

Mediating Effect of Learning Motivation and Engagement on the Relationship between Generative Artificial Intelligence (Gen AI) Implementation and English as Foreign Language (EFL) Proficiency

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Abstract

Generative Artificial Intelligence (Gen AI) has emerged as a transformative innovation in English language education, offering content creation, personalized learning experiences, adaptive feedback, and automated assessment capabilities. However, few contemporary studies have examined how learning motivation and engagement mediate the relationship between Generative AI use and English as a Foreign Language (EFL) proficiency. A study of 383 vocational students in China was investigated through Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the motivational and engagement factors on the relationship between Gen AI and EFL proficiency. The outcome shows that neither motivation nor AI use independently guarantees language improvement unless learners actively engage in learning processes. Despite promising results, research gaps remain in longitudinal effect and future directions call for integrative, ethically grounded frameworks to optimize Gen AI's role in English language acquisition through motivation and engagement.

1. Introduction

1.1 Background

In the context of English language education, Generative Artificial Intelligence (Gen AI) supports the development of course content and teaching strategies tailored to learners' data and behavior patterns, enabling personalized learning experiences. Such systems can adapt course difficulty and content based on learners' progress, provides timely and constructive feedback that is crucial for language development, and offer targeted suggestions that enhance writing skills and overall language proficiency (Huang & Mizumoto, 2024; Noroozi et al., 2024). Unlike earlier forms of artificial intelligence that primarily rely on predictive algorithms based on historical data. Gen AI is characterized by its ability to generate novel outputs. Specifically, it generates new textual and multimodal content through technologies such as large language models, image-based models, and video-generation systems (Law, 2024). Examples of widely used Gen AI tools include OpenAI's ChatGPT and DeepSeek (Zhou & Liu, 2025).

1.2 Problem Statement

In English education, the application of Gen AI remains relatively, as many educators primarily use these tools for text generation rather than leveraging them to enhance learner's motivation and promote meaningful learning engagement (Zhang et al, 2024). This issue is particularly evident among vocational college students in China, who often demonstrate relatively level of intrinsic motivation toward English learning (Muliyah & Aminatun, 2020; Zeng et al., 2020). Additionally, the potential for AI tools to generate inaccurate or harmful information poses challenges to the credibility and reliability of educational content, thereby necessitating the development of framework for responsible AI use in EFL contexts (Zhu, 2023). Furthermore, the adoption of Gen AI may raise additional concerns including algorithmic bias and data privacy risks (Yang et al, 2023; Küçük et al 2025).

2. Literature Review

2.1 Generative Artificial Intelligence

Feuerriegel et al. (2024) defined Gen AI as a form of generative modeling implemented through machine learning architectures capable of producing new data samples based on learned patterns. In contrast, Swindell et al. (2024) argued that Gen AI represents a transformative advancement in educational technology, fundamentally distinct from earlier digital tools and capable of reshaping traditional teaching and learning models.

2.2 Motivation

In the context of learning, motivation refers to the set of internal and external factors that drive individuals to engage in the process of acquiring knowledge and skills (Bandhu et al., 2024). Learning motivation can be defined as a motivational tendency that initiates and sustains academic behavior while directing it toward specific academic goals (Liu, 2025).

Within motivational theory frameworks, self-determination theory (SDT) categorizes motivation into different types according to the reasons or goals underlying a particular behavior. Ryan and Deci, (2000; 2008) proposed that the satisfaction of basic psychological needs, including autonomy, competence, and relatedness, plays a crucial role in fostering intrinsic motivation and promoting students' psychological well-being in educational contexts.

Intrinsic factors like personal enjoyment and extrinsic motivational factors like teacher clarity and teacher immediacy, influence learners' language learning behavior through distinct mechanisms (Zheng, 2021). Howard et al. (2021) emphasized the importance of fostering supportive learning environments that enhance intrinsic and identified regulations to promote better performance and well-being among students. However, they also noted that excessive reliance on external rewards may undermine intrinsic interest and long-term engagement in learning activities.

2.3 Engagement

Philp and Duchesne (2016) defined engagement as a state of focused attention and participation that encompasses cognitive, social and emotional dimensions.

Self-regulated learning and metacognition are widely recognized as critical components for future tasks, while metacognition supported through instructional or technological scaffolding enables learners to monitor and regulate their learning processes (Fan et al. 2024). Cognitive presence, teaching presence, and social presence have also been shown to contribute significantly to learner motivation and academic outcomes (An et al, 2025). However, excessive controlled motivation may hinder participation by increasing anxiety, fear of making mistakes, and fear of negative evaluation, which can reduce learners' engagement in communicative interactions (Amoah & Yeboah, 2021).

