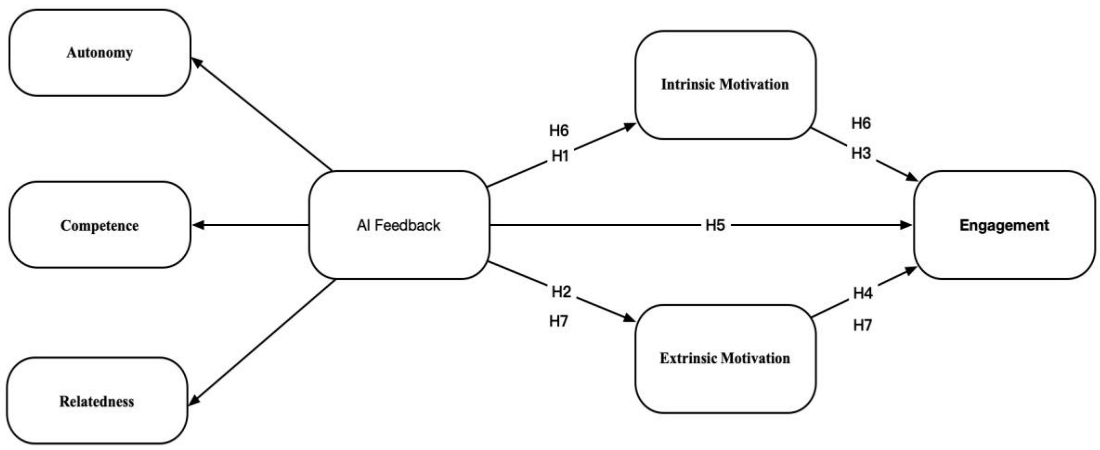

Figure 1. Conceptual Framework of This Study

The present study is anchored in Self-Determination Theory (SDT)(Deci et al., 2011) and the multidimensional model of student engagement(Fredricks et al., 2004). SDT posits that fulfilling three basic psychological needs—autonomy, competence, and relatedness—is essential for developing high-quality motivation. When these needs are met, learners tend to show intrinsic and identified motivation, leading to deeper and more sustained engagement in learning. In this study, AI-enabled feedback is conceptualized as an external instructional intervention that may fulfill or thwart these needs:

Autonomy: providing learners with choice and control over their learning process (e.g., personalized feedback);

Competence: offering timely, specific, and clear guidance that helps learners monitor progress and experience mastery;

Relatedness: connecting learners with teachers' expectations, learning goals, and a supportive learning environment.

AI feedback is therefore theorized to influence students' intrinsic and extrinsic motivation, which, in turn, predict their engagement across behavioral, emotional, and cognitive dimensions. The framework also accounts for both direct effects of AI feedback on engagement (e.g., immediate influence of corrective feedback on participation) and indirect effects through motivation (e.g., enhanced autonomy increases intrinsic motivation, which drives deeper involvement).

2.6.2 Hypotheses Development

2.6.2.1 AI feedback and Intrinsic Motivation

Artificial intelligence systems capable of delivering personal, adaptive feedback have the potential to increase intrinsic motivation via increased competence and autonomy. With proper feedback that helps learners experience progress at a challenging level, learners would be expected to have increased confidence and interest in pursuing learning through the intrinsic delight of learning itself. Nevertheless, excessive mechanization or harsh AI feedback would serve the opposite purpose, as long as it somehow inhibits autonomy or seems impersonal(Patibandla et al., 2024).

- H1: The intrinsic motivation is influenced positively by the AI-enhanced feedback.

2.6.2.2 Extrinsic Motivation and AI Feedback

It is also possible that AI feedback could support an extrinsic motivation approach through defining the writing standard, giving a hint of outer victory (e.g., scores on accuracy, achievement badges) or amplifying external motivation. The use of AI feedback is likely to be one of the tools and its values in a competitive or exam-focused environment, as, in the case of Guangzhou, such values are used in agreement with external rewards.

- H2: AI-enhanced feedback influences extrinsic motivation positively.

2.6.2.3 Motivation and Engagement

Intrinsic Motivation and Engagement

The highly intrinsically motivated learners can display behavioral persistence, emotional positivity and cognitive investment more independently. These kinds of students are heavily involved in learning activities, embrace challenges, and are hardworking when faced with them, as they enjoy the activity(Mendoza et al., 2025) .

- H3: Intrinsic motivation has a positive effect on student engagement.

