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Issue Overview

This issue of Journal of Psychology & Education brings together five articles on student health behavior, AI-supported higher education, ChatGPT adoption, mobile-assisted English speaking, and ethical communication in obstetric care. Together, these contributions show how psychological regulation, responsible technology use, institutional guidance, and human-centered professional practice shape contemporary education and care.

The issue opens with a study of Chinese college student smokers, examining self-control, sleep quality problems, and nicotine dependence through a cross-sectional statistical mediation model. It then turns to Malaysian higher education through two AI-focused contributions: one develops a model of AI-enabled learning support, self-regulated learning, academic engagement, and learning performance; the other proposes a UTAUT-based empirical framework for understanding students' ChatGPT utilisation and the role of ethical awareness.

A further article examines mobile-assisted English-speaking practice among Malaysian university students, showing how anxiety reduction and trust in AI feedback may shape perceived speaking fluency. The issue concludes with an ethical reflection on nurse-patient communication in obstetric practice, emphasizing autonomy, beneficence, nonmaleficence, justice, privacy, empathy, and clinical trust. As a whole, the issue reflects the journal's interdisciplinary concern with psychological mechanisms, educational transformation, AI governance, language learning, and ethical professional practice.



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**The Relationship Between Self-Control and Nicotine Dependence Among
Chinese College Student Smokers: A Cross-Sectional Statistical Mediation
Analysis of Sleep Quality Problems**

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Abstract

Objective: College student smokers are in a transitional developmental stage from late adolescence to early adulthood, during which smoking behavior may be associated with self-regulation difficulties, sleep quality problems, and nicotine dependence. Although previous studies have examined the relationships between smoking and sleep, self-control and health behavior, and sleep quality problems and addictive behavior, relatively limited research has incorporated self-control, sleep quality problems, and nicotine dependence into the same cross-sectional statistical mediation model among Chinese college student smokers. This study examined the associations among self-control, sleep quality problems, and nicotine dependence, and tested whether sleep quality problems played a cross-sectional statistical mediating role between self-control and nicotine dependence.

Methods: A cross-sectional questionnaire survey was conducted, and 945 Chinese college student smokers with at least one year of smoking history were included in the final analysis. The Self-Control Scale was used to assess self-control, the Pittsburgh Sleep Quality Index was used to assess sleep quality problems, and the Fagerström Test for Nicotine Dependence was used to assess nicotine dependence. SPSS 26.0 was used for descriptive statistics, correlation analysis, and regression analysis, and PROCESS macro Model 4 was used to test the cross-sectional statistical mediation effect. The indirect effect was estimated using 5,000 bootstrap samples to obtain 95% confidence intervals. Sex, age, only-child status, and long-term residence were controlled in the model.

Results: Self-control was significantly negatively correlated with both sleep quality problems and nicotine dependence, whereas sleep quality problems were significantly positively correlated with nicotine dependence. After controlling for demographic variables, the reported path

coefficients were standardized regression coefficients: self-control significantly negatively predicted sleep quality problems ($\beta = -0.330$, $p < 0.001$), sleep quality problems significantly positively predicted nicotine dependence ($\beta = 0.103$, $p = 0.002$), and the direct path from self-control to nicotine dependence remained significant ($\beta = -0.119$, $p < 0.001$). Bootstrap analysis indicated that the completely standardized indirect effect of sleep quality problems between self-control and nicotine dependence was significant (effect = -0.0341 , BootSE = 0.0118 , 95% bootstrap CI [-0.0579 , -0.0116]).

Conclusion: Among Chinese college student smokers, lower self-control was associated with higher nicotine dependence both directly and indirectly through more severe sleep quality problems. These findings suggest that sleep quality problems may represent a meaningful behavioral link between self-control and nicotine dependence in a cross-sectional statistical mediation model. Campus tobacco-control and student health interventions may benefit from integrating self-control training, sleep health education, routine management, and nicotine dependence risk screening.

Keywords: college student smokers; self-control; sleep quality problems; nicotine dependence; cross-sectional mediation analysis

1 Introduction

Smoking is an important public health issue affecting the physical and mental health of college students. College students are in a critical transitional period from adolescence to early adulthood, during which academic arrangements, social relationships, daily routines, and health behaviors gradually shift from external regulation by family and school to individual self-management. At this stage, smoking behavior is easily influenced by peer interaction, emotion regulation,

immediate reward, life stress, and self-control. For college student smokers, smoking is not merely a single behavioral choice; it may also be part of a complex chain of health behaviors involving insufficient sleep, irregular routines, negative affect, and addiction risk. Previous research has shown that tobacco use among college students is associated with psychological distress, sleep quality problems, and negative emotions (Boehm et al., 2016; Fluharty et al., 2017). Therefore, examining the mechanisms related to nicotine dependence among college student smokers is helpful not only for understanding the psychological and behavioral basis through which smoking develops into dependence, but also for providing more targeted evidence for campus tobacco control, sleep health education, and mental health services.

Nicotine dependence is one of the most important outcomes in smoking-related problems. Compared with occasional or social smoking, nicotine dependence means that individuals have developed relatively stable physiological and psychological needs for nicotine, reflected in morning smoking, increased cigarette consumption, difficulty controlling smoking, withdrawal discomfort, and continued use. Nicotine exerts reinforcing effects through the brain reward system, and long-term use may increase the risk of tolerance, withdrawal, and relapse (Benowitz, 2009). For college students, the formation of nicotine dependence has developmental specificity. On the one hand, college life involves relatively high behavioral autonomy, making students more likely to encounter tobacco in social, recreational, or stressful situations. On the other hand, the self-regulation system of young people is still developing and stabilizing. Once smoking becomes combined with immediate relief, social integration, or coping with fatigue, smoking behavior may gradually shift from experimentation to dependence. Studies of adolescent and young adult smoking suggest that early symptoms of nicotine dependence may appear at

relatively low smoking frequency, and daily heavy smoking should not be regarded as the only criterion for identifying dependence risk (DiFranza et al., 2002).

From a measurement perspective, nicotine dependence differs from general smoking frequency. Smoking frequency or daily cigarette consumption mainly reflects how often the behavior occurs, whereas nicotine dependence emphasizes difficulty controlling nicotine use, physiological need, and withdrawal-related manifestations. Although the FTND contains relatively few items, it can quickly identify dependence severity based on morning smoking, daily cigarette consumption, difficulty refraining from smoking in restricted places, and smoking while ill (Heatherton et al., 1991). In addition, nicotine dependence can be understood as a multidimensional construct involving automatic use, craving, tolerance, withdrawal, and situational smoking motives (Etter et al., 2003; Piper et al., 2004; Shiffman et al., 2004). Therefore, examining nicotine dependence among college student smokers should go beyond whether a student smokes and should further attend to whether smoking has developed into a relatively stable physiological and psychological dependence.

Previous studies of college student smokers have often started from stress, anxiety, depression, and negative emotions, emphasizing that smoking may be used as an emotion-regulation strategy. The negative reinforcement model suggests that individuals may smoke to temporarily relieve tension, anxiety, irritability, or discomfort, and this temporary relief can reinforce subsequent smoking behavior (Baker et al., 2004). Relevant reviews have also indicated stable associations between smoking, anxiety, depression, and negative affect, suggesting that smokers may use smoking as a way to cope with negative emotions (Akbari et al., 2020; Leventhal & Zvolensky, 2015). However, explaining nicotine dependence among college student smokers only from the perspective of emotional problems may still fail to reveal the everyday behavioral mechanisms

behind it. Common problems among college students, such as staying up late, bedtime smartphone use, irregular routines, academic procrastination, and daytime fatigue, may play an important role between insufficient self-control and nicotine dependence. In other words, nicotine dependence may arise not only from wanting to smoke or feeling bad, but also from failure in managing daily rhythms and impaired sleep health.

Self-control is an important psychological capacity that enables individuals to inhibit impulses, delay gratification, maintain long-term goals, and regulate daily behavior. Individuals with high self-control are usually better able to resist immediate temptations and maintain stable academic, daily-life, and health behaviors; individuals with low self-control are more likely to show impulsive behavior, procrastination, addictive behavior, and health behavior dysregulation. Tangney et al. (2004) showed that self-control is associated with better adjustment, fewer psychological problems, and better behavioral performance. The longitudinal study by Moffitt et al. (2011) further showed that childhood self-control predicts health, economic, and public safety outcomes in adulthood. The meta-analysis by Ridder et al. (2012) also indicated that trait self-control is broadly related to multiple behavioral outcomes, especially habitual health behaviors and automatic behavioral regulation. For college student smokers, insufficient self-control may be reflected not only in difficulty controlling smoking impulses, but also in difficulty maintaining regular routines, stopping recreational activities in time, reducing bedtime smartphone use, and choosing immediate relief when fatigued or stressed.

From a self-regulation perspective, smoking and sleep are not independent daily behaviors. Both involve management of immediate reward, bodily sensations, and daily rhythms. Students with lower self-control may be more likely to pursue immediate gratification and neglect long-term health goals when facing tobacco, smartphones, games, social media, or nighttime entertainment.

Such self-regulation failure may increase smoking frequency and nicotine exposure on the one hand and reduce sleep quality on the other. Among student smokers, sleep quality problems may also interact with the physiological effects of nicotine. Nicotine has stimulant effects and may influence sleep onset and sleep structure; declining nicotine levels at night may also lead to awakening or discomfort, thereby disrupting sleep continuity (Jaehne et al., 2009; Wetter & Young, 1994). Therefore, self-control, sleep quality problems, and nicotine dependence may form a psychological and behavioral risk chain worthy of attention.

Sleep quality problems may constitute an important pathway linking self-control and nicotine dependence. The Pittsburgh Sleep Quality Index evaluates sleep problems in terms of subjective sleep quality, sleep latency, sleep duration, sleep efficiency, sleep disturbances, use of sleep medication, and daytime dysfunction (Buysse et al., 1989). Sleep problems are common among college students and are closely related to mental health, learning status, and daytime functioning (Becker et al., 2018; Lund et al., 2010). Sleep is not only a physiological recovery process, but is also associated with emotion regulation, reward processing, and cognitive control (Goldstein & Walker, 2014; Palmer & Alfano, 2016). When individuals experience long-term insufficient sleep or reduced sleep quality, their impulse control, stress tolerance, and capacity for delayed gratification may be further impaired, increasing dependence on immediate rewards such as nicotine. In other words, sleep quality problems may be a concrete manifestation of low self-control in daily life, and may also further weaken individuals' ability to control smoking behavior.

Research on bedtime procrastination provides important insight into this mechanism. Kroese et al. (2014) conceptualized bedtime procrastination as a form of self-regulation failure, in which individuals delay going to bed even when they are not prevented from doing so by external circumstances and know that they may feel tired the next day. Kühnel et al. (2018) further

examined the relationships among chronotype, self-control resources, and bedtime procrastination using a diary design. Studies of Chinese college students also suggest that self-regulation and bedtime procrastination play important roles in the relationship between problematic smartphone use and sleep quality (Zhang & Wu, 2020), and that bedtime procrastination and self-control are related to smartphone addiction, depression, and anxiety (Geng et al., 2021). Although these studies do not all focus directly on smokers, they collectively indicate that sleep behavior is strongly influenced by self-control and lifestyle. Among college student smokers, if low self-control is associated with irregular routines and reduced sleep quality, individuals may be more likely to obtain short-term stimulation or relief through smoking when they are tired, sleepy, inattentive, or emotionally unstable, thereby showing higher nicotine dependence risk.

Although previous studies have separately explored the relationships between self-control and addictive behavior, sleep quality and mental health, and smoking and sleep quality problems, relatively limited research has incorporated self-control, sleep quality problems, and nicotine dependence into the same cross-sectional statistical mediation model among Chinese college student smokers. Compared with directly examining the bivariate relationship between self-control and nicotine dependence, testing the mediating role of sleep quality problems can more specifically reveal how self-control is related to nicotine dependence through daily rhythms and sleep health. Based on the above theory and empirical research, this study proposed the following hypotheses: first, self-control would be significantly negatively correlated with nicotine dependence; second, self-control would be significantly negatively correlated with sleep quality problems, while sleep quality problems would be significantly positively correlated with

nicotine dependence; third, sleep quality problems would play a significant cross-sectional statistical mediating role between self-control and nicotine dependence.

2 Methods

2.1 Participants

This study used a cross-sectional questionnaire survey design. Participants were recruited from several universities in China through online questionnaire links, campus publicity, and class notifications. Eligible participants were required to meet the following criteria: (1) aged 18 years or older; (2) currently enrolled in an institution of higher education; (3) having a history of cigarette smoking for at least one year; (4) continuing to smoke and not currently undergoing smoking cessation or receiving smoking-cessation treatment at the time of the survey; and (5) understanding the purpose of the study and voluntarily providing informed consent. Participants were subsequently screened using the 11 DSM-5 symptom criteria for tobacco use disorder, which assess symptoms occurring during the previous 12 months across four domains: impaired control, social impairment, risky use, and pharmacological features, including tolerance and withdrawal. Each criterion was coded as present or absent, and participants who endorsed two or more criteria were considered to have met the DSM-5 screening threshold for tobacco use disorder. Questionnaires were excluded if participants did not meet the eligibility or DSM-5 screening criteria or if the responses showed obvious invalid patterns, including an abnormally short completion time, an unusually high proportion of consecutive identical responses, almost all items answered using the same response option, or other clearly invalid response patterns.

A total of 1,962 questionnaires were initially collected. Following eligibility screening, Following eligibility screening, DSM-5 screening, and predefined data-quality-control procedures, 1,017 questionnaires were excluded, leaving 945 Chinese college student smokers with at least one year of smoking history in the final analytic sample. No additional outlier-based exclusions were applied beyond these predefined screening and data-quality-control procedures. Because the online survey required completion of all core items before submission, no item-level missing data were present for the main study variables in the final analytic dataset. This study was approved by the Human Research Ethics Committee of Zunyi Medical University (Approval No. ZMU[2025]3-009) and was conducted in accordance with the Declaration of Helsinki and its subsequent amendments. All participants provided informed consent before participating in the study. Participants ranged in age from 18 to 30 years, with a mean age of 20.44 years ($SD = 1.49$). The sample included 706 males (74.7%) and 239 females (25.3%). Among the participants, 722 were enrolled in general undergraduate institutions (76.4%), whereas 223 were enrolled in higher vocational colleges (23.6%). A total of 143 participants were only children (15.1%), and 802 were not only children (84.9%). Regarding long-term residence before college, 550 participants were from rural areas (58.2%) and 395 were from urban areas (41.8%). Based on FTND scores, 496 participants were classified as having mild nicotine dependence (52.