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Perceived Influence of AI-mediated Tools on Writing Autonomy among Non-English Major University Students

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ABSTRACT: *Artificial intelligence (AI) has become increasingly prevalent in today's world, transforming the landscape of worldwide education in recent years. A large body of research has delved into the implementation of AI in educational contexts as well as its effect on teaching and learning outcomes, especially in foreign language education. This paper aims to examine AI's influence on non-English major students' autonomous writing, focusing on behavioural dimensions derived from Zimmerman's model of self-regulated learning (Zimmerman, 1989), including goal setting, planning, self-monitoring, and self-assessment. To collect data for analysis, a survey was carried out among non-English major students across several universities in Ho Chi Minh City. Data were analysed using correlation and multiple regression to examine the relationship between students' engagement with AI and different dimensions of writing autonomy. Despite its reliance on self-reported data, the findings revealed a strong positive association between AI engagement and learners' autonomy in self-assessment, while the reverse was true for the other constructs of autonomy: goal setting, planning, and self-monitoring, with perceived autonomy in planning showing the strongest negative association with AI engagement.*

KEYWORDS: Artificial intelligence, autonomy, self-regulated learning, non-English major.

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1. Introduction

Although a growing body of research has explored its capability and the use of AI-assisted tools in education, the role of AI in teaching and learning still remains at the heart of discussion. In a globalization era, language learning has become more crucial than ever, and learning experience has also improved thanks to the integration of AI. However, there have been conflicting reports on the effects of AI on learners' autonomy, i.e., whether the use of AI improves or compromises learners' agency in learning. While several studies have examined the effectiveness of AI on teaching and learning English in general, few studies manage to provide a closer look into how AI helps shape learners' writing autonomy. This gap is largely due to the complex and multi-dimensional nature of writing autonomy itself. Moreover, isolating the impact of AI on writing autonomy, without conflating it with overall writing proficiency, may present a challenge to researchers. The paper, therefore, seeks to address this gap and shed light on the association between engagement with AI tools and writing autonomy among non-English major students, considering learners' perspective on different dimensions, including planning, goal setting, self-monitoring, and self-assessment.

2. Literature Review

2.1. Autonomy and Writing Autonomy

2.1.1. Learner's Autonomy

Learner's autonomy is a broad term that encompasses different meanings and interpretations, both in theory and in practice (Benson, 2013; Oxford, 2003; Palfreyman, 2003). However, it is commonly defined as the ability of learners to take control of their own learning, which involves making related decisions, carrying out tasks, and proceeding adaptation when necessary (Dickinson, 1987, as cited in Horwitz, 1989; Holec, 1981, as cited in Némethová, 2020; Littlewood, 1996). This definition, despite giving an overview of autonomy by highlighting

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learners' independence, rather than reliance on external sources of instruction, fails to shed light on what factors contribute to autonomy, and the process involved to achieve that.

Examining autonomy from its multifaceted dimensions, some researchers perceived autonomy as the process of shaping psychological reaction to their learning, such as critical reflection and decision making (Little, 1996). In contrast, Gardner and Miller (as cited in Ersoy & Çetin, 2023), while acknowledging psychological outcome such as self-evaluation skills as part of autonomy, suggested that this 'fuzzy' concept can actually be measured by a rather tangible, observable sets of behaviour. According to the researchers, an autonomous learner knows why they learn what they learn, is able to identify defects in their learning and proactively take measures to compensate for such deficiencies.

Similarly, however, with a more structured approach to the concept, Schunk and Zimmerman (as cited in Boekaerts *et al*., 1999) suggested a model of self-regulated learning (SRL), characterizing it based on both psychological and behavioural dimension. In this respect, there are three phases of SRL: the forethought phrase when learners formulate their aims and make plan accordingly; the performance phase during which learners conduct the task; and self-reflection phase during which learners assess task alignment with original goals, the effectiveness of the selected strategies, and make adjustment for improved accuracy. Building on the current literature, especially Zimmerman and Schunk's framework of self-regulated learning, metacognitive awareness, a less observable construct, evidently underlies all of the behavioural expressions through which learners' autonomy is manifested, namely goal setting, planning, self-monitoring, and self-assessment. Despite its crucial role in shaping learners' autonomy, metacognitive awareness is excluded from the investigation, primarily due to its less observable nature and the risk of bias from self-reported data.

In the light of all the aforementioned views, learners' autonomy can be comprehensively defined as:

- having the required self-motivation and self-directed belief in their ability and the task, as well as the underlying cognitive foundation that allows task performance to occur;
- their ability to perform independently in different phases of task execution, typically involving goal setting, planning, and self-monitoring;
- their ability to reflect on themselves and the task to assess the degree to which the task has been achieved, and more importantly, what needs improving for future growth.