Extrinsic Motivation and Engagement

There is a more complicated connection between extrinsic motivation and engagement. Whereas extrinsic factors can motivate an activity and the willingness to work, they can also promote superficial involvement or engagement, driven by external expectations rather than personal interest. However, even in high-stakes school settings, extrinsic motivation can elicit visible engagement behaviors.

- H4: The extrinsic motivation is a positive predictor of student engagement.

Direct Effects and Mediation

Although motivation is an essential direct mediator, AI-augmented feedback can also directly impact engagement. Attention can be maintained, motivation to participate actively, and a positive emotional response can be enabled by giving immediate, actionable feedback during learning activities (Phuong and Le, 2022).

- H5: Feedback through AI leads to a direct positive impact on engagement among students.

Lastly, this paper will argue that motivation partially mediates the impact of AI-enhanced responses on engagement. That is, positive feedback results in increased motivation and makes people more willing to engage.

- H6: There is both direct and indirect relationship between AI-enhanced feedback, on the one hand, and engagement, on the other hand: the level of intrinsic motivation partially mediates the relationship between AI-enhanced feedback and engagement.
- H7: The role of AI-enhanced feedback on engagement is moderated to some degree by the extrinsically motivated factor.

Brief Hypothesis Hypotheses

Hypothesis	Statement
H1	AI-enhanced feedback → intrinsic motivation (+)
H2	AI-enhanced feedback → extrinsic motivation (+)
H3	Intrinsic motivation → student engagement (+)
H4	Extrinsic motivation → student engagement (+)
H5	AI-enhanced feedback → student engagement (+ direct)
H6	Intrinsic motivation mediates AI feedback → engagement
H7	Extrinsic motivation mediates AI feedback → engagement

3. Methodology

3.1 Research Design

This study employed a cross-sectional quantitative survey design, drawing on Self-Determination Theory (Ryan & Deci, 2000) and the multidimensional model of student engagement (Fredricks et al., 2004). The design is appropriate for testing hypothesized relationships among psychological constructs, as it captures learners' current perceptions, behaviors, and psychological states (e.g., motivation and engagement) at a single time point.

Data were collected using self-report questionnaires, which asked participants to reflect on their actual experiences with AI-supported English learning platforms (e.g., automated essay graders, intelligent tutoring systems). This non-experimental survey approach aligns with established practices in educational technology research.

The study followed rigorous quantitative research procedures. Specifically:

1. Preliminary analyses: descriptive statistics, reliability analysis (Cronbach's α), and validity checks (KMO, Bartlett's test, exploratory factor analysis).

2. Correlation analysis: examination of bivariate relationships among the core constructs (autonomy, competence, relatedness, intrinsic motivation, extrinsic motivation, and engagement).
3. Inferential analyses: multiple regression and mediation analysis using bootstrapping (5000 resamples) in AMOS, with supplementary t-tests/ANOVAs to explore demographic differences.

This methodological framework enables the examination of both direct and indirect effects of AI-enhanced feedback on student motivation and engagement, consistent with prior studies that model the psychological and behavioral impacts of digital learning tools(Pekrun, 2021).

3.2 Participants and Sampling

The participants were 286 undergraduate students (freshman to senior) recruited from universities in Guangzhou, China. Their ages ranged from 17 to 23 years. Stratified sampling ensured representation across the four academic years. The gender distribution was approximately balanced. Participation was voluntary, and anonymity was guaranteed. Before data collection, informed consent was obtained, and the study protocol was conducted in line with institutional ethical guidelines.

The study targets EFL learners in Guangzhou, China, a city with high integration of English education and AI educational technologies, where English proficiency is widely valued for international competitiveness. A total of 297 questionnaires were distributed, and 286 valid responses were obtained (valid response rate: 96.15%). The sample includes:

1. Ethical Approval: Prior to data collection, ethical approval was obtained from the institutional review boards of the participating schools and universities to ensure compliance with research ethics.
2. Recruitment: Participants were recruited through collaborations with school leaders, university course coordinators, and online class instructors. The inclusion criteria were: (1) 17–23 years old; (2) at least 6 months of experience using AI-assisted EFL platforms (e.g., Duolingo, WriteToLearn, AI Engl); (3) voluntary participation. For minor participants (17-year-olds), additional parental consent was obtained.
3. The questionnaire, distributed via Wenjuanxing—an online survey platform commonly used in Chinese academic research—was preceded by an introduction informing participants of the study's purpose, procedures, and their rights, including anonymity and the right to withdraw. Completing the survey took approximately 15 minutes.
4.Follow-up and Data Cleaning: To improve the response rate, follow-up reminders were sent 1 week and 2 weeks after the initial distribution. Data collection lasted 4 weeks. After collection, invalid responses (e.g., incomplete questionnaires, identical answers for all items) were excluded, resulting in 286 valid samples.