2.4 English as Foreign Language Proficiency

In this study, foreign language ability refers to English proficiency acquired after the mastery of one's native language (Ellis, 1994). Professional development is essential for educators to effectively integrate Gen AI into English language teaching (Kong, 2024) as improved academic achievement in AI-supported learning environments is associated with enhanced performance in listening, speaking, reading and writing skills ultimately contributing to students' overall academic success (Wu & Kang, 2023).

2.5 The Relationship Between Variables

2.5.1 Gen AI and EFL Proficiency

Fostering AI literacy is necessary for maximizing the benefits of Gen AI in language learning contexts. Xia (2024) discussed the relationship in foreign language education, suggesting that the ability to engage in human-machine interaction can enhance learning efficiency and educational outcomes. Chu (2024) demonstrated that Gen AI can provide tailored learning materials and support intelligent teaching, which aligned with the findings of Estaiteyeh and McQuirter (2024), which leads to the first hypothesis, H1.

H1: Gen AI has a significant positive influence on students' EFL proficiency.

2.5.2 Gen AI and Learning Motivation

Research has shown that the use of AI tools can significantly enhance motivation in the language learning process (Huang & Mizumoto, 2024; Liu et al. 2024; Noroozi et al., 2024; Xiao et al. 2024). Huang and Mizumoto (2024) specifically examined the impact of ChatGPT on student motivation in EFL learning and found that students who utilized ChatGPT reported higher level of motivation. Nevertheless, the extent to which Gen AI plays a positive role in shaping learners' motivation remains under discussion, which leads to the second hypothesis, H2.

H2: Gen AI has a significant positive influence on students' learning motivation.

2.5.3 Gen AI and Engagement

Aligning AI-supported learning with learners' ideal self-concepts may enhance learning enjoyment, which can partially mediate the relationship between the ideal self and AI-integrated autonomous language learning, thereby increasing cognitive engagement (Liu et al., 2024; Noroozi et al, 2024). Empirical evidence indicates that AI-driven personalized instruction can significantly enhance student learning outcomes, including improved language proficiency and increased classroom engagement (Yuan 2025), which lead to the third hypothesis, H3.

H3: Gen AI has a significant positive influence on students' engagement.

2.5.4 Learning Motivation and Engagement

Research has also demonstrated positive associations between motivation and pragmatic engagement across different proficiency groups, suggesting that motivation predicts pragmatic engagement

(Alsmari, 2023). Empirical studies have consistently reported a positive relationship between motivation and learning engagement in language learning contexts (Ghavamnia & Kashkouli, 2022; Sotelo Muñoz et al., 2023). Although educational research had indicated that engagement plays fundamental role in the learning process and students' psychological well-being, relatively few studies have examined the relationship between motivation and engagement in foreign language learning context. (Feng & Hong, 2022), which lead to the fourth hypothesis, H4.

H4: Learning motivation has a significant positive influence on students' engagement.

2.5.5 Learning Motivation and EFL Proficiency

Research has shown that EFL proficiency is positively associated with motivation, with advanced learners often demonstrating stronger motivational orientations that contribute to greater engagement (Alsmari, 2023). The use of Gen AI tools may enhance students' motivation to participate in English learning activities, thereby increasing learning effort and improving academic performance (Ghavamnia & Kashkouli, 2022; Hellín et al., 2023). This leads to the fifth hypothesis, H5.

H5: Learning motivation has a significant positive influence on students' EFL proficiency.

2.5.6 Engagement and EFL Proficiency

Research has indicated that foreign language enjoyment, a positive motivational factor, is strongly correlated with learner engagement (Guo, 2021). However, some students have reported negative effects of online learning on their engagement with peers and teachers (Akpen et al., 2024) which form the sixth hypothesis, H6.

H6: Engagement has a significant positive influence on students' EFL proficiency.

2.5.7 The Mediating Effect of Learning Motivation and engagement on the Relationship Between Gen AI and EFL Proficiency

Recent studies have suggested that the use of Gen AI tools in educational contexts may enhance students' motivation and stimulate greater engagement in learning activities. By providing personalized feedback, adaptive learning resources, and interactive learning environments, Gen AI can increase learners' willingness to participate in English language assessments (Hellín et al., 2023; Liu et al., 2024).