However, expanded the concept of autonomy might be, this paper seeks to consider it in its narrow term, which equates autonomy with the ability to perform different phases of a task independently of any external support. The ability to autonomously seek necessary help is also worth looking into, nonetheless, it leaves room for huge questions concerning how much support the learners need, as well as how much they rely on these sources of support. With that in mind, help-seeking behaviours, while acknowledged in the literature, do not fall into the scope of the current investigation.

2.1.2. Writing Autonomy

Learner's autonomy is reflected, and desired, across different skills: listening, reading, speaking, and writing. This paper will, specifically, examine learners' autonomy in writing. Although autonomy is typically examined from a wide range of perspectives, ranging from cognitive, social-behavioural, to affective dimensions, this study will look at autonomy under four distinct constructs: goal setting, planning, self-monitoring, and self-assessment. This perfectly aligns with the self-regulated cyclical model suggested by Zimmerman (1989) that emphasizes three phases involved in autonomous learning, namely forethought, performance, and self-reflection. Some researchers even incorporate psychological components into the concept of autonomy, particularly motivation and self-belief, which shapes learners' choices, persistence, and engagement in self-regulated learning (Fan & Wang, 2024; Pintrich, 2000). However, motivation, though extremely important, is a sophisticated factor that requires differentiation between its sub-categories, such as intrinsic and extrinsic, task-specific and general. Such clarification would necessitate drawing on various psychology-related theories, including expectancy-value theory and attribution theory, and would, therefore, not only complicate the study but also potentially dilute the research's focus. The four selected constructs that represent the cognitive and behavioural dimensions of writing autonomy, namely goal setting, planning, self-monitoring, and self-assessment, will be explained in the part that follows.

- Goal setting

Goal setting is the first and foremost step of the writing process and is shown to have significant effects on their learning outcome, as goals motivate learners to make necessary effort to attain them (Schunk, 2003). At this stage, students identify what they intend to, and are required to, achieve in their writing, across different aspects that typically include task content fulfilment, the targeted skills to be enhanced, as well as strategy selection and evaluation. They also assess the feasibility of their goals given their strengths, weaknesses and the sources of support available (Bloom, 2013).

- Planning

Planning is an integral component of the forethought phase in the self-regulated learning model by Zimmerman (1989). At this stage, students make plans to help realize their goal, including visualizing different steps, breaking tasks into transitional stages, selecting appropriate strategy, preparing intended linguistic medium, and foreseeing possible problems and how to overcome them (Adler *et al.*, 2025). In order to plan effectively, it is necessary that learners' metacognitive awareness is activated.

- Self-monitoring and self-assessment

As these two concepts often cause confusion as one may be seen as part of the other, let us make a side-by-side presentation of self-monitoring and self-assessment. Self-monitoring can be understood as learners' ability to control their own writing progress, which involves on-going evaluating their goal during composition and making necessary adjustments. Self-assessment, on the other hand, is the comprehensive evaluation of themselves after each individual task, and over a period of time (Eva & Regehr, 2011). In general, self-monitoring is characterized by its circumstantial nature, referring to on-the-moment response to perceived limitations and task requirements during composition while self-assessment focuses on how learners cumulatively see their growth and progress over time (Boekaerts *et al.*, 1999; Zimmerman, 1989).

2.2. Previous Studies into Artificial Intelligence and Its Role in Language Learning

2.2.1. Artificial Intelligence and Language Learning

Artificial intelligence (AI) and its various applications have become one of the most prolific fields of research during the past few years. However, the notion of AI is still subjected to great controversy. In a broad term, AI can be defined as any technique that allows computers and other similar machines to replicate human's cognition and behaviour, in order to conduct complicated tasks and proceed with problem-solving. AI technologies, considered in the educational context, have been found to influence language learning in various ways, across different skills including reading, writing, speaking, and listening (Huang *et al.*, 2023). According to Zhu and Wang (2025), the variety of AI tools can be overwhelming, ranging from "bots (such as chatbots, robots, and so forth), machine translation, automatic speech recognition, and intelligent systems."

2.2.2. Artificial Intelligence and How It Affects Writing Autonomy

Over the past few years, AI has been increasingly integrated into the teaching and learning of writing skills. A number of empirical studies have suggested that AI has positive impacts on students' overall writing performance by providing them with instant, personalized feedback regarding different language aspects and facilitating idea generation process. Experiment and survey-based studies have reported that AI interventions are associated with students' advancements in grammar and vocabulary accuracy (Karagoz, 2025; Song & Song, 2023).