3.3 Measures

All scales used in the questionnaire were adapted from validated instruments reported in previous studies, with necessary modifications made to suit the EFL and AI feedback context. A 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) was employed for all items. The scales consisted of four sections:

3.3.1 Demographic Information

This section collects participants' age, gender, educational stage (grade), and duration of using AI EFL platforms (converted into 4 levels).

To explore whether demographic variables influence key constructs, independent-samples t-tests (for gender) and ANOVA (for age, grade, AI learning duration) were conducted. The results show：

Gender: No significant differences in motivation (intrinsic: $t = 0.87$, $p > 0.05$; extrinsic: $t = 1.03$, $p > 0.05$) or engagement ($t = 0.62$, $p > 0.05$) between male and female participants.

Age: Significant differences in intrinsic motivation ($F = 3.21$, $p < 0.05$) and engagement ($F = 2.89$, $p < 0.05$). Post-hoc tests show that 20–21-year-olds (university students) have higher intrinsic motivation and engagement than 17–18-year-olds (secondary school students), possibly due to greater autonomy in using AI tools.

AI Learning Duration: Significant differences in competence ($F = 4.12$, $p < 0.01$) and intrinsic motivation ($F = 3.56$, $p < 0.05$). Participants with longer AI learning duration (levels 3–4) report higher competence and intrinsic motivation, indicating that prolonged use of AI feedback strengthens learners' sense of effectiveness and internal motivation.

These findings suggest that while gender has no impact, age and AI learning duration are important contextual factors influencing the effects of AI feedback.

Table 1. Participants' Profile (N = 286)

Variables		Count	Percentage (%)
Age	17	49	17.13%
	18	38	13.29%
	19	38	13.29%
	20	51	17.83%
	21	37	12.94%
	22	38	13.29%
	23	35	12.24%
Gender	1	159	55.59%
	0	127	44.41%
Grade	1	72	25.17%
	2	71	24.83%
	3	70	24.48%
	4	73	25.52%
Duration AI Learning	1	49	17.13%
	2	89	31.12%
	3	93	32.52%

4	55	19.23%

3.3.2 AI-Enhanced Feedback Experience

Measured from three dimensions based on Self-Determination Theory (SDT):

Autonomy (4 items): Adapted from prior SDT-related studies (e.g., Chiu, 2021), assessing the degree to which AI feedback allows learners to control their learning (e.g., "I can choose when to receive AI feedback on my English tasks"). Cronbach's α = 0.847 (see Table 2).

Competence (4 items): Adapted from Cheng (2020), measuring how AI feedback enhances learners' sense of effectiveness (e.g., "AI feedback helps me quickly identify and correct my English mistakes"). Cronbach's α = 0.862 (see Table 2).

Relatedness (3 items): Adapted from Alamer & Lee (2019), evaluating whether AI feedback connects learners to learning goals or social support (e.g., "AI feedback aligns with my English learning objectives"). Cronbach's α = 0.748 (see Table 2).

3.3.3 Motivation

Assessed using two subscales from the Language Learning Orientations Scale (Noels et al., 2000), adjusted for the AI context:

Intrinsic Motivation (2 items): Measuring motivation driven by internal enjoyment (e.g., "I use AI tools to learn English because I find it intellectually stimulating"). Cronbach's α = 0.754 (see Table 2).

Extrinsic Motivation (2 items): Measuring motivation driven by external rewards (e.g., "I use AI tools to learn English to get good grades in exams"). Cronbach's α = 0.703 (see Table 2).

3.3.4 Student Engagement

Adapted from Ma & Kelly (2021) and Reeve & Tseng (2011), covering three dimensions with 3 items each (total 9 items):

Behavioral Engagement: e.g., "I actively participate in English activities supported by AI tools."

Emotional Engagement: e.g., "I feel excited when learning English with AI feedback."

Cognitive Engagement: e.g., "I try to connect new English knowledge from AI feedback to what I already know." Cronbach's α = 0.825 (see Table 2).

