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# Research on Enhancing College Students' English Writing Ability Driven by Multimodal Generative AI

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**Abstract:** This study investigates the relationships among Multimodal Generative AI Usage Frequency (MGAIUF), Multimodal Generative AI Function Perception (MGAIFP), English Writing Learning Engagement (EWLE), English Writing Confidence and Attitude (EWCA), and English Writing Ability (EWA). Grounded in Multimodal Learning Theory (MLT), Student Engagement Theory (SET), and Self-Determination Theory (SDT), this study employed a quantitative survey design by means of a self-developed questionnaire. Data were collected from 221 Chinese college students with experience using generative AI (GenAI) tools for English writing and analyzed using SPSS 25.0 and AMOS 24.0 through reliability testing, confirmatory factor analysis (CFA), and structural equation modeling (SEM). The results indicate that both MGAIUF and MGAIFP significantly and positively affect EWLE and EWCA. Moreover, EWLE and EWCA significantly enhance EWA, with EWCA demonstrating the strongest predictive effect. However, the direct effects of MGAIUF and MGAIFP on EWA are not statistically significant. Bootstrap mediation analysis further confirms that EWLE and EWCA fully mediate the relationships between multimodal generative AI (MGAI, such as MGAIUF and MGAIFP) and EWA, with writing confidence and attitude serving as the most influential mediating factors. The findings suggest that the effectiveness of MGAI in improving EWA is achieved primarily through promoting students' learning engagement and strengthening their writing confidence and positive attitudes rather than through direct technological effects. This study enriches the literature on AI-assisted language learning by proposing a "technology–learning behavior–learning outcomes" framework and provides practical implications for the pedagogically effective integration of MGAI into English writing instruction at higher education.

**Keywords:** Multimodal Generative AI (MGAI); English Writing Ability (EWA); English Writing Learning Engagement (EWLE); English Writing Confidence and Attitude (EWCA); College students

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## 1. Introduction

With the rapid development of artificial intelligence (AI), generative AI (GenAI) technologies have increasingly been applied in higher education, particularly in language learning and teaching. Recently, multimodal generative AI (MGAI) tools, such as ChatGPT, Gemini, DeepSeek, Kimi, Doubao and other AI-generated content (AIGC) writing assistants, have shown strong capabilities in text generation, grammar correction, idea organization, and interactive feedback through the integration of multiple modalities. Compared with traditional writing tools, MGAI can provide more personalized and immediate support for learners, offering new opportunities for improving college students' English writing ability. Besides, English writing is widely regarded as one of the most difficult skills for Chinese college students. Many learners struggle with vocabulary use, grammatical accuracy, coherence, and logical organization. In traditional writing classrooms, limited interaction and delayed teacher feedback often reduce students' learning engagement and writing confidence. In this context, MGAI may effectively support students by providing instant feedback, diversified language input, and individualized writing guidance. These advantages may help learners improve writing performance, increase learning motivation, and strengthen confidence in English writing. Thus, this study endeavors to construct a structural equation model to investigate the relationships among Multimodal Generative AI Usage Frequency (MGAIUF), Multimodal Generative AI Function Perception (MGAIFP), English Writing Learning Engagement (EWLE), English Writing Confidence and Attitude (EWCA), and English Writing Ability (EWA). The findings are expected to provide theoretical and practical implications for improving college English writing teaching in the AI era.

## 2. Literature review

### 2.1. Generative AI (GenAI) and foreign language teaching

The application of GenAI in English as a Foreign Language (EFL) environments has become a growing topic of interest in academia. In an empirical study of 140 undergraduate students in Hong Kong, Wang and Ren (2024) found that "ChatGPT has multiple functions, including forming opinions, providing definitions, and serving as a language repository. Students can critically integrated AIGC while being aware of academic integrity issues, and systematic instructional guidance is proposed" [1]. Similarly, a quasi-experimental study by Tiandem-Adamou (2024), highlighting peer collaboration and AI-driven personalized feedback as key success factors, showed that "combining GenAI with collaborative learning can result in significantly higher writing scores than traditional feedback methods in the Chinese EMI university setting" [2]. This is consistent with previous findings on the effectiveness of teacher feedback, with Alharbi (2016) confirming that "Saudi EFL students who receive systematic written corrective feedback performed better than those who do not, and that students have a positive attitude towards the feedback" [3]. What is more, Kohnke, L., Moorhouse, B. L., & Zou, D. (2023) pointed out that "while ChatGPT offers significant affordances for language education, teachers must guide students in its appropriate use rather than treating it as a complete solution" [4]. Barrot, J. S. (2023) systematically examined both the benefits and risks of using ChatGPT in second language (L2) writing instruction, argued for a balanced, pedagogical approach where ChatGPT served as a cognitive tool under teacher supervision, and called for updated assessment practices to maintain academic integrity while leveraging AI's capabilities [5]. Cotton, D. R., Cotton, P. A., & Shipway, J. R. (2024) declared that "banning AI is neither feasible nor desirable in teaching; instead, institutions must adapt assessment practices to uphold academic standards while embracing technological change" [6]. Together, these studies demonstrate that generative AI (GenAI) can enhance EFL writing performance when combined with collaborative learning and systematic instructional guidance. However, researchers unanimously caution that GenAI should function as a cognitive tool under teacher supervision rather than a complete solution, requiring updated assessment practices that balance technological integration with academic integrity.