Beyond linguistic outcomes, several studies have explored the relationship between AI tools and learner autonomy. Building on this, Wang and Li (2024) observed that AI mediated tools have a positive influence on students' willingness for autonomous learning, given perceived usefulness and the level of digital literacy remain high. In a study conducted among Chinese undergraduates, it was discovered that AI assistance not only helps English learners to generate better, more diverse ideas, but also benefits affective aspects of language learning, including writing confidence and self-regulation (Chen & Gong, 2025; Wei, 2023; Zhu & Wang, 2025). However, empirical findings remain inconsistent, with opposing views towards AI's positive role being recorded. Alm (2024) noted that the use of AI may compromise learners' self-control ability and independence in writing as they become overly reliant on AI tool support. Farhan (2025) also shared the view. When looking into the role of AI critically, he warned that the technology can be double-edged as it, once misused, likely hinders learners' ability to write independently. Additionally, although AI helps enhance learners' surface-level accuracy, its instant response means that learners will grow more dependent on AI-facilitated discussion and less willing to discuss in-person with their peers (Bastani *et al.,* 2025). It is also revealed that learners tend to believe AI's recommendations without questioning their relevance and appropriateness, which may in a long run compromise their capability of meaning-negotiation and self-reflection.

To sum up, several attempts have been made to investigate the effects of AI use in language learning across different subskills, with particular attention to writing. However, existing research is largely central on AI intervention and its effects on linguistic outcomes, while autonomy-centric dimensions are rather underexamined. In addition, most studies about AI and language learning focus on examining AI's influence on different specifications of writing skills while overlooking the factors that help drive learners towards learning autonomy, like goal setting, planning, and self-assessment. More importantly, research into whether AI benefits or hinders students' autonomy has showed considerable controversy. The certainty is even less evident in Vietnam when AI tools are used indiscriminately in higher-education settings but research results on how they affect students' autonomy remains mixed (Nguyen, 2025). In the light of this, the current study seeks to answer the following question:

1. Do students' frequency and depth of AI-tool use likely improve writing autonomy of non-English majors in Ho Chi Minh City?

2. Which dimensions of writing autonomy, goal-setting, planning, self-monitoring, and self-assessment, are most strongly affected by AI-tool engagement?

In order to answer the two questions, 4 hypotheses were proposed and tested:

H1: AI use frequency and depth of engagement likely improves learners' writing autonomy in goal setting.

H2: AI use frequency and depth of engagement likely improves learners' writing autonomy in planning.

H3: AI use frequency and depth of engagement likely improves learners' self-monitoring in writing.

H4: AI use frequency and depth of engagement likely improves learners' self-assessment in writing.

3. Methodology

3.1. Research Design

The current research seeks to determine whether the use of AI tools enhances or hinders university students' writing autonomy. To achieve this, a quantitative design was carried out. An online questionnaire, created through Google Form, was administered to 178 non-English majors from different universities in Ho Chi Minh City who have experienced AI integration in writing as part of their English course, regardless of genres, types of assignments, and of the learning context, i.e., at their school's department or from external language centres. The majority of them were enrolled at Ton Duc Thang University (TDTU) and University of Foreign Languages and Information Technology (HUFLIT). Both of the institutions are interdisciplinary schools that have internal units to provide non-English majors with General English courses.

Regarding sampling procedure, a non-probability convenience sampling approach was employed, by which the survey reached the participants mostly via social media - the researcher invited social media users who meet a predefined set of criteria to take part. Lecturers from the two universities in Ho Chi Minh City, TDTU and HUFLIT, also assisted in distributing the survey to their students. Though acknowledging certain limitations of non-probability convenience sampling, especially possible bias and limited representativeness, we chose this sampling approach as our study targeted university students with prior experience with AI tools, which is challenging to identify through standard probability sampling.

In terms of survey, it was designed to collect students' self-perceived responses, with seven main sections. Across all sections B to G, the participants were instructed to rate their responses using Likert scale 1 to 5 from strongly disagree to strongly agree, based on their own perception of the item being surveyed.

Section A collects the study's demographic information. Sections B and C are devoted to measuring the two predictors, AI usage frequency and Depth of AI engagement. Similarly, sections D through G each capture data on the 4 autonomy aspects: goal setting, planning, self-monitoring and self-assessment. These measures reflect learners' self-perception of how AI usage influences their autonomy, viewed through the lens of self-regulated learning (Zimmerman, 1989).

3.2. Data

The raw dataset underwent a rigorous cleaning process, including the removal of missing values and incomplete responses, resulting in a final sample of 172 observations. Overall, the sample spreads across 4 age groups, 2 genders, 22 university majors, and 4 stages of exposure to English learning measured by the participant's number of years studying English.

Regarding these demographic characteristics, they were formally coded for hypothesis testing purposes throughout the study. To maintain simplicity and parsimony, Age group and Years of study English were ordered linear coded and treated as numeric reflecting their ordinal nature and approximate natural progression. Particularly, the age groups of 18-20; 20-22; 22-24; 24-26 were coded from 1 to 4 respectively, with higher value indicating older age group. Likewise, years of studying English were coded from 1 to 4, with 1 = <1 year; 2 = 1-3 years; 3 = 3-6 years and 4 = >6 years, reflecting increasing exposure to English learning.