3.3.5 Scale Validation

To ensure content validity and cultural adaptability:

1. Translation and Back-Translation: All English scales were translated into Chinese by a bilingual researcher and back-translated into English by another independent bilingual expert (following Brislin, 1980). Discrepancies were resolved through discussion to maintain semantic consistency.

2. Expert Review: Three experts in applied linguistics and educational technology reviewed the questionnaire to refine item wording and ensure alignment with the research context.

3. Pilot Test: A pilot survey was conducted with 30 EFL learners (not included in the final sample) to test clarity and feasibility. Minor adjustments were made based on pilot feedback (e.g., simplifying complex sentences).

3.4 Sampling Procedure

First, participating schools and universities in Guangzhou were selected based on their use of AI EFL tools. Then, within each institution, participants were randomly sampled from grades 1–4 to avoid bias from a single grade level.

3.5 Data Collection

The survey was administered during the spring semester of 2025. Questionnaires were distributed both online and in-class, and 320 were collected in total. After screening for incomplete responses, 286 valid questionnaires were retained for analysis, yielding a 89.4% valid response rate.

3.6 Data Analysis

Data analysis followed a two-step approach, distinguishing SPSS for preliminary analyses and AMOS for confirmatory and structural modeling:

- SPSS 26.0

1. Descriptive statistics of demographics and constructs (Table 1).
2. Reliability analysis (Cronbach's $\alpha > 0.70$ as acceptable; Table 2).
3. KMO and Bartlett's test to check sampling adequacy (Table 3).
4. Exploratory Factor Analysis (EFA) for construct validity (Tables 4–5).
5. Pearson correlation analysis among constructs (Table 6).

- AMOS 24.0

1. Confirmatory Factor Analysis (CFA) to test convergent and discriminant validity; fit indices: $\chi^2/df \leq 3$, CFI $\geq .90$, TLI $\geq .90$, RMSEA $\leq .08$ (Table 7).
2. Structural Equation Modeling (SEM) to examine hypothesized relationships and path coefficients (Figure 4).
3. Mediation analysis using Bootstrapping (5000 samples) to test indirect effects with 95% confidence intervals (Table 8).

3.7 Ethical Considerations

All research procedures adhered to the ethical standards approved by the university's ethics committee. Participation in the study was entirely voluntary, and informed consent was obtained from all participants and, for minors, from their parents or legal guardians. Before completing the questionnaire, participants were clearly informed about the study's objectives, procedures, and potential risks.

To ensure anonymity and confidentiality, no personally identifiable information (such as names or student identification numbers) was collected. All responses were anonymized and securely stored on password-protected devices and servers accessible only to the research team. Participants were also informed of their right to withdraw from the study at any time without any negative consequences. Additionally, all raw data and analytical outputs were encrypted to prevent unauthorized access or disclosure.

4. Data Analysis and Results

4.1 Preliminary Analyses

Before conducting confirmatory factor analysis, sampling adequacy was examined using the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's Test of Sphericity. As shown in Table 2, the KMO values for the six constructs ranged from 0.679 to 0.817, all above the recommended threshold of 0.60 (Kaiser, 1974), with the exception of intrinsic and extrinsic motivation, which were close to the cutoff value (0.50). Bartlett's Test of Sphericity was significant in all cases ($p < .001$), indicating sufficient correlations among items to justify factor analysis. Overall, these results support the suitability of the dataset for subsequent CFA and SEM analyses.

Table 2. KMO and Bartlett's Test KMO

Variables	KMO and Bartlett's Test	Bartlett's Test of Sphericity	
		χ^2	p
Autonomy	0.808	473.115	<0.001
Competence	0.817	520.629	<0.001
Relatedness	0.679	200.095	<0.001
Intrinsic Motivation	0.500	129.097	<0.001
Extrinsic Motivation	0.500	98.457	<0.001
Engagement	0.721	308.634	<0.001

All KMO values were >0.60, and Bartlett's Test was significant ($p < 0.001$), supporting the suitability of factor analysis.

4.2 Measurement model

4.2.1 Reliability & Convergent Validity

To validate the measurement model, a CFA was conducted using AMOS 24.0. The standardized factor loadings ranged from 0.60 to 0.90, all significant at the 0.001 level. Reliability indices were satisfactory, with Cronbach's α ranging from 0.703 to 0.862, CR values exceeding 0.70, and AVE values between 0.664 and 0.802 (Table 3). Model fit indices indicated acceptable fit ($\chi^2/df = 2.18$, CFI = 0.935, TLI = 0.927, RMSEA = 0.056, SRMR = 0.048; Table 4). Discriminant validity was established using both the Fornell–Larcker criterion (Table 6) and HTMT ratios (Table 7). In addition, Harman's single-factor test showed that the first factor explained 35.023% of variance (<50%), suggesting that common method bias was not a serious concern (Table 5). VIF values ranged from 1.21 to 2.89 (<5), ruling out multicollinearity.