Furthermore, the integration of Gen AI has also been found to influence learner engagement, which may function as a mediating mechanism linking AI-assisted learning and improvements in English proficiency (Quintero et al., 2022; Hellín et al., 2023; Ormzyar, 2023). Previous research has also suggested that emotional and motivational factors may influence learning outcomes indirectly through behavioral engagement, highlighting the critical role of engagement in facilitating effective learning processes (Feng & Hong, 2022; Wang et al., 2023).

Existing research has also provided valuable insights into the potential role of Gen AI in shaping learners' motivation and engagement in English language learning environments (Huang & Mizumoto, 2024; Jamshed et al., 2024). The relationship between motivation and engagement can be further interpreted through the lens of SDT, according to which the satisfaction of basic psychological needs, namely autonomy, competence and relatedness, can foster higher levels of intrinsic motivation, which in turn promotes deeper engagement in learning activities. (Ryan & Deci, 2000; Huang & Wang, 2023).

Based on these theoretical and empirical considerations, this study proposes that learning motivation and engagement may function as important mediating mechanisms in the relationship between Gen AI use and EFL proficiency. Accordingly, the following hypotheses are proposed:

H7: Learning motivation mediates the relationship between Gen AI and EFL proficiency.

H8: Engagement mediates the relationship between Gen AI and EFL proficiency.

H9: Learning motivation and engagement sequentially mediate the relationship between Gen AI and EFL proficiency.

2.6 Conceptual Framework

Drawn upon Self-Determination Theory and previous empirical studies in technology-enhanced language learning, the proposed conceptual framework assumes that Gen AI may directly influence students' EFL proficiency while also indirectly affecting proficiency through the mediating roles of learning motivation and engagement.

3. Methodologies

3.1 Sample selection

This study adopted a quantitative research design to examine the mediating effects of learning motivation and student engagement on the relationship between generative artificial intelligence (Gen AI) use and English as a Foreign Language (EFL) proficiency among vocational college students in China. The sample size was determined using the Krejcie and Morgan (1970) sampling table. Considering the large population of vocational college students in China (approximately 5.68 million; Ministry of Education, 2021), a minimum sample size of 384 was deemed sufficient to achieve adequate statistical power.

Data were collected from three vocational colleges representing different academic orientations—two science and engineering institutions and one liberal arts college: Liaoning Mechatronics College, Liaoning Petrochemical College, and Jinzhou Teachers College. A convenience sampling strategy was employed to facilitate access to participants while ensuring diversity in disciplinary backgrounds.

3.2 Reliability and Validity of questionnaires

The questionnaire consisted of four established scales: the AI Literacy Scale (Zhou et al., 2024), the Language Learning Motivation Scale (Noels et al., 2000), the Student Engagement in School—Four Dimensional Scale (Veiga et al., 2014), and the Chinese English Proficiency Scale (Ministry of Education, 2018). A pilot study was conducted to evaluate the clarity and construct validity of the instruments, and principal component analysis indicated that the items loaded strongly on their respective factors.

3.3 Data Collection and Analysis Procedure

After data screening, including the treatment of missing values, outliers, and reverse-coded items, the dataset was analyzed using SPSS and SmartPLS. The measurement model was evaluated by examining indicator reliability, internal consistency reliability, convergent validity, discriminant validity, and multicollinearity. Subsequently, the structural model was assessed using path coefficients, effect sizes, predictive relevance, and bootstrapping procedures. Finally, mediation analysis and PLS-Predict were conducted to evaluate indirect effects and the predictive accuracy of the proposed model.

4. Discussion

4.1 Descriptive Analysis

Data collection was conducted via questionnaire survey. After excluding invalid responses, a total of 383 valid questionnaires were obtained. The following summarizes some basic information regarding the questionnaire sample:

Table 1
Demographic Information

Category	Option	Frequency	Percent
Gender	male	259	67.62%
	female	124	32.38%
Grade	first year	308	80.42%
	second year	28	7.31%
	third year	47	12.27%
Birth of place	city	150	39.16%
	countryside	233	60.84%
Income per person per month	1000–2000	116	30.29%
	2001–3000	93	24.28%
	3001 and above	174	45.43%
Major	science	230	60.05%
	art	83	21.67%
	others	70	18.28%

According to survey data, males accounted for 67.62% of participants, while females constituted 32.38%. First-year students were the largest participants with the percentage of 80.42%. Most participants were from rural areas and nearly half reported a monthly per capita household income above 3,001 RMB, suggesting relatively favorable economic conditions. Science and engineering students formed the largest disciplinary group with the percentage of 60.05%. Overall, participants represented diverse demographic and socioeconomic backgrounds.