The remaining two demographic dimensions Gender and University major were dummy coded. Gender was assigned as Male = 0 and Female = 1. University majors were classified into two groups, namely writing-intensive (coded 1) and non-writing intensive (coded 0). Writing intensive fields included disciplines such as Business, Law, Marketing whereas the latter included Engineering, Electronics, and Construction.

Sample Characteristics

Overall, more than 70% of participants belonged to Age group 1 18 – 20, whereas those aged 24-26 only made up just above 5 % of the total respondents. The duration of English learning also varied considerably among the participants, with 62% of respondents reported longer than 6 years exposure, followed by 22% with immediate exposure 1 - 3 year, the rest combined accounted for a mere 15% of the total sample. Noticeably, the gender distribution indicates female predominance in the study, with a female-to-male ratio of nearly 2:1. It is also noteworthy that students majoring in writing-intensive fields constituted the largest proportion of the sample (65%), while the remaining 35% came from non-writing-intensive majors. Given these demographic imbalances, they were assessed for inclusion as control variables in the regression model. Further details on the control variable selection process shall be provided following the introduction of the main study variables.

Regarding the main variables, the subscales under predictors and outcome constructs were evaluated for internal consistency using Cronbach's Alpha (α). It is a key statistic that measures how closely related a set of items are as a group. Its coefficient ranges from 0 to 1, with higher values (usually above 0.7) indicating items are strongly correlated and measure the same underlying construct, while lower values mean poor consistency. In this study, the scale-level alpha exceeded 0.8 across all constructs implying excellent reliability, except Depth of AI use which recorded an alpha slightly above 0.7, still considered acceptable. These results substantiated significant internal consistency, meaning the sub-scales effectively capture the same underlying construct. Consequently, a composite score for each construct was computed as the mean of its respective subscales. Descriptive statistics for the main variables are presented below.

Table 1. Descriptive Statistics (N = 172)

Variable (composited)	M	SD	Min	Max
AI_Frequency	3.46	0.84	1.14	5.00
AI_Depth	3.39	0.58	1.73	4.55
Goal Setting	2.90	1.10	1.00	5.00
Planning	2.77	0.98	1.00	5.00
Self-Monitoring	2.64	0.94	1.00	5.00
Self-Assessment	3.36	0.83	1.00	5.00

Note: M = Mean; SD = Standard Deviation; Min = Minimum; Max = Maximum.

AI_ Frequency had a mean of 3.46 with a standard deviation of 0.84, ranging from 1.14 to 5 with higher value representing increasing level of usage frequency. Likewise, regarding AI_Depth the sample mean lied at 3.39 with 0.58 average deviation from the mean. Value ranged from 1.73 to 4.55 representing the acceleration of Depth of AI engagement.

Across the four autonomy dimensions, the mean varied from 2.64 to 3.36 with corresponding standard deviation between 0.83 and 1.1. The observed values spanned from a minimum of 1 (the lowest perceived autonomy) to a maximum of 5 (the highest).

Control Variables

To address control variable selection, we inspected omitted variable bias (OVB) and improvements in model fit. For each regression, one control was added at a time for comparison vs base line model. OVB was assessed by examining the changes in the regression coefficient (Δβ) between controlled and base model. Furthermore, we compared models fit using AIC and BIC; lower values indicate better fit accounting for complexity. Changes in AIC and BIC (ΔAIC, ΔBIC) were used to determine the model fit enhancement between the two models.

Base model (M0):

Autonomy = β0 + β1 AI_Frequency + β2 AI_Depth + ε

Controlled / Augmented model (M1):

Autonomy = β0 + β1 AI_Frequency + β2 AI_Depth + β3 Control ∈ {Age, Gender, Writingintensive, Years of English}

Altogether, across all regression models in the study, Δβ was not statistically significant for both predictors with any single control included, hence no evidence of omitted variable bias issue. However, there were clear model fit improvement in H2 (autonomy in planning) and H4 (autonomy in self-assessment) when Age was controlled for. Other than Age, the rest did not seem to contribute meaningfully to model fit improvement. Therefore, Age is added to H2 and H4 regression equation, while H1 and H3 continued to be tested using the base line model.

3.3. Data Analysis

Correlation:

To examine the relationship between the AI usage (in terms of frequency and depth) and learners' writing autonomy, we first computed the Pearson correlation to form a view on the direction and strength of the relationship. Its value ranged from -1 to 1 representing perfectly negative and positive correlation between the predictor and outcome variables. If Pearson r = 1 and significant at 5%, it signifies that the two variables move in the same direction, in particular, an increase in AI usage correlates with an increase in learner's writing autonomy, and vice versa in case r = -1. If r = 0, no correlation is detected.