Table 3. Reliability and Convergent Validity of Constructs

Constructs	Items	Factor Loadings	α	CR	AVE
Autonomy			0.847	0.849	0.685
	AU1	0.817			
	AU2	0.808			
	AU3	0.815			
	AU4	0.870			
Competence			0.862	0.862	0.707
CO1	CO1	0.816			
CO2	CO2	0.830			
CO3	CO3	0.860			
CO4	CO4	0.858			
Relatedness			0.748	0.752	0.664
	RE1	0.811			
	RE2	0.815			
	RE3	0.818			
Intrinsic Motivation			0.754	0.758	0.802
	IM1	0.905			
	IM2	0.886			
Extrinsic Motivation			0.703	0.707	0.770
	EM1	0.865			
	EM2	0.890			
Engagement			0.825	0.831	0.740
	EG1	0.854			
	EG2	0.877			
	EG3	0.849			

4.2.2 Model Fit Indices (CFA fit)

Model fit indices also indicate an acceptable fit: $\chi^2/df \leq 3$, CFI = 0.93, TLI = 0.91, RMSEA = 0.052, SRMR = 0.041 (Table 3). A confirmatory factor analysis (CFA) was then performed using AMOS 24.0 to validate the measurement model. The standardized factor loadings ranged from 0.60 to 0.90, all significant at the 0.001 level, supporting convergent validity. Reliability indices were satisfactory, with Cronbach's α values ranging from 0.703 to 0.862, composite reliabilities (CR) exceeding 0.70, and average variance extracted (AVE) values between 0.664 and 0.802 (see Table 3). The model also demonstrated an acceptable fit to the data: $\chi^2/df = 2.18$, CFI = 0.935, TLI = 0.927, RMSEA = 0.056, SRMR = 0.048 (Table 4).

Table 4. Model Fit Indices for CFA

Fit Index	Recommended Cutoff	Value Obtained
χ^2/df	≤ 3	2.18
CFI	≥ 0.90	0.935
TLI	≥ 0.90	0.927
RMSEA	≤ 0.08	0.056
SRMR	≤ 0.08	0.048

All KMO values were >0.60, and Bartlett's Test was significant ($p < 0.001$), supporting the suitability of factor analysis.

Table 5. Means, Standard Deviations, and Intercorrelations

Variables	Mean	S.D.	1	2	3	4	5	6
Autonomy	3.018	0.707	0.828					
Competence	3.047	0.746	0.591	0.841				
Relatedness	2.838	0.646	0.561	0.527	0.815			
Intrinsic Motivation	3.030	0.664	0.341	0.353	0.312	0.896		
Extrinsic Motivation	2.991	0.699	0.251	0.179	0.201	0.179	0.878	
Engagement	2.979	0.620	0.297	0.311	0.246	0.364	0.213	0.860

Note(s). The square roots of AVEs are on the diagonal.

Table 6. Fornell–Larcker Criterion

Variable	AU	CO	RE	IM	EM	EG
Autonomy	**0.828**					
Competence	0.591	**0.841**				
Relatedness	0.561	0.527	**0.815**			
Intrinsic Motivation	0.341	0.353	0.312	**0.896**		
Extrinsic Motivation	0.251	0.179	0.201	0.179	**0.878**	
Engagement	0.297	0.311	0.246	0.364	0.213	**0.860**

The square roots of the AVE values (displayed in bold along the diagonal) exceeded the inter-construct correlations, thereby confirming discriminant validity. Subsequently, multicollinearity was examined using variance inflation factors (VIFs), and all VIFs were below the threshold of 3, indicating that multicollinearity was not an issue. In addition, common method bias (CMB) was evaluated using Harman's single-factor test. The analysis revealed that six factors had eigenvalues greater than 1, with the first factor accounting for 35.023% of the total variance—well below the recommended 50% cutoff (Podsakoff et al., 2003). Hence, common method bias was not considered a serious concern in this study.