4.2 Reliability and Convergent Validity Analysis

4.2.1. Reliability Analysis

The reliability and convergent validity of the measurement model were evaluated by examining indicator loadings, Cronbach's alpha (α), composite reliability (CR), and average variance extracted (AVE), following established guidelines for PLS-SEM analysis. To ensure the reliability of the indicators, the external load should be higher than 0.708. However, if the measurement model passes the threshold of internal consistency and convergent validity standards, a load higher than 0.5 is also acceptable. (Hair, et al, 2017).

Table 2
Factor Loading, Cronbach's Alpha, Composite Reliability, and AVE

Item	Outer loading	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
AE1	0.769	0.848	0.898	0.688
AE2	0.858			
AE3	0.893			
AE4	0.791			
AI1	0.705	0.962	0.966	0.67
AI2	0.779			
AI3	0.731			
AI4	0.819			
AI5	0.842			
AI6	0.838			
AI7	0.855			
AI8	0.753			
AI9	0.849			
AI10	0.848			
AI11	0.852			
AI12	0.857			
AI13	0.859			
AI14	0.849			
CE1	0.859	0.899	0.93	0.768
CE2	0.878			
CE3	0.91			
CE4	0.856			
EE1	0.888	0.805	0.886	0.722
EE2	0.901			
EE3	0.752			
EF1	0.821	0.937	0.946	0.615

Item	Outer loading	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
EF2	0.798			
EF3	0.779			
EF4	0.843			
EF5	0.852			
EF6	0.851			
EF7	0.783			
EF8	0.787			
EF9	0.709			
EF10	0.68			
EF11	0.697			
IM1	0.898	0.903	0.939	0.837
IM2	0.937			
IM3	0.91			
NM1	0.897	0.896	0.935	0.828
NM2	0.917			
NM3	0.916			
OM1	0.851	0.937	0.949	0.726
OM2	0.821			
OM3	0.871			
OM4	0.879			
OM5	0.813			
OM6	0.864			
OM7	0.861			

As shown in Table 2, all measurement items demonstrated satisfactory outer loadings. Specifically, the majority of indicators loaded above the recommended threshold of 0.70, indicating strong indicator reliability despite EF10's outer loading 0.680 and EF11 0.697. However, these values remained acceptable in exploratory and applied social science research when composite reliability and AVE meet recommended standards. Therefore, all items were retained for further analysis.

Cronbach’s alpha values ranged from 0.805 to 0.962, exceeding the recommended minimum of 0.70, which indicated adequate to excellent internal consistency reliability across all constructs. In addition, composite reliability values ranged from 0.886 to 0.966, further confirming the high reliability of the measurement scales. Notably, constructs such as Artificial Intelligence (AI), EFL Proficiency (EF), and Outer Motivation (OM) demonstrated particularly strong internal consistency, with CR values well above 0.90.

Convergent validity was assessed using the average variance extracted AVE. All constructs exhibited AVE values exceeding the recommended threshold of 0.50, ranging from 0.615 to 0.837. This indicated that each latent construct explained more than 50% of the variance in its associated indicators, thereby providing strong evidence of convergent validity. Constructs such as Intrinsic Motivation (IM) and None Motivation (NM) showed especially high AVE values, suggesting a substantial shared variance among their indicators.

4.2.2 Discriminant validity

In Table 3, Discriminant Validity was measured by HTMT and Fornell–Larcker Criterion. Specifically, the HTMT values ranged from 0.552 to 0.895. Although the HTMT association between AE and EFL proficiency was 0.895, approaching the upper threshold, it remained within the acceptable limit, suggesting that the two constructs were empirically distinct. Similarly, relatively high HTMT values were observed between OM and IM and between OM and CE. However, these values did not exceed the recommended cut-off, thereby supporting adequate discriminant validity.