Multiple Linear Regressions:

Following correlation results, to further validate the relationship and assess the predictive power of AI usage on autonomy, multiple linear regression model was employed. AI_Frequency and AI_Depth served as predictors, while Autonomy was the outcome variable analysed across four dimensions - goal setting, planning, self-monitoring, and self-assessment, each corresponding to a separate hypothesis. Assumption checks for linear regression are presented in a later section.

As concluded from the control variable selection, H1 and H3 regression was established based on the base line model, while H2 and H4 regression was controlled for Age. Specifically:

H1 and H3:

$$Autonomy = \beta0 + \beta1\ AI\_Frequency + \beta2\ AI\_Depth + \in$$

H2 and H4 regression:

$$Autonomy = \beta0 + \beta1\ AI\_Frequency + \beta2\ AI\_Depth + \beta3\ Age + \in$$

β0 is the estimate of autonomy when all independent variables equal 0, which serves as a mathematical base line rather than bringing meaningful interpretation due to the non-zero nature of all the independent variables in the study. β1 and β2 each represent the association of AI use frequency and Depth of AI engagement with learner's writing autonomy while keeping other variables constant (including Age). β3 reflects the association between Age and writing autonomy, holding others unchanged (only relevant for H2 and H4).

The key assumptions for linear regression include linearity, homoscedasticity, normality of residuals, and absence of multicollinearity. Overall, no evidence of deviation was found.

Firstly, linearity was examined by plotting each of the four autonomy variables against each predictor AI_Frequency and AI_Depth. In all cases, datapoints appeared to scatter reasonably around the fitted straight line which confirmed the linearity assumption. Specifically, a downward trend was observed in all hypotheses except H4 (autonomy in self-assessment) which exhibited an upward trend. Concerning homoscedasticity, residual plots visually showed moderately consistent spread across predicted values, indicating the validity of homoscedasticity. Empirically, Breusch-Pagan test for homoscedasticity in each regression was carried out. The null hypothesis of constant variance of error across all independent variables failed to be rejected at significant level 5% (p-value > 0.05). This further confirmed the assumption of homoscedasticity.

As for the normality assumption, histogram and Q-Q plot for all hypotheses were examined. Each histogram displayed a bell-shaped curve, with the Shapiro-Wilk test yielding p-value greater than 0.05 indicating that the null hypothesis of normality could not be rejected. The residuals therefore appear to approximately followed a normal distribution. This assumption was further validated by the corresponding Q-Q plots in which residuals lied along the 45-degree reference line.