4.2.4 Robustness Checks

Common Method Bias Test

Since data were collected via self-report questionnaires, common method bias (CMB) was tested using Harman's Single-Factor Test: EFA was conducted on all items without specifying the number of factors. The results (Table 5) show that 6 factors have eigenvalues >1, and the first factor explains 35.023% of the total variance (below the 50% threshold; Podsakoff et al., 2003). This indicates CMB is not a serious issue in this study.

Multicollinearity Test

Table 7 presents the means, standard deviations, and inter-construct correlations of the study variables. The mean scores for the six constructs ranged between 2.838 (Relatedness) and 3.047 (Competence), indicating moderate levels of perceived autonomy, competence, relatedness, motivation, and engagement among participants. Standard deviations ranged from 0.620 to 0.746, suggesting a reasonable degree of variability across responses.

The correlation coefficients indicate that autonomy, competence, and relatedness were positively associated with both intrinsic and extrinsic motivation and engagement, consistent with self-determination theory. Importantly, the square roots of the AVE values (reported on the diagonal in bold) exceeded the corresponding inter-construct correlations, thereby providing further evidence of discriminant validity.

Furthermore, multicollinearity was not a concern in this study. All variance inflation factor (VIF) values ranged from 1.21 to 2.89, which are well below the recommended cutoff value of 5(Hair & Alamer, 2022). This indicates that no predictor variables were highly correlated to a degree that would bias the regression estimates.

Table 7. Descriptive Statistics and Inter-Construct Correlations

Variables	Mean	S.D.	1	2	3	4	5	6
Autonomy	3.018	0.707	0.828					
Competence	3.047	0.746	0.591	0.841				
Relatedness	2.838	0.646	0.561	0.527	0.815			
Intrinsic Motivation	3.030	0.664	0.341	0.353	0.312	0.896		

Extrinsic Motivation	2.991	0.699	0.251	0.179	0.201	0.179	0.878	
Engagement	2.979	0.620	0.297	0.311	0.246	0.364	0.213	0.860

Note(s). The square roots of AVEs are on the diagonal.

4.3 Structural Model Evaluation

The structural model was tested using AMOS 24.0 SEM with 5000 bootstrap samples to assess the hypothesized relationships. The model explained 15.8% of the variance in intrinsic motivation ($R^2 = 0.158$), 5.9% in extrinsic motivation ($R^2 = 0.059$), and 18.2% in student engagement ($R^2 = 0.182$). Although the explained variance for extrinsic motivation is modest, it is acceptable for exploratory studies in educational psychology (Sarstedt et al., 2020).

The standardized path coefficients are summarized in Table 8, with a visual representation provided in Figure 2. All hypothesized paths were statistically significant, supporting H1–H5. Specifically, AI-enhanced feedback positively predicted intrinsic motivation ($\beta = 0.402$, $p < 0.001$) and extrinsic motivation ($\beta = 0.253$, $p < 0.001$), both of which, in turn, significantly predicted student engagement ($\beta = 0.262$, $p < 0.001$; $\beta = 0.116$, $p < 0.05$, respectively). AI-enhanced feedback also directly predicted engagement ($\beta = 0.210$, $p < 0.01$).

4.3.1 Variance Explained (R^2)

The model explains:

- 15.8% of the variance in intrinsic motivation ($R^2 = 0.158$),
- 5.9% of the variance in extrinsic motivation ($R^2 = 0.059$),
- 18.2% of the variance in student engagement ($R^2 = 0.182$).

While the R^2 values for extrinsic motivation are relatively low, they are acceptable for exploratory studies in educational psychology (Hair et al., 2022), as motivation is influenced by multiple factors (e.g., teacher support, peer interaction) not fully captured in this model.

4.3.2 Direct Effects (Hypothesis Testing)

The direct effects of AI-enhanced feedback on motivation and engagement, and of motivation on engagement, are shown in Table 7 and Figure 4. All hypotheses are supported:

1. H1 (AI Feedback → Intrinsic Motivation): AI-enhanced feedback has a significant positive effect on intrinsic motivation ($\beta = 0.402$, $t = 7.912$, $p < 0.001$, 95% CI [0.295, 0.494]). This confirms that personalized, timely AI feedback enhances learners' internal motivation (e.g., enjoyment of learning).
2. H2 (AI Feedback → Extrinsic Motivation): AI-enhanced feedback has a significant positive effect on extrinsic motivation ($\beta = 0.253$, $t = 4.995$, $p < 0.001$, 95% CI [0.147, 0.342]). This indicates that AI feedback (e.g., score-based feedback, achievement badges) reinforces external motivation.
3. H3 (Intrinsic Motivation → Engagement): Intrinsic motivation has a significant positive effect on engagement ($\beta = 0.262$, $t = 4.803$, $p < 0.001$, 95% CI [0.144, 0.358]). Intrinsically motivated learners show higher behavioral, emotional, and cognitive engagement.