Table 3
Discriminate Validity (HTMT)

AE	AE	AI	CE	EE	EFL Proficiency	IM	NM	OM
AE	0.615	0.615	0.615	0.615	0.615	0.615	0.615	0.615
AI	0.552	0.615	0.615	0.615	0.615	0.615	0.615	0.615
CE	0.759	0.763	0.615	0.615	0.615	0.615	0.615	0.615
EE	0.787	0.652	0.832	0.615	0.615	0.615	0.615	0.615
EFL Proficiency	0.895	0.697	0.823	0.835	0.615	0.615	0.615	0.615
IM	0.604	0.843	0.816	0.707	0.728	0.615	0.615	0.615
NM	0.695	0.664	0.802	0.733	0.645	0.694	0.615	0.615
OM	0.655	0.802	0.884	0.752	0.747	0.869	0.8	0.615

The discriminant validity was assessed using the Fornell-Larcker criterion, which compares the square root of the average variance extracted (AVE) for each construct with the correlations between constructs. As shown in Table 4, in most cases, the square root of the variance for each construct is

greater than its correlation with other constructs, indicating that the variance shared by each construct and its own indicators is greater than the variance shared with other constructs.

Table 4
Discriminate Validity (Fornell-Larcker Criterion)

AE	AE	AI	CE	EE	EFL Proficiency	IM	NM	OM
	0.829							
AI	0.508	0.818						
CE	0.668	0.713	0.876					
EE	0.651	0.587	0.718	0.85				
EFL Proficiency	0.807	0.671	0.759	0.731	0.784			
IM	0.538	0.787	0.735	0.61	0.678	0.915		
NM	0.613	0.622	0.723	0.627	0.605	0.627	0.91	
OM	0.593	0.763	0.811	0.662	0.709	0.8	0.736	0.852

Specifically, the diagonal values for AE 0.829, AI 0.818, CE 0.876, EE 0.850, IM 0.915, NM 0.910, and OM 0.852 exceeded their correlations with other constructs, supporting adequate discriminant validity. Although relatively high correlations were observed between CE and OM, AI and IM, and AE and EFL proficiency, these correlations remained below the corresponding square roots of AVE.

4.2.3 Path Analysis

This study employed PLS version 4.0 to analyze and elucidate the hypothesized pathways. The specific data analysis for path testing is as follows.

4.2.4 Model Fitting

The structural model demonstrated strong explanatory power. In Table 5, the R-square values indicated that the model explained 75.8% of the variance in EFL proficiency, 68.7% of the variance in student engagement, and 64.5% of the variance in learning motivation. According to PLS-SEM benchmarks, these values indicate strong predictive accuracy.

Table 5
Predict Power of R- square

EFL Proficiency	R-square	R-square adjusted
	0.758	0.756
Engagement	0.687	0.685
Learning Motivation	0.645	0.644

The adjusted R-square values were highly consistent with the original R-square values, suggesting that the model was not affected by overfitting and that the structural relationships were stable. Minimal differences between R^2 and adjusted R^2 suggest stable estimates without overfitting. According to the criteria proposed by Hair et al (2019), these values represented moderate to substantial explanatory power.

Table 6
Predict Power of F-square

AI -> EFL Proficiency	f-square
	0.041
AI -> Engagement	0.005
AI -> Learning Motivation	1.814
Engagement -> EFL Proficiency	0.811
Learning Motivation -> EFL Proficiency	0.002
Learning Motivation -> Engagement	0.682

Effect sizes (f^2) in Table 6 indicated differentiated predictive contributions. Gen AI showed a small effect on EFL proficiency ($f^2 = .041$) and a negligible effect on engagement ($f^2 = .005$), but a very large effect on learning motivation ($f^2 = 1.814$). Engagement exerted a large effect on EFL proficiency ($f^2 = .811$). Learning motivation had a negligible direct effect on proficiency ($f^2 = .002$) but a large effect on engagement ($f^2 = .682$), supporting its indirect influence.

4.2.5 Predictive Correlation

The predictive relevance of the structural model was assessed using the Stone–Geisser Q^2 statistic obtained through the blindfolding procedure. Q^2 values greater than zero indicate that the model has predictive relevance for a given endogenous construct (Hair et al., 2022).

Table 7
Predict Power of Q-square

AI	SSO	SSE	$Q^2 (= 1-SSE/SSO)$
	5362	2062.498	0.615
EFL Proficiency	4213	1940.363	0.539
Engagement	4213	2141.508	0.492
Learning Motivation	4979	2029.314	0.592

Predictive relevance was assessed using Q^2 via blindfolding in Table 7. All endogenous constructs showed positive Q^2 values, indicating adequate predictive relevance. Q^2 values were .539 for EFL

proficiency, .492 for engagement, and .592 for learning motivation, reflecting strong predictive capability. Consistent with PLS-SEM guidelines, Q² values above zero confirmed out-of-sample predictive accuracy, suggesting that the model demonstrated robust predictive power

4.2.6 Collinearity Test

The variance inflation factor (VIF) was used to test the collinearity among the predictor variables in the structural model. According to the generally accepted criteria of the Partial Least Squares Structural Equation Modeling (PLS-SEM), a VIF value below 5.0 indicates that collinearity does not pose a serious threat to the estimation of path coefficients, while a value below 3.3 is considered an ideal level. (Hair et al., 2019).