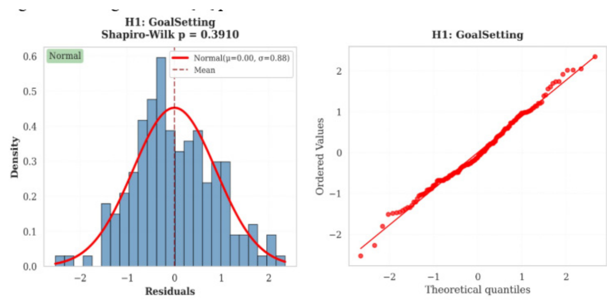


Figure 1. Histogram and Q-Q Plot of Residuals for H1 Regression Model

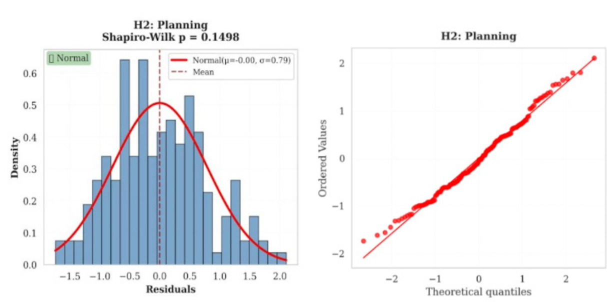


Figure 2. Histogram and Q-Q Plot of Residuals for H2 Regression Model

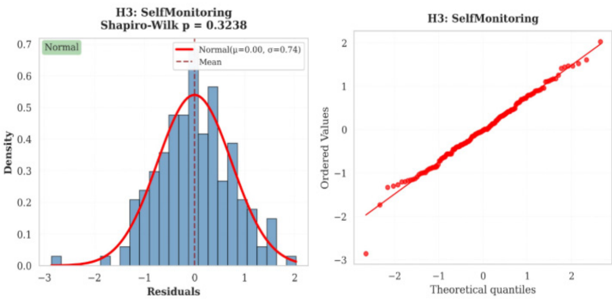


Figure 3. Histogram and Q-Q Plot of Residuals for H3 Regression Model

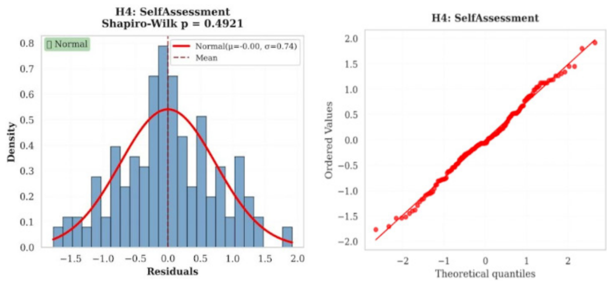
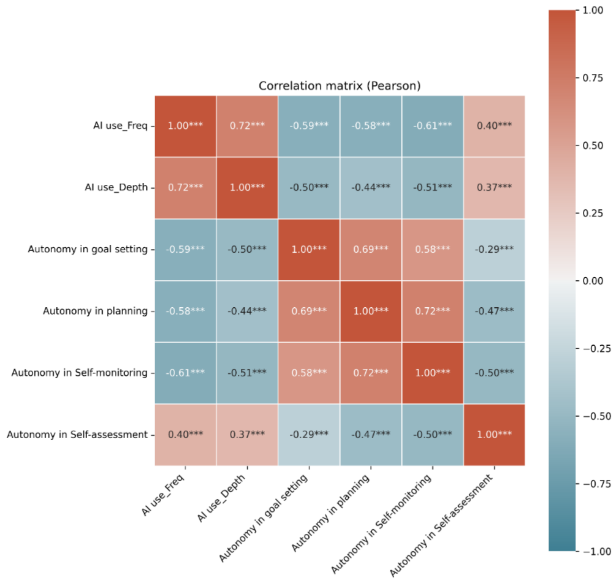


Figure 4: Histogram and Q-Q Plot of Residuals for H4 Regression Model

Lastly, Variance Inflation Factor (VIF) was calculated for AI_Frequency and AI_Depth to verify the absence of multicollinearity between the two predictors. Overall, despite their relatively strong correlation (r=0.72), VIF was just around 2 which is well below the threshold of concern (VIF=5). Therefore, non-multicollinearity assumption was satisfied in all regression models.

Correlation (X,Y)

The Pearson correlation matrix suggests moderate to strong negative relationships between AI usage (both frequency and depth) and autonomy across three dimensions: goal setting, planning, and self-monitoring. Practically, it implies higher AI usage tends to align with lower autonomy in these dimensions, and vice versa. Interestingly, autonomy in self-assessment is the only dimension that demonstrates a positive and significant correlation with both predictors. This implies that higher AI usage tends to correspond with higher perceived autonomy in self-assessment.



*Note: * p<.05, ** p<.01, *** p<.001*

Figure 5. Correlation Matrix Heatmap between AI Usage and Writing Autonomy

4. Results

This section presents the findings regarding the correlation between students' engagement with AI and four aspects of writing autonomy, namely goal setting, planning, self-monitoring, and self-assessment.

H1: AI use frequency and depth of engagement likely improves learner's writing autonomy in goal setting.

To examine whether students' engagement with AI was associated with goal-setting autonomy in writing, a multiple linear regression analysis was conducted. According to table 2, the overall regression model was statistically significant, $F(2, 169) = 46.57$, $p < .001$, accounting for approximately 36% of the variance in goal-setting autonomy ($R^2 = .36$, adjusted $R^2 = .35$). Specifically, AI use frequency was found to negatively predict goal-setting autonomy ($\beta = -0.61$, $SE = 0.12$, $t = -5.32$, with p value < .001, hence statistically significant. 95% CI [−0.84, −0.39]) indicates a strong negative association between how frequently students use AI tools in writing and their self-reported autonomy in goal setting. That is, the more frequently AI is used, the lower levels of self-perceived goal-setting autonomy are recorded

Table 2. Standardized Regression Coefficients for Predicting Goal Setting

Predictor	β	SE	t	p	95% CI
AI use frequency	−.61	0.12	−5.32	< .001	[−.84, −.39]
Depth of AI engagement	−.30	0.17	−1.81	.072	[−.64, .03]

Note. N = 172. R^2 = .36, adjusted R^2 = .35. SE = standard error. CI = confidence interval. All p values are two-tailed.

when depth of engagement was controlled for. In contrast, depth of engagement with AI was not a significant predictor of learners' autonomy in setting writing goals when AI use frequency was controlled for ($\beta = -0.30$, $SE = 0.17$, $t = -1.81$, $p = .072$), suggesting that its unique contribution to goal-setting autonomy was not statistically supported in this model.

H2: AI use frequency and depth of engagement likely improves learner's writing autonomy in planning.