4. H4 (Extrinsic Motivation → Engagement): Extrinsic motivation has a significant positive effect on engagement ($\beta = 0.116$, $t = 2.242$, $p < 0.05$, 95% CI [0.010, 0.212]). While the effect size is smaller than intrinsic motivation, external rewards still promote engagement (e.g., participating in AI activities to pass exams).

5. H5 (AI Feedback → Engagement): AI-enhanced feedback has a direct significant positive effect on engagement ($\beta = 0.210$, $t = 3.418$, $p < 0.01$, 95% CI [0.092, 0.328]). This suggests AI feedback (e.g., immediate corrective feedback) directly increases learners' participation and focus.

Table 8. Structural Model Evaluation

Hypotheses and path	β	T	P	95%CI	Supported
AI Feedback → IM	0.402	7.912	0.000	[0.295, 0.494]	Supported
AI Feedback → EM	0.253	4.995	0.000	[0.147, 0.342]	Supported
IM → EG	0.262	4.803	0.000	[0.144, 0.358]	Supported
EM → EG	0.116	2.242	0.025	[0.010, 0.212]	Supported
AI Feedback → EG	0.210	3.418	0.001	[0.092, 0.328]	Supported

Note(s). IM = intrinsic motivation; EM = extrinsic motivation; EG = student engagement; AI Feedback = AI-enhanced feedback; The 95% confidence intervals are estimated using the bias-corrected method.

4.4 Mediating Effect Test

Mediation analysis was conducted using the PROCESS macro (Model 4) to test whether motivation (intrinsic/extrinsic) mediates the relationship between AI feedback and engagement. The results (Table 8) support both mediating hypotheses:

4.3.1 Mediating Effect of Intrinsic Motivation (H6)

The indirect effect of AI feedback on engagement via intrinsic motivation is significant ($\beta = 0.105$, $t = 3.920$, $p < 0.001$, 95% CI [0.054, 0.159]). The 95% confidence interval does not include 0, confirming that intrinsic motivation plays a partial mediating role. Specifically, AI feedback enhances intrinsic motivation (e.g., by satisfying autonomy and competence needs), which in turn increases engagement.

4.4.2 Mediating Effect of Extrinsic Motivation (H7)

The indirect effect of AI feedback on engagement via extrinsic motivation is significant ($\beta = 0.029$, $t = 1.985$, $p < 0.05$, 95% CI [0.004, 0.060]). The 95% confidence interval does not include 0, indicating extrinsic motivation also plays a partial mediating role. However, the effect size (0.029) is smaller than that of intrinsic motivation (0.105), suggesting intrinsic motivation is a stronger mediator.

4.4.3 Summary of Mediating Mechanisms

The total effect of AI feedback on engagement is the sum of the direct effect (β = 0.210) and the two indirect effects (β = 0.105 + 0.029 = 0.134), with the direct effect accounting for ~61% (0.210/0.344) of the total effect. This confirms that AI feedback influences engagement through two pathways:

1. Direct pathway: Immediate, personalized AI feedback directly promotes engagement.
2. Indirect pathway: AI feedback enhances both intrinsic and extrinsic motivation, which further drive engagement (intrinsic motivation contributes more to this indirect effect).

Table 9. Specific Mediating Influence Evaluation

Hypotheses and path	Indirect effect	T	P	95%CI	Supported
AI Feedback → IM→EG	0.402	7.912	0.000	[0.295, 0.494]	Supported
AI Feedback →EM →EG	0.210	3.418	0.001	[0.092, 0.328]	Supported

Note. The 95% confidence intervals are estimated using the bias-corrected method.