Table 8
Collinearity Test of VIF

AI -> EFL Proficiency	VIF
	2.828
AI -> Engagement	2.814
AI -> Learning Motivation	1
Engagement -> EFL Proficiency	3.195
Learning Motivation -> EFL Proficiency	4.733
Learning Motivation -> Engagement	2.814

Collinearity was assessed using variance inflation factor (VIF) values. All VIFs ranged from 1.000 to 4.733, below the recommended threshold of 5.00 (Hair et al., 2022), indicating no serious multicollinearity concerns. VIFs for predictors of AI to EFL proficiency, engagement to EFL proficiency and learning motivation to EFL proficiency were 2.828, 3.195 and 4.733. Other paths also remained within acceptable limits, supporting the stability and robustness of the structural model.

4.3 Mediating Effect Analysis

The table below presented the path coefficient results, illustrating the specific influence relationships across different pathways within the model. It provided the path coefficient, T-value, and significance level (P-value) for each pathway.

Table 9
Direct and Indirect Path Analysis Results

AI -> EFL Proficiency	β	Sample mean	Standard deviation	T statistics	P values
	0.167	0.169	0.052	3.235	0.001
AI -> Engagement	0.066	0.067	0.071	0.936	0.349
AI -> Learning Motivation	0.803	0.804	0.027	29.595	0
Engagement -> EFL Proficiency	0.791	0.798	0.062	12.835	0
Learning Motivation -> EFL Proficiency	-0.051	-0.059	0.088	0.582	0.561
Learning Motivation -> Engagement	0.775	0.775	0.07	11.079	0
AI -> Learning Motivation -> Engagement -> EFL Proficiency	0.492	0.499	0.073	6.712	0
AI -> Learning Motivation -> EFL Proficiency	-0.041	-0.048	0.071	0.578	0.563
AI -> Engagement -> EFL Proficiency	0.052	0.052	0.055	0.95	0.342

Table 9 reported the structural path coefficients with bootstrapped standard errors, T values, and P values. AI had a significant positive direct effect on EFL proficiency ($\beta = .167$, $t = 3.235$, $p = .001$) but did not significantly predict engagement ($\beta = .066$, $t = 0.936$, $p = .349$). AI strongly predicted learning motivation ($\beta = .803$, $t = 29.595$, $p < .001$). Engagement exerted a substantial effect on EFL proficiency ($\beta = .791$, $t = 12.835$, $p < .001$), whereas learning motivation did not directly predict proficiency ($\beta = -.051$, $t = 0.582$, $p = .561$) but significantly predicted engagement ($\beta = .775$, $t = 11.079$, $p < .001$).

Mediation analysis indicated that the sequential indirect effect of AI on EFL proficiency via learning motivation and engagement was significant ($\beta = .492$, $t = 6.712$, $p < .001$). However, indirect effects through learning motivation alone ($\beta = -.041$, $t = 0.578$, $p = .563$) and engagement alone ($\beta = .052$, $t = 0.950$, $p = .342$) were nonsignificant. These findings supported a sequential mediation pathway from AI to motivation, to engagement, and ultimately to proficiency.

5. Limitations and future research directions

The existing research on artificial intelligence-assisted English learning has several significant gaps. This study was conducted in Liaoning Province, China, relying on cross-sectional data collected at a single point in time, which inherently limits the ability to capture the development and dynamic interactions among variables. Therefore, causal inferences should be interpreted with caution, as the observed correlations may not fully reflect the temporal sequence or long-term effects of learning motivation, participation, and English as a Foreign Language (EFL) ability. Although the observed reliability and

validity indicators are high, the reliance on self-reporting measurement methods may introduce common method bias. Additionally, more empirical research is needed to evaluate the effectiveness of general artificial intelligence (Gen AI), while also considering algorithmic biases and ethical considerations. More importantly, there is a lack of longitudinal studies, particularly in terms of the long-term impact of Gen AI on language learning motivation and participation, which requires a combination of quantitative methods to deepen understanding.

Future research could combine behavioral analysis or log data from artificial intelligence platforms to more objectively capture participation. Moreover, since the sample was drawn from vocational colleges with specific educational backgrounds, research should be conducted among college students to gain more perspectives.

6. Conclusion

This study examines how an artificial intelligence-supported learning environment affects the proficiency of vocational college students in English as a Foreign Language (EFL), with a particular focus on the mediating role of learning motivation and student engagement. Using a robust partial least squares structural equation modeling approach, the research findings indicate that artificial intelligence is not a direct determinant of language proficiency. Instead, its educational value is mainly achieved through a sequential motivational behavior pathway. Specifically, artificial intelligence significantly enhances students' learning motivation, which in turn promotes higher levels of engagement, ultimately leading to a substantial improvement in English proficiency. Engagement becomes the most direct and powerful predictor of language outcomes, and neither the use of artificial intelligence alone nor learning motivation itself is sufficient to directly improve proficiency. These results provide compelling empirical evidence that the effectiveness of artificial intelligence in language education fundamentally depends on the psychological and behavioral responses of learners, rather than technical exposure.

Declarations

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Ethics Statements, Consent for Publication and Competing Interests

This study was conducted in accordance with the principles of the Helsinki Declaration. The research received approval from the ethics committee. The data collection process required preliminary authorization and cooperation from the university administrative office and coordinators of each college. After obtaining approval, participants were recruited through institutional WhatsApp and WeChat groups as well as classroom announcements.

All participants were informed of the purpose of this study and provided written informed consent before participating. We assured the participants that their responses would remain anonymous and confidential, and that the data would only be used for academic research purposes. This document does not contain any identifiable personal information. All participants agreed to publish the aggregated research results.

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Data availability statements

Data used in Chapters 4 and 5 in this study have been deposited in a public, permanent repository. Access to these files is unrestricted, allowing other researchers to verify the statistical findings and

conduct secondary analyses. This data has been stripped of all direct and indirect identifiers to ensure participant confidentiality.

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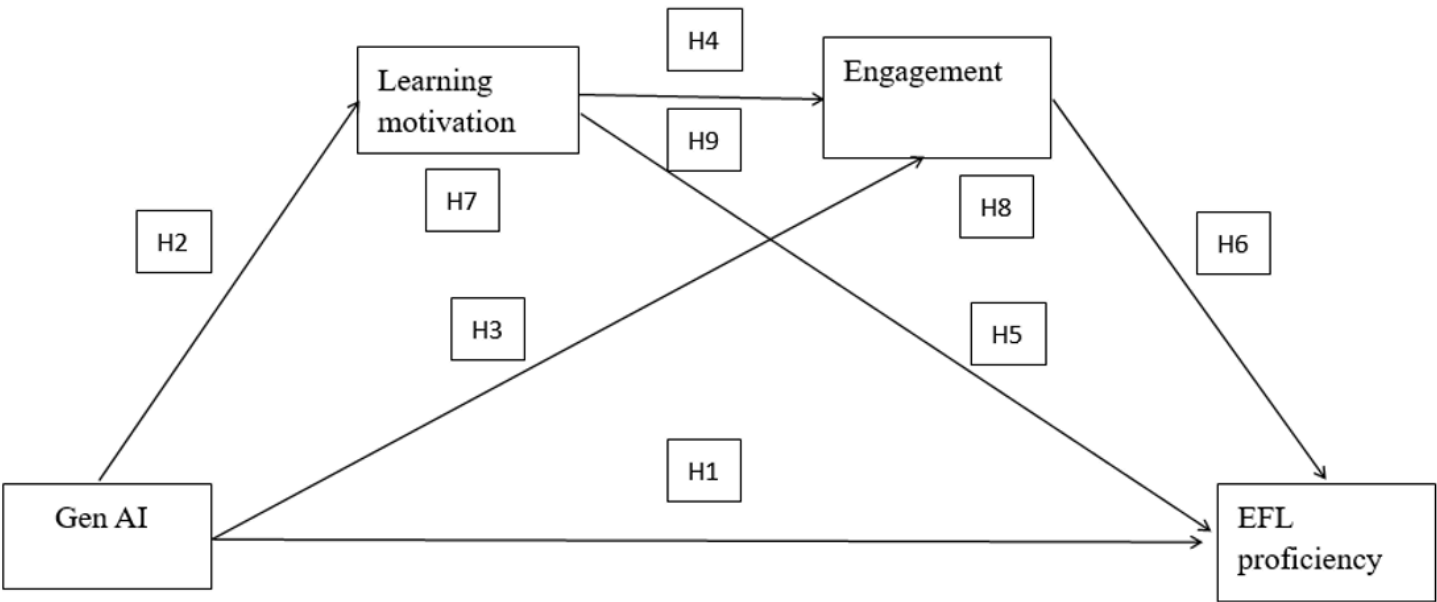
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Figures