As to whether engagement with AI was associated with learners' autonomy in planning their writing, the overall regression model was statistically significant, with $p < .001$, accounting for approximately 36% of the variance in planning autonomy ($R^2 = .36$, adjusted $R^2 = .34$). AI use frequency negatively predicted planning autonomy ($\beta = -.65$, $SE = 0.10$, $t = -6.29$), with p value < .001, hence statistically significant. 95% CI [−.86, −.45]) indicates a negative association between how frequently students use AI tools in writing and their self-reported autonomy in planning, as depth of engagement with AI was controlled for. However, how deeply students engage with AI tools was not a significant predictor ($\beta = -.09$, $t = -0.6$, $p = .550$), suggesting that depth of engagement with AI may not explain the variance in their planning autonomy beyond frequency. Interestingly, learners' age was found to be positively associated with planning autonomy ($\beta = .16$, $t = 2.23$, $p = .027$), indicating that the older the students get, the higher level of self-perceived autonomy is reported.

H3: AI use frequency and depth of engagement likely improves learner's self-monitoring in writing.

Regarding whether engagement with AI was associated with learners' self-monitoring in writing, the overall regression model was statistically significant, with $p < .001$, accounting for approximately 38% of the variance in self-

Table 3. Regression Coefficients for Predicting Planning

Predictor	β	SE	t	p	95% CI
AI use frequency	−.65	0.10	−6.29	< .001	[−.86, −.45]
Depth of AI engagement	−.09	0.15	−0.60	.550	[−.39, .21]
Age	.16	0.07	2.23	.027	[.02, .31]

Note. N = 172. R^2 = .36, adjusted R^2 = .34. SE = standard error. CI = confidence interval. All p values are two-tailed.

Table 4. Regression Coefficients for Predicting Self-Monitoring

Predictor	β	SE	t	P	95% CI
AI use frequency	−.55	0.10	−5.69	< .001	[−.74, −.36]
Depth of AI engagement	−.26	0.14	−1.86	.064	[−.54, .02]

Note. N = 172. R^2 = .38, adjusted R^2 = .38. SE = standard error. CI = confidence interval. All p values are two-tailed.

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monitoring autonomy (R^2 = .38, adjusted R^2 = .38). AI use frequency was found to negatively predict learners' self-monitoring (β = −.55, *SE* = .10, *t* = −5.69), with *p* value < .001, hence statistically significant. 95% CI [−.74, −.36]) indicates a negative association between how frequently students use AI tools in writing and self-reported self-monitoring, as depth of engagement was controlled for. However, how deeply students engage with AI tools was not a significant predictor (*t* = −1.86, *p* = .064), suggesting that depth of engagement, given that frequency is controlled for, may not explain the variance in self-monitoring.

H4: AI use frequency and depth of engagement likely improves learner's self-assessment in writing.

Regarding whether engagement with AI was associated with learners' self-assessment in writing, the overall regression model reveals that AI engagement accounts for approximately 21% of the variance in self-assessment autonomy (R^2 = .21, adjusted R^2 = .19). AI use frequency was found to positively predict learners' self-assessment (β = 0.25, *SE* = 0.10, *t* = 2.61), with *p* value < .01, hence statistically significant. 95% CI [.06, .44]) indicates a strong positive association between how frequently students use AI tools in writing and self-reported self-assessment, as depth of engagement was controlled for. However, how deeply students engage with AI tools was not a significant predictor (*t* = 1.71, *p* = .090), suggesting that depth of engagement, given that frequency is controlled for, may not explain the variance in self-assessment.

Noticeably, learners' age was found to be positively associated with self-assessment autonomy (β = .17, *t* = 2.55, *p* = .012), indicating that the older the students get, the higher level of self-perceived autonomy is reported.

Regarding the second research question on which behavioural dimension of autonomy is most affected, the results indicate that AI use frequency tended to influence planning most strongly (β = −.65), followed by goal-setting (β = −.61) and self-monitoring (β = −.55). All three associations were statistically significant (*p* < .001).

5. Discussions

This study seeks to establish the correlation between' engagement with AI tools and learners' autonomy in writing, taking into consideration four different behavioural constructs of autonomy. The results show that the frequency of AI use in writing is negatively associated with learners' self-reported autonomy in goal setting, planning, and self-monitoring; whereas the reverse is was recorded for self-assessment, which tended to increase when AI use frequency increased. The regression model explained 20-38% variance in autonomy level, suggesting that AI engagement may play a role in shaping students' perceived writing autonomy, although it is unlikely to be the sole contributing factor.

As goal setting and planning autonomy tends to decline as students increasingly use AI tools, this may partly reflect learners' reliance on AI to determine what they should achieve and how to achieve it. However, AI often makes suggestions without explicitly explaining rationales. Therefore, students may have fewer opportunities to develop self-efficacy in planning and will possibly continue to rely on AI's suggestions in future tasks. Also, in an exam-oriented educational context like in

Table 5. Regression Coefficients for Predicting Self-Assessment

Predictor	β	SE	t	p	95% CI
AI use frequency	.25	0.10	2.61	.010	[.06, .44]
Depth of AI engagement	.24	0.14	1.71	.090	[−.04, .52]
Age	.17	0.07	2.55	.012	[.04, .31]

Note. N = 172. R^2 = .21, adjusted R^2 = .19. SE = standard error. CI = confidence interval. All p values are two-tailed.

Vietnam, learners tend to treat the task assigned as an academic requirement for scoring rather than to reach personal growth. This approach to studying may reduce their tendency to critically evaluate AI's recommendations. Besides, in a context where AI use has become the norm, their recommendations may gradually be perceived as authoritative rather than optional. Students may thus feel a sense of insecurity if they break themselves from that standard to pursue their own goals and plans. This is rather worrying, as such AI-favoured thought potentially compromises students' sense of agency and autonomy.

What probably is noteworthy, though, is a decline in self-reported self-monitoring that was observed when AI was involved at a higher frequency. Self-monitoring, by definition, is learners' ability to manage different aspects of writing and make timely adjustments during the process of written text production. This is a very important trait for an autonomous learner, as the process of "producing text" tends to play a more important role in learners' personal growth compared to the final product. The compromise of self-monitoring autonomy may partly reflect learners' "fix-it-later" mentality, i.e., their belief in AI's ability to check mistakes, suggest corrections and, in many cases, even make improvements for them. This psychology, perhaps, accidentally reduces learners' mental effort during the writing process and leaves the burden for AI tools when their production has finished. Over time, students' ability to detect mistakes and adjust their in-process writing may suffer a decline.

Another interesting point of discussion is that, self-assessment - one crucial construct of autonomy, tends to increase when students use AI tools more frequently. One possible explanation is AI's instant feedback on errors and suggestions of how to upgrade the text, which forces students to rethink their original use of language. If this persists for an extended period of time, it is likely that students may subconsciously gain the ability to assess themselves and their own writing.

This research has made theoretical contributions to the current research landscape on technology-assisted language learning, showing that frequent AI use likely decreases most autonomy constructs. The increase in self-perceived self-assessment is noteworthy as it possibly reflects an alignment with the broader goal of modern education: facilitating learners' agency and self-efficacy. More importantly, the current study has managed to add a new dimension to autonomy research in Vietnam, with the involvement of AI-mediated tools. Past research, especially those conducted in the era when AI use was not prevalent, typically focused on different constructs of autonomy, without accounting for AI tools' effects Alm (2024). It is also notable that the close correlation between AI frequency and depth of engagement suggests a novel approach to future research models in which the two variables can be integrated. Regarding practical implications, the research suggests that guided AI use may be beneficial if incorporated into writing instruction, yet its implementation and its actual influence on learners' writing autonomy requires further examination. The negative association between AI use frequency and most learners' autonomy constructs does not necessarily mean AI use should be reduced or banned. Instead, the findings suggest that the ways in which AI is used may deserve greater attention, particularly in terms of promoting deeper engagement. That is, learners may benefit from guidance on how to set their own goals, debate with AI's suggestion and critically evaluate AI's feedback. This will allow students to balance the use of AI as a cognitive scaffold that supports their personal growth, rather than an authoritative decision-maker. However, given the correlational nature of the study, the pedagogical implications should be interpreted with caution, and will be better informed by longitudinal research and those exploring causal relationships.

The research, however, is not without limitations. First, the research employed non-probability convenience sampling, with participants being mostly recruited from two tertiary institutions in Ho Chi Minh City. While this approach allowed the researcher to access a large number of participants and effectively gather responses, it may reduce the representativeness of the findings due to self-selection bias. Therefore, the interpretation of the results need to be treated with caution, and the results may not be applicable broadly to different educational contexts when different teaching practices and learners are in place. Additionally, the study employed a correlational design, with reliance on self-reported data, which may not fully capture the construct of writing autonomy as it can be subjected to social desirability bias. The findings, therefore, should be better interpreted as exploration of learners' beliefs rather than a direct measurement of autonomy. A more objective, experimental research model is thus required to validate the behavioural shifts in writing autonomy. Future research may also involve qualitative analysis, such as an interview with teachers and learners, to add more insight into the investigation. Longitudinal research into the effects of control variables, including age, gender, profession, and language proficiency, either individually or cumulatively, should be carried out.

6. Conclusions

To sum up, the study was able to provide more insight into how non-English-majored students perceive the effect of AI-mediated tools on their writing autonomy. The research was based on four constructs of self-regulated learning theory proposed by Zimmerman (1989). The main findings were that learners tend to perceive an increase in self-assessment autonomy as engagement with AI tools increase. Meanwhile, learners' self-perceived autonomy in goal-setting, planning, and self-monitoring autonomy, tended to decline as AI tools were used more frequently, with planning autonomy likely being the most affected construct. With theoretical and practical implications, the study has contributed to the current research landscape that revolves around AI-assisted teaching and learning. However, with its exhausted reliance on correlational design and self-reported data, the study's findings should be treated with caution, and further empirical research is needed to address these limitations.

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