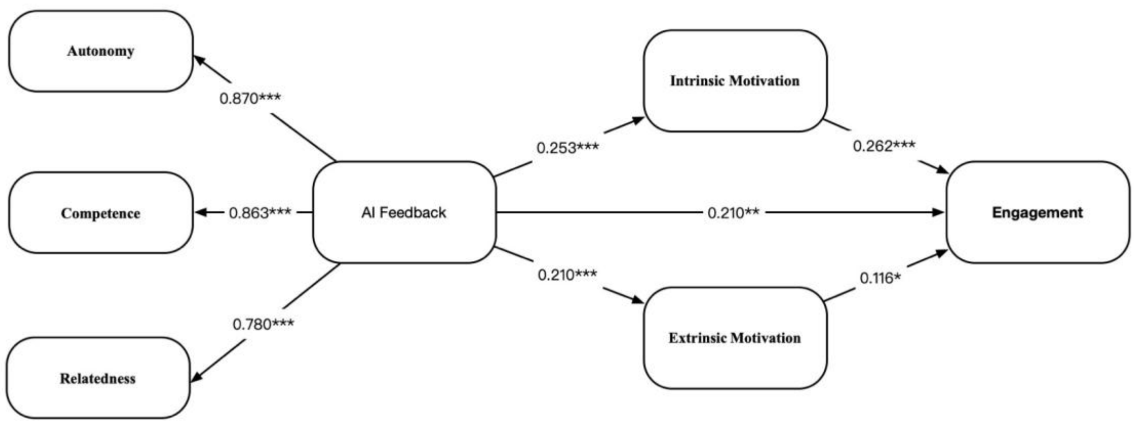

Figure 2. Structural Model Results (AMOS SEM)

Figure 2 presents the results of the structural model tested with SEM in AMOS 24.0. All hypothesized paths were significant.

5. Discussions

This study examined the impact of AI-enhanced feedback on EFL learners' motivation and engagement. The results revealed that AI feedback significantly promoted both intrinsic and extrinsic motivation, and that intrinsic motivation exerted a stronger mediating role in predicting student engagement. These findings are consistent with the self-determination theory (Deci & Ryan, 2000), which emphasizes the importance of autonomy, competence, and relatedness in fostering motivation.

Compared with previous research, our results provide robust evidence that AI feedback functions not only as a technical tool but also as a pedagogical mechanism that enhances learners' motivation through psychological need satisfaction. While prior studies often emphasized extrinsic incentives (e.g., scores or badges), the current findings highlight that intrinsic motivation—such as enjoyment and interest—plays a more powerful role in sustaining engagement. This discrepancy may be explained by cultural and contextual factors, including the exam-driven learning culture in China and the novelty of AI integration in EFL classrooms.

6. Implications of This Study

6.1 Theoretical Implications

1. Extension of SDT: This study empirically demonstrates that AI feedback supports the three basic psychological needs, thus extending the application of self-determination theory in technology-mediated learning.
2. Contribution to AI-enabled pedagogy: The findings provide evidence that AI tools influence not only immediate learning outcomes but also motivational processes that shape long-term engagement.
3. Proposed mechanism: The study identifies a cognitive–motivational–behavioral pathway (AI feedback → motivation → engagement), offering a theoretical lens for future investigations in educational technology.

6.1 Practical Implications

For teachers: Educators can leverage AI systems to provide personalized, timely, and adaptive feedback that enhances learners' autonomy and competence, thereby increasing engagement.

For students: AI-based feedback enables learners to monitor their progress, build confidence, and sustain interest, ultimately fostering self-regulated learning.

For institutions: Findings suggest the value of integrating AI tools into EFL and business English curricula, particularly in contexts such as cross-border e-commerce education, where motivation and engagement are critical.

For developers: Educational technology providers should design AI feedback systems that balance extrinsic rewards with features that nurture intrinsic interest.

7. Conclusion and Future Research Directions

This study concludes that AI-enhanced feedback positively predicts EFL learners'

motivation and engagement, with intrinsic motivation serving as a stronger mediator than extrinsic motivation. These results underscore the role of AI in shaping not only cognitive outcomes but also motivational and behavioral dimensions of learning.

7.1 Contributions

The study contributes theoretically by extending SDT to the domain of AI-mediated feedback and practically by offering insights into the effective use of AI in EFL and cross-border business English education.

7.2 Limitations

Despite its contributions, the study has several limitations. First, the data relied on self-reported questionnaires, which may be subject to common method bias. Second, the sample was limited to a specific educational context, restricting the generalizability of findings. Third, the cross-sectional design prevents strong causal inferences.

7.3 Future Research Directions

Future studies should employ longitudinal or experimental designs to validate causal relationships, explore potential moderators such as AI proficiency or learning anxiety,and examine the applicability of the model across different cultural and disciplinary contexts, including digital trade and e-commerce English training.

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