Note:

H7: Gen AI → Learning Motivation → EFL Proficiency

H8: Gen AI → Engagement → EFL Proficiency

H9: Gen AI → Learning Motivation → Engagement → EFL Proficiency

Figure 1

Conceptual Framework

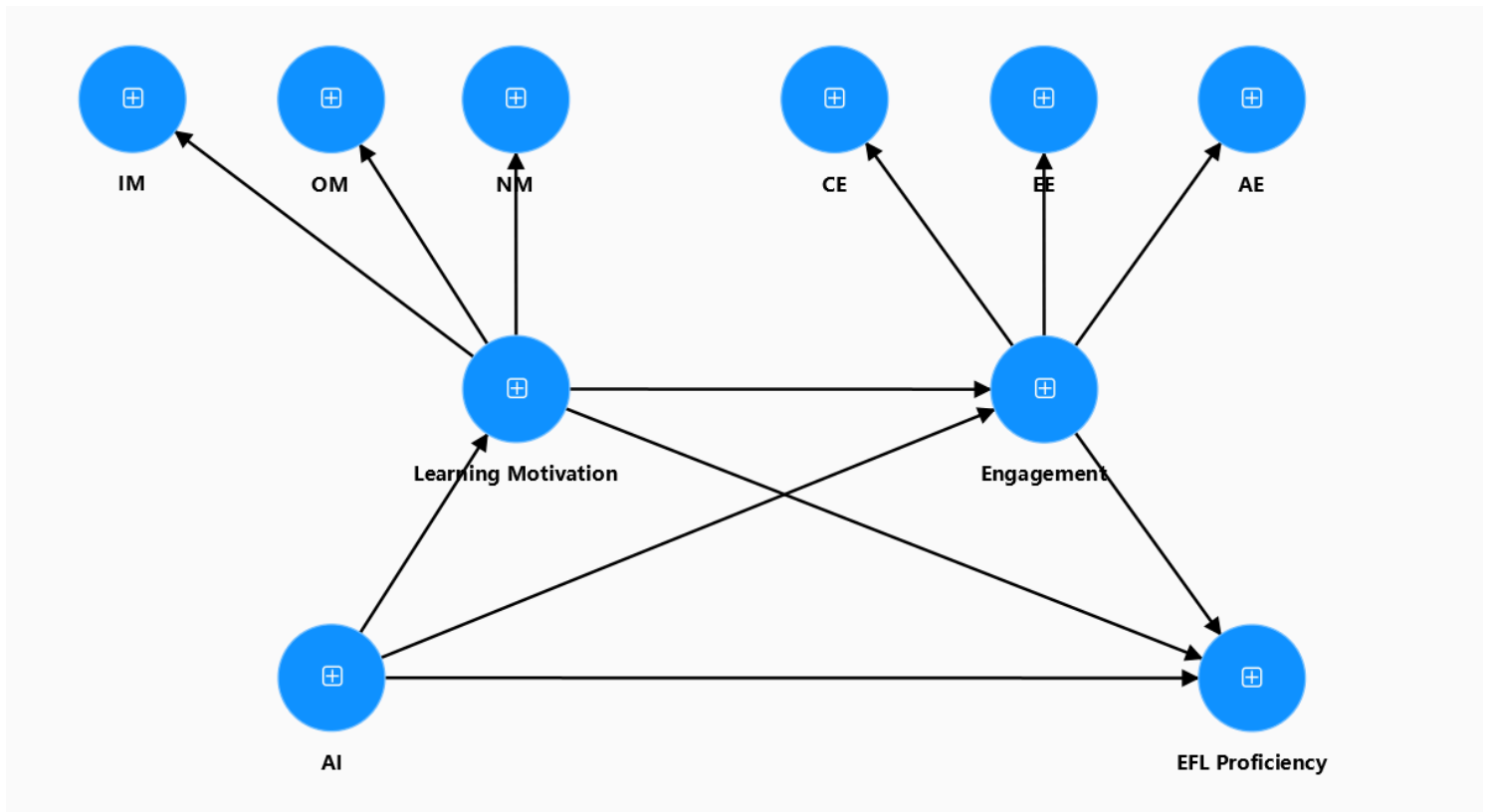


Figure 2

Structural Path