## 2.2. Multimodal learning theory (MLT) and writing teaching

Multimodal learning theory (MLT), which emphasizes the synergistic role of multiple sensory channels and semiotic resources such as text, images, sound, and animation [7,8], has profoundly influenced writing teaching research. Paivio's (1990) dual-coding theory provides a foundational explanation for the superiority of multimodal input by demonstrating that simultaneous verbal and non-verbal information facilitates dual memory representations [9], while Mayer (2005) further proposed that "combining text with images reduces extraneous cognitive load" [10]. In writing teaching, Yeh, H.C., Heng, L., & Tseng, S.S. (2020) found that students who utilized different modes in video-making learned to be more inventive and skillful in writing than those who only read text [11], and Perez, M.M. (2020) demonstrated through empirical research that multimodal input activates situated cognition, thereby enhancing content originality [12]. Meanwhile, Tomchakovskyi et al. (2026) directly supported the role of multimodal AI tools in academic writing in English as a foreign language, and found that tools like ChatGPT's multimodal interface, Grammarly, and speech-to-text systems significantly improved vocabulary complexity, syntactic complexity, and text coherence [13]. Additionally, research on the integration of generative AI in K-12 settings found that a multimodal approach that combines teacher scaffolding with AI support significantly improved students' ability to construct coherently descriptive textual and visual elements, improving vocabulary and multimodal literacy skills [14]. Regarding feedback, Carless (2006) early noted the limitations of traditional written feedback as single-modal and emotionally distant [15]. West and Turner (2016) found that audio feedback conveys teacher tone and emotion, enhancing learner receptivity [13], while Borup, West, and Thomas (2015) concluded in a systematic review that "screencast feedback offers greater instructional clarity than static written comments" [16], and Grigoryan, A. (2017) proved that "the use of a combination of audio-visual and text-based commentary in online writing courses was more effective in promoting substantive revision and improvement in students' writing than the use of text-based commentary alone" [17]. Salamanti, E., Park, D., Ali, N., & Brown, S. (2023) investigated the effectiveness of combining collaborative learning (group work, peer interaction) with multimodal input (images, videos, audio) for improving English language proficiency among ESL/EFL learners [18]. As a matter of fact, compared with single-modal learning, multimodal learning environments provide richer cognitive stimulation and stronger learner engagement, which are beneficial for language acquisition and writing development.

## 2.3. Measurement and influencing factors of English writing ability (EWA)

English writing ability (EWA) is widely conceptualized as a multidimensional construct. Different scholars define EWA from their own perspectives. For example, Cumming (1989) regarded it as a three-dimensional framework of linguistic accuracy, content organization, and fluency [19]. Polio (2017) refined this into four core dimensions: linguistic accuracy (grammar, vocabulary, spelling, punctuation), content and organization (logical coherence, paragraph cohesion, relevance of claims), fluency (T-unit length, syntactic variety), and content richness and originality [20], while Weigle (2002) emphasized that dimension weighting should adjust dynamically by task type and learner proficiency [21]. Regarding influencing factors, Chapelle (2009) proposed that “learners' actual usage behaviors mediate technology's effect on L2 ability [22], and Warschauer and Liaw (2011) found that automated writing evaluation effectiveness depends on technology acceptance [23]. In terms of motivation, Deci and Ryan's (2000) self-determination theory (SDT) has been widely adopted to explain writing behavior [24], and Pintrich (2003) identified intrinsic motivation as a key predictor of writing engagement and achievement [25]. With respect to learning engagement, Fredricks, Blumenfeld, and Paris (2004) distinguished behavioral, cognitive, and emotional dimensions [26], and Kahu (2013) emphasized engagement as a critical mediator linking educational contexts to learning outcomes [27]. Specifically in writing research, Han and Hyland (2019) found that learner engagement fully mediated the relationship between feedback delivery mode and writing improvement, demonstrating that instructional tools only produce effects insofar as they promote actual revision behaviors[28], and Yu, S., Zhou, N., Zheng, Y., Zhang, L., Cao, H., & Li, X. (2019) similarly confirmed in an empirical study of Chinese university students that “learning motivation predicts English writing performance through learning engagement in the second language (L2) writing courses” [29].

### 2.4. Research gaps

Synthesizing the literature reviewed above, several gaps emerge. First, fragmented research perspectives, as most GenAI studies focus exclusively on text-based interaction and rarely integrate multimodality theory [4]. Second, limited methodological diversity, with the majority of existing studies relying on small-sample qualitative or short-term experimental designs and lacking large-scale survey-based quantitative research [5]. Third, weak theoretical frameworks, as few studies have tested mediation mechanisms using a “technology→behavior→outcome” framework, with most research remaining at the level of direct effects. Fourth, key unresolved debates, including whether AI promotes or inhibits writing creativity and whether multimodal feedback is equally effective across all learner proficiency levels [6,18]. To address these gaps, the present study introduces three innovations. Firstly, it focuses on MGAI rather than text-only capabilities, investigating tools that possess both multimodal input presentation and multimodal feedback output, thereby bridging Kress and van Leeuwen's (2001) multimodality theory [8]. Secondly, it adopts empirical analysis using a questionnaire survey with a relatively large sample, responding to calls by Barrot (2023) for quantitative research and employing descriptive statistics, correlation analysis, and regression analysis to enhance external validity [5]. Thirdly, it constructs a “technology→learning behavior→writing ability” framework drawing on Fredricks et al.'s (2004) three-dimensional engagement structure, Kahu's (2013) integrative framework, and Deci and Ryan's (2000) SDT, which mediates technology characteristics (e.g., MGAI) through learning behavior (motivation, engagement) to learning outcomes (writing ability), thereby addressing the neglect of behavioral mediators in existing research [24,26,27].

## 3. Theoretical model and research hypothesis

### 3.1. Theoretical model

Grounded in Kress and van Leeuwen's (2001) multimodality theory, Fredricks et al.'s (2004) three-dimensional engagement structure, Kahu's (2013) integrative framework, and Deci and Ryan's (2000) SDT, this study constructs a structural equation model following the framework of “technology use→learning process→learning outcomes” to systematically examine the mechanisms through which MGAI enhances college students' English writing ability [8,24,26,27]. The model comprises a total of six latent variables, which are categorized according to their theoretical roles within the proposed framework (see **Figure 1**). Specifically, the model includes two exogenous latent variables: MGAIUF and MGAIFP. These variables serve as independent predictors and are not influenced by any other variables in the model. The model further incorporates two mediating latent variables: EWLE and EWCA. These variables are positioned as intermediate mechanisms through which the exogenous variables exert their influence. Finally, the model includes one endogenous latent variable as the outcome variable, namely EWA, which represents the ultimate learning outcome affected by both the direct and indirect effects of the other variables. This structural configuration enables a systematic examination of how multimodal generative AI usage behaviors and functional perceptions influence college students' EWA through the mediating pathways of learning engagement and writing-related affective factors.

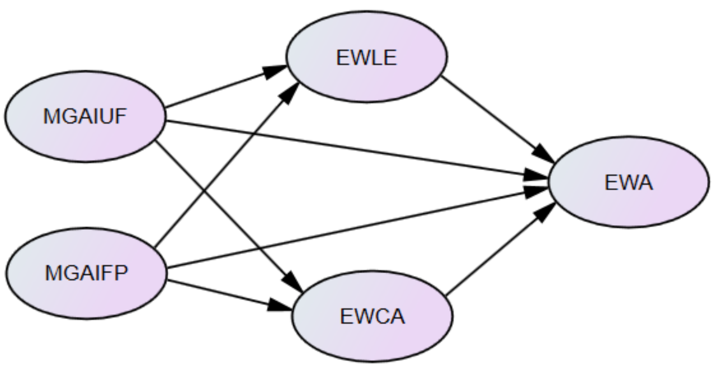


**Figure 1.** Theoretical Model of the Study.

## 3.2. Research hypothesis

Based on the theoretical model, the following research hypotheses in this study are pointed out:

H1: MGAIUF has a positive impact on EWLE.

H2: MGAIUF has a positive impact on EWCA.

H3: MGAIFP has a positive impact on EWLE.

H4: MGAIFP has a positive impact on EWCA.

H5: EWLE has a significant positive impact on EWA.

H6: EWCA has a significant positive impact on EWA.

H7: MGAIUF has a direct positive impact on EWA.

H8: MGAIFP has a direct positive impact on EWA.

H9: EWLE mediates the relationship between MGAIUF and EWA.

H10: EWLE mediates the relationship between MGAIFP and EWA.

H11: EWCA mediates the relationship between MGAIUF and EWA.

H12: EWCA mediates the relationship between MGAIFP and EWA.

## 4. Methodology

### 4.1. Research design

This study employed a quantitative cross-sectional survey design. This design aimed to efficiently collect data from a sufficient sample to test the proposed theoretical model and research hypotheses through statistical methods, including structural equation modeling (SEM).

### 4.2. Participants

The target population for this study was Chinese college students currently engaged in English writing instruction, particularly those with experience using GenAI tools to support their writing tasks. A convenience sampling strategy was employed to recruit participants through Wenjuanxing (a widely used online survey platform in China). A total of 221 valid responses were collected. The sample came from multiple universities in China, primarily from Guangdong Province. Demographic characteristics are summarized in **Table 1**. Among participants, 151 (68.33%) were female and 70 (31.67%) male. Grade distribution included seniors (N = 106, 47.96%), juniors (N = 56, 25.34%), sophomores (N = 40, 18.1%), and freshmen (N = 19, 8.6%). English/foreign language majors comprised the majority (N = 175, 79.19%). Self-assessed English proficiency was mostly “average” (N = 95, 42.99%) or “moderate” (N = 65, 29.41%).

**Table 1.** Demographic Characteristics of Participants (N = 221)

| Variable | Category | Frequency (N) | Percentage (%) |
|---|---|---|---|
| Gender | Male | 70 | 31.67 |
| | Female | 151 | 68.33 |
| Grade | Freshman | 19 | 8.60 |
| | Sophomore | 40 | 18.10 |
| | Junior | 56 | 25.34 |
| | Senior | 106 | 47.96 |
| Major | English/Foreign Languages | 175 | 79.19 |
| | Non-English (Humanities) | 22 | 9.95 |
| | Non-English (STEM) | 24 | 10.86 |
| Self-rated English Proficiency | Weak | 24 | 10.86 |
| | Average | 95 | 42.99 |
| | Moderate | 65 | 29.41 |
| | Good | 28 | 12.67 |
| | Excellent | 9 | 4.07 |

### 4.3. Instrument design

The self-compiled “Multimodal Generative AI-Assisted English Writing Questionnaire for College Students” was used. The questionnaire employed a Likert 5-point scale (1 = strongly disagree, 5 = strongly agree), containing 24 measurement items divided into six parts, such as 1) participants’ demographic information (4 items), 2) MGAIUF (4 items), 3) MGAIFP (4 items), 4) EWLE (4 items), 5) EWCA (4 items), and 6) EWA (4 items).

## 4.4. Data collection and analysis

Data collection was conducted electronically using the Wenjuanxing online survey platform (www.wjx.cn), a widely used survey tool in Chinese academic research. The questionnaire was distributed over three weeks. Invitation links were disseminated through university course WeChat groups and email lists targeting students enrolled in English courses across several universities in Guangdong Province, China. Then, 221 valid questionnaires were collected. Simultaneously, data analysis was conducted using SPSS version 25.0 and AMOS version 24.0. Descriptive statistical analysis, reliability and validity testing, and structural equation modeling (SEM) were performed to test the theoretical model and research hypotheses.

# 5. Results

## 5.1. Reliability and validity test results

As shown in **Table 2**, the reliability of the measurement instrument was assessed using Cronbach's α coefficient for each dimension and the total scale. The MGAIUF dimension, consisting of 4 items, demonstrated good internal consistency with a Cronbach's α of 0.849. The MGAIFP dimension (4 items) showed excellent reliability with α = 0.912, while the EWLE dimension (4 items) also exhibited strong reliability at α = 0.890. The EWCA) dimension achieved the highest reliability among the subscales at α = 0.915, and the EWA dimension demonstrated solid internal consistency with α = 0.899. Notably, the total scale, comprising all 20 measurement items, yielded an outstanding Cronbach's α coefficient of 0.958, indicating excellent overall reliability. These values all substantially exceed the commonly accepted threshold of 0.70, suggesting that the questionnaire possesses strong internal consistency and that the items within each dimension reliably measure their respective underlying constructs.

**Table 2.** Reliability Test Results (N = 221)

| Dimension | Number of Items | Cronbach's α Coefficient |
|---|---|---|
| MGAIUF | 4 | 0.849 |
| MGAIFP | 4 | 0.912 |
| EWLE | 4 | 0.890 |
| EWCA | 4 | 0.915 |
| EWA | 4 | 0.899 |
| Total Scale | 20 | 0.958 |

Meanwhile, Confirmatory Factor Analysis (CFA) was employed by means of AMOS version 24.0 to verify the construct validity of the scale. As **Table 3** shows, the model fit indices indicate an acceptable to good fit between the hypothesized model and the observed data. For example, the CMIN/DF value is 2.410, falling within the recommended range of 1 to 3 for an excellent fit. The RMSEA is 0.074, which is below the 0.08 threshold for a good fit. Additionally, the incremental fit indices—IFI (0.939), TLI (0.927), and CFI (0.938)—all exceed the 0.9 criterion for an excellent fit, all suggesting that the measurement model is well-specified.

**Table 3.** Model Fit Test Results (N = 221)

| Indicator | ReferenceStandard | Result |
|---|---|---|
| CMIN/DF | Excellent (1-3), Good (3-5) | 2.410 |
| RMSEA | Excellent ( < 0.05)，Good ( < 0.08) | 0.074 |
| IFI | Excellent ( > 0.9)，Good ( > 0.8) | 0.939 |
| TLI | Excellent ( > 0.9)，Good ( > 0.8) | 0.927 |
| CFI | Excellent ( > 0.9)，Good ( > 0.8) | 0.938 |

Meanwhile, **Table 4** presents the convergent validity and composite reliability (CR) results for each dimension of the scale. All factor loadings for the five dimensions—MGAIUF, MGAIFP, EWLE, EWCA, and EWA—exceed the recommended threshold of 0.70, ranging from 0.724 to 0.888, confirming each item adequately represents its respective construct. The average variance extracted (AVE) values are from 0.590 to 0.731 (all surpassing the acceptable cutoff of 0.50), and the composite reliability (CR) values range from 0.852 to 0.916 (exceeding the recommended threshold of 0.70). These findings collectively demonstrate that the five dimensions exhibit satisfactory convergent validity and internal consistency reliability, supporting the adequacy of the measurement model.

**Table 4.** The Results of Convergent Validity and Composite Reliability (CR) (N = 221)

| Path Relationship | | | Estimate | AVE | CR |
|---|---|---|---|---|---|
| MGAIUF4 | < --- | MGAIUF | 0.724 | 0.590 | 0.852 |
| MGAIUF3 | < --- | MGAIUF | 0.791 | | |
| MGAIUF2 | < --- | MGAIUF | 0.771 | | |
| MGAIUF1 | < --- | MGAIUF | 0.785 | | |
| MGAIFP4 | < --- | MGAIFP | 0.888 | 0.725 | 0.913 |
| MGAIFP3 | < --- | MGAIFP | 0.873 | | |
| MGAIFP2 | < --- | MGAIFP | 0.823 | | |
| MGAIFP1 | < --- | MGAIFP | 0.820 | | |
| EWLE4 | < --- | EWLE | 0.873 | 0.673 | 0.891 |
| EWLE3 | < --- | EWLE | 0.814 | | |
| EWLE2 | < --- | EWLE | 0.819 | | |
| EWLE1 | < --- | EWLE | 0.771 | | |
| EWCA4 | < --- | EWCA | 0.876 | 0.731 | 0.916 |
| EWCA3 | < --- | EWCA | 0.854 | | |
| EWCA2 | < --- | EWCA | 0.842 | | |
| EWCA1 | < --- | EWCA | 0.848 | | |
| EWA4 | < --- | EWA | 0.874 | 0.698 | 0.902 |
| EWA3 | < --- | EWA | 0.863 | | |
| EWA2 | < --- | EWA | 0.788 | | |
| EWA1 | < --- | EWA | 0.813 | | |

What is more, **Table 5** also manifests the discriminant validity results for the five variables: MGAIUF, MGAIFP, EWLE, EWCA, and EWA. The diagonal elements (in bold) represent the square root of the average variance extracted (√AVE) for each construct, with values ranging from 0.768 to 0.855. These values are all greater than the corresponding off-diagonal inter-construct correlations (which range from 0.288 to 0.495), thereby satisfying the Fornell-Larcker criterion for discriminant validity. In other words, these results support that each construct is distinct from the others while demonstrating adequate convergent validity.

**Table 5.** Discrimination Validity Test Results (N = 221)

| Variable | MGAIUF | MGAIFP | EWLE | EWCA | EWA |
|---|---|---|---|---|---|
| MGAIUF | 0.590 | | | | |
| MGAIFP | 0.397 | 0.725 | | | |
| EWLE | 0.288 | 0.378 | 0.673 | | |
| EWCA | 0.334 | 0.355 | 0.421 | 0.731 | |
| EWA | 0.495 | 0.277 | 0.310 | 0.314 | 0.698 |
| √AVE | 0.768 | 0.851 | 0.820 | 0.855 | 0.835 |

## 5.2. Normality test results

**Table 6** shows the descriptive statistics and normality test results for each dimension of the scale. For the five dimensions—EWLE, EWCA, EWA, MGAIUF, and MGAIFF—the mean values range from 3.611 to 3.956, with standard deviations ranging from 0.749 to 0.831, indicating moderate levels of central tendency and variability across respondents. Regarding univariate normality, the skewness values for all dimensions are from -0.678 to -0.202, and the kurtosis values range from 0.162 to 1.510. All absolute skewness values are below the common threshold of 3, and all absolute kurtosis values are below the common threshold of 10, suggesting that the data for each dimension approximately follow a univariate normal distribution. These results support the use of maximum likelihood estimation in subsequent structural equation modeling (SEM).

**Table 6.** Normality Test Results (N = 221)

| Variable | Mean | Standard Deviation | Skewness | Kurtosis |
|---|---|---|---|---|
| EWLE | 3.611 | 0.831 | -0.202 | 0.271 |
| EWCA | 3.691 | 0.831 | -0.318 | 0.162 |
| EWA | 3.786 | 0.779 | -0.474 | 0.543 |
| MGAIUF | 3.884 | 0.749 | -0.678 | 1.510 |
| MGAIFP | 3.956 | 0.761 | -0.638 | 1.215 |

## 5.3. Results of correlation analysis

**Table 7** presents the results of the correlation analysis among the five variables—MGAIUF, MGAIFP, EWLE, EWCA, and EWA—based on a sample of 221 respondents. All inter-variable correlations are positive and statistically significant at the 0.01 level (2-tailed), with coefficients ranging from 0.564 to 0.838. For instance, MGAIUF shows strong correlations with MGAIFP ($r = 0.801$), and moderate correlations with EWLE ($r = 0.599$), EWCA ($r = 0.564$), and EWA ($r = 0.613$). Similarly, MGAIFP exhibits strong correlations with MGAIUF ($r = 0.801$) and moderate correlations with EWLE ($r = 0.607$), EWCA ($r = 0.604$), and EWA ($r = 0.617$). Among the variables, the strongest correlation is observed between EWCA and EWA ($r = 0.838$), while the weakest yet still significant correlation is between MGAIUF and EWCA ($r = 0.564$). These results demonstrate that all five variables are positively associated, providing preliminary evidence for the absence of multicollinearity concerns while also indicating that the constructs are related but distinct.

**Table 7.** Results of Correlation Analysis (N = 221)

| Variable | MGAIUF | MGAIFP | EWLE | EWCA | EWA |
|---|---|---|---|---|---|
| MGAIUF | 1 | | | | |
| MGAIFP | 0.801** | 1 | | | |
| EWLE | 0.599** | 0.607** | 1 | | |
| EWCA | 0.564** | 0.604** | 0.738** | 1 | |
| EWA | 0.613** | 0.617** | 0.715** | 0.838** | 1 |

** Correlation is significant at the 0.01 level (2-tailed).

## 5.4. SEM results

### 5.4.1. Model fit indices

**Table 8** presents the model fit test results for a sample of 221 participants. All key indicators suggest a good to excellent model fit. Namely, the CMIN/DF value is 2.021 (falling within the excellent range of 1-3), the RMSEA is 0.068 (indicating good fit), and the IFI (0.946), TLI (0.959), and CFI (0.913) all exceed the excellent threshold of 0.90. By and large, the results demonstrate that the measurement model meets or exceeds recommended standards.

**Table 8.** Model Fit Test Results (N = 221)

| Indicator | Reference Standard | Result |
|---|---|---|
| CMIN/DF | Excellent (1-3), Good (3-5) | 2.021 |
| RMSEA | Excellent ( < 0.05), Good ( < 0.08) | 0.068 |
| IFI | Excellent ( > 0.9), Good ( > 0.8) | 0.946 |
| TLI | Excellent ( > 0.9), Good ( > 0.8) | 0.959 |
| CFI | Excellent ( > 0.9), Good ( > 0.8) | 0.913 |

### 5.4.2. Results of path relationship and hypothesis test

**Table 9** and **Figure 2** display the results of SEM path analysis, including standardized estimates, standard errors (S.E.), critical ratios (C.R.), and p-values for each hypothesized relationship. The findings indicate that MGAIUF has a strong positive effect on EWLE (Estimate = 0.687, C.R. = 6.063, $p < 0.001$) and a moderate positive effect on EWCA (Estimate = 0.473, C.R. = 6.442, $p < 0.001$). Similarly, MGAIFP positively influences EWLE (Estimate = 0.189, C.R. = 3.174, $p < 0.01$) and EWCA (Estimate = 0.375, C.R. = 5.738, $p < 0.001$). Regarding the predictors of EWA, EWCA exhibits a strong positive impact (Estimate = 0.730, C.R. = 9.467, $p < 0.001$), while EWLE shows a weaker but still significant positive effect (Estimate = 0.176, C.R. = 2.423, $p < 0.05$). However, the direct paths from MGAIUF (Estimate = 0.123, C.R. = 1.520, $p > 0.05$) and MGAIFP (Estimate = 0.024, C.R. = 0.459, $p > 0.05$) to EWA are not statistically significant, suggesting that EWLE and EWCA fully mediate the effects of the two incentive types on willingness to pay.

In the meantime, based on the results presented in Table 9, six of the eight research hypotheses (H1-H8) are supported. Specifically, H1 (MGAIUF→EWLE), H2 (MGAIUF→EWCA), H3 (MGAIFP→EWLE), and H4 (MGAIFP→EWCA) are all supported, with significant positive effects ($p < 0.01$ or $p < 0.001$). H5 (EWLE→EWA) and H6 (EWCA→EWA) are also supported, with EWCA showing a particularly strong positive impact (Estimate = 0.730, $p < 0.001$) and EWLE showing a weaker but still significant effect (Estimate = 0.176, $p < 0.05$). However, H7 (MGAIUF→EWA) and H8 (MGAIFP→EWA) are not supported, as both direct paths to EWA are statistically non-significant ($p > 0.05$). These findings indicate that EWLE and EWCA fully mediate the effects of MGAIUF and MGAIFP on EWA.

**Table 9.** Results of Path Relationship and Hypothesis Test (N = 221)

| Path Relationship | | | Estimate | S.E. | C.R. | P | Hypothesis Test |
|---|---|---|---|---|---|---|---|
| EWLE | < --- | MGAIUF | 0.687 | 0.050 | 6.063 | *** | H1 (Valid) |
| EWCA | < --- | MGAIFP | 0.375 | 0.064 | 5.738 | *** | H2 (Valid) |
| EWLE | < --- | MGAIFP | 0.189 | 0.063 | 3.174 | 0.002 | H3 (Valid) |
| EWCA | < --- | MGAIUF | 0.473 | 0.097 | 6.442 | *** | H4 (Valid) |
| EWA | < --- | EWLE | 0.176 | 0.058 | 2.423 | 0.015 | H5 (Valid) |
| EWA | < --- | EWCA | 0.730 | 0.068 | 9.467 | *** | H6 (Valid) |
| EWA | < --- | MGAIFP | 0.024 | 0.045 | 0.459 | 0.646 | H7 (Invalid) |
| EWA | < --- | MGAIUF | 0.123 | 0.094 | 1.520 | 0.129 | H8 (Invalid) |

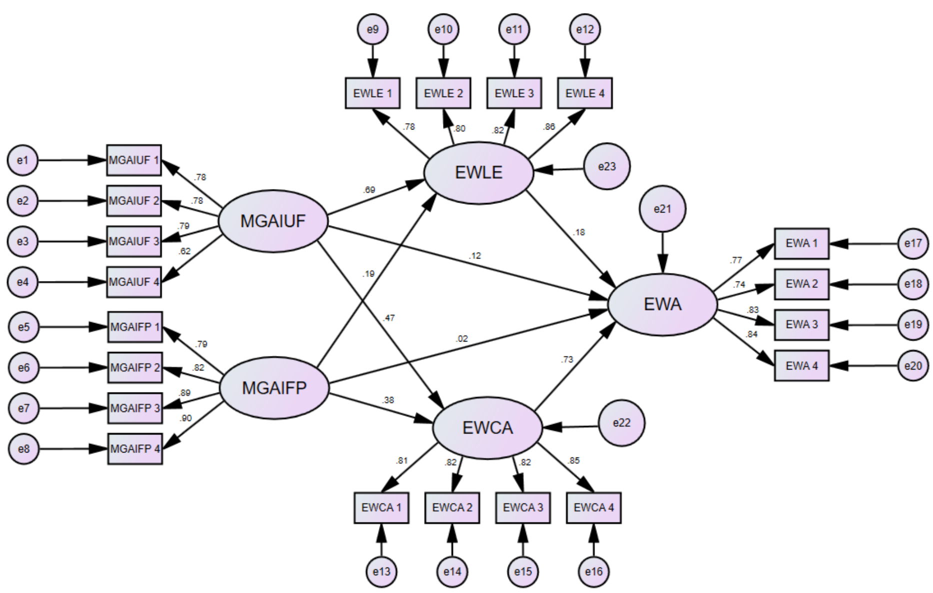


**Figure 2.** The SEM Path Diagram of Measurement Model (N = 221).

As for research hypotheses H9, H10, H11 and H12, **Table 10** reveals the results of the Bootstrap analysis (5, 000 resamples) used to test the indirect effects in the four hypothesized mediating paths (H9-H12). All four indirect effects are significant, as none of the 95% confidence intervals contain zero, proving that the four hypothesized mediating effects are supported. The total mediating effect is also significant, with a value of 0.773 and a confidence interval of [0.187, 1.569].

**Table 10.** Mediation effect Bootstrap Test Results (N = 221)

| Mediating Path | Indirect Effect | SE | 95% Confidence Interval | Significant |
|---|---|---|---|---|
| MGAIUF→EWLE→EWA (H9) | 0.121 | 0.087 | [0.064, 0.433] | Yes |
| MGAIFP→EWLE→EWA (H10) | 0.033 | 0.091 | [0.025, 0.351] | Yes |
| MGAIUF→EWCA→EWA (H11) | 0.345 | 0.089 | [0.082, 0.452] | Yes |
| MGAIFP→EWCA→EWA (H12) | 0.274 | 0.090 | [0.016, 0.333] | Yes |
| Total Mediating Effect | 0.773 | 0.357 | [0.187, 1.569] | Yes |

# 6. Discussion

## 6.1. The Relationships among MGAIUF, MGAIFP, EWLE, EWCA and EWA

The present study explored the mechanisms through which MGAI enhances college students' EWA. The findings provide empirical support for the proposed theoretical framework and offer new insights into the role of AI-assisted learning in English writing instruction.

First, the results indicate that both MGAIUF and MGAIFP significantly and positively influence EWLE and EWCA. This finding confirms Hypotheses H1–H4 and suggests that students who frequently use MGAI tools and perceive these tools as useful are more likely to actively participate in English writing activities and develop positive writing attitudes. This result is consistent with Wang and Ren (2024), who found that GenAI can support idea generation, language refinement, and writing revision, thereby increasing students' willingness to engage in writing tasks [1]. It also supports the findings of Tiandem-Adamou (2024), who reported that AI-assisted writing environments can improve learners' motivation and participation in EFL writing contexts [2]. From the perspective of SDT, MGAI satisfies learners' needs for autonomy and competence through personalized support and immediate feedback, which subsequently promotes engagement and positive learning attitudes [24].

Second, the study demonstrates that both EWLE and EWCA positively affect EWA, supporting Hypotheses H5 and H6. Notably, EWCA exerts a much stronger effect on EWA than EWLE. This finding suggests that affective factors, particularly writing confidence and positive attitudes, play a crucial role in students' writing development. According to Pintrich (2003), learners' beliefs about their abilities significantly influence their learning behaviors and academic performance [25]. Similarly, Fredricks et al. (2004) argued that emotional engagement is an important predictor of learning outcomes [26]. Thus, students who feel confident and motivated in writing are more likely to invest effort in drafting, revising, and improving their written work, which ultimately contributes to higher writing proficiency.

Third, contrary to expectations, the direct effects of MGAIUF and MGAIFP on EWA were not statistically significant. Consequently, Hypotheses H7 and H8 were rejected. This finding indicates that the mere use of AI technologies does not automatically improve writing ability. Instead, the educational effectiveness of MGAI depends on how students engage with the learning process and whether they develop positive attitudes toward writing. This result supports Chapelle's (2009) argument that technology itself does not directly determine language learning outcomes; rather, its influence is mediated through learners' interactions, engagement, and learning behaviors [22]. In other words, AI functions as a learning facilitator rather than a direct determinant of writing achievement.

Finally, the mediation analysis confirmed that both EWLE and EWCA significantly mediate the relationship between MGAI and EWA. The mediating effects of EWCA were stronger than those of EWLE, suggesting that confidence and attitudes constitute the most important pathway through which MGAI improves writing ability. This finding is consistent with Kahu's (2013) student engagement framework, which emphasizes that educational technologies influence learning outcomes through students' psychological and behavioral engagement [27]. The results also support Han and Hyland's (2019) view that learners' engagement with feedback plays a decisive role in writing improvement [28]. Therefore, the effectiveness of MGAI lies not only in its technological capabilities but also in its capacity to enhance students' motivation, confidence, and active participation in the writing process.

### 6.2. Implications for English writing instruction

The findings of this study provide several important implications for English writing instruction in colleges and universities.

Firstly, it is urgent for English writing teachers to integrate MGAI tools into classroom teaching and writing practice actively. Rather than viewing AI solely as a technological innovation, educators should regard it as a pedagogical resource that can provide students with immediate feedback, writing suggestions, vocabulary support, and idea generation assistance. Through appropriate instructional design, AI technologies can complement traditional teacher feedback and create a more interactive writing environment.

Secondly, teachers need to focus on enhancing students' writing confidence and positive attitudes when implementing AI-assisted writing activities. Since EWCA was found to be the strongest predictor of EWA, instructional practices should emphasize confidence building, encouragement, and positive writing experiences. Teachers can guide students to use AI tools as learning partners rather than replacement writers, helping them develop a sense of achievement and self-efficacy throughout the writing process.

Thirdly, educators need to encourage active learning engagement when using MGAI. Students should not merely accept AI-generated outputs passively but should critically evaluate, revise, and improve the suggestions provided by AI systems. Writing tasks can be designed to promote interaction between students and AI tools through drafting, peer review, reflection, and revision activities. Such practices may strengthen students' cognitive and behavioral engagement and facilitate deeper learning.

Fourthly, colleges and universities should establish clear guidelines for the ethical and responsible use of GenAI in academic writing. Although AI technologies offer substantial educational benefits, concerns related to academic integrity, plagiarism, and excessive dependence should not be ignored. Institutions need to provide training programs that help students understand both the opportunities and limitations of AI-assisted writing and develop responsible AI literacy.

Lastly, considering incorporating AI literacy and multimodal writing competence into English writing courses is vital for curriculum designers. As GenAI becomes increasingly prevalent in educational and professional settings, students need to develop the ability to effectively utilize AI technologies while maintaining critical thinking, creativity, and independent writing skills. Such an approach will better prepare learners for academic study and future workplace communication in the era of AI.

## 7. Conclusion

### 7.1. Summary of key findings

This study investigated the impact of MGAI on college students' EWA by constructing a structural equation model based on MLT, Student Engagement Theory (SET), and SDT. Specifically, the study examined the relationships among MGAIUF, MGAIFP, EWLE, EWCA, and EWA. Using data collected from 221 Chinese university students, the proposed model was empirically tested through SEM.

The findings unveil several important conclusions. First, both MGAIUF and MGAIFP significantly and positively influence students' WELE and EWCA. This suggests that frequent use of MGAI tools and positive perceptions of their functions can effectively enhance students' engagement in writing activities and foster more positive attitudes toward English writing. Second, both EWLE and EWCA significantly contribute to the improvement of EWA. Among these factors, EWCA demonstrates the strongest predictive effect, indicating that writing confidence and positive attitudes play a particularly important role in writing development. Third, the direct effects of MGAIUF and MGAIFP on EWA are not statistically significant, suggesting that the impact of MGAI on writing ability is primarily indirect rather than direct. Finally, the mediation analysis confirms that EWLE and EWCA fully mediate the relationship between MGAI and EWA, with EWCA exhibiting the strongest mediating effect. These findings indicate that the effectiveness of MGAI depends largely on its ability to enhance students' learning engagement, confidence, and positive attitudes toward writing.

## 7.2. Limitations and future research directions

Despite its theoretical and practical contributions, this study has several limitations that should be acknowledged.

In the first place, the study employed a cross-sectional survey design, which limits the ability to establish causal relationships among the variables. Although the structural equation model provides evidence of significant associations and mediating mechanisms, longitudinal and experimental studies are needed to further verify the causal effects of MGAI on English writing development.

In the second place, the sample consisted of 221 university students primarily from Guangdong Province, China. Although the sample size met the requirements for SEM analysis, the geographical concentration and convenience sampling approach may limit the generalizability of the findings. Future research should include participants from different regions, universities, and educational backgrounds to improve external validity.

In the third place, all variables were measured using self-reported questionnaires. While the reliability and validity tests demonstrated satisfactory measurement quality, self-reported data may be influenced by social desirability bias and subjective perceptions. Future studies may incorporate objective measures of English writing performance, classroom observations, writing portfolios, and AI usage records to provide more comprehensive evidence.

In the fourth place, this study focused primarily on learning engagement and writing confidence and attitude as mediating variables. Other potentially important factors, such as AI literacy, self-regulated learning, critical thinking ability, writing anxiety, technology acceptance, and digital competence, were not included in the current model. Future studies may explore more complex mediating and moderating mechanisms to understand better how MGAI influences English writing outcomes.

Last but not least, as GenAI technologies continue to evolve rapidly, future research should examine the educational effectiveness of emerging multimodal AI tools across different writing genres, instructional contexts, and learner proficiency levels. Comparative studies involving different AI platforms, such as ChatGPT, Gemini, DeepSeek, Kimi, and Doubao, may also provide valuable insights into the differential effects of AI-assisted writing support.

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## Disclosure statement

The authors declare no conflict of interest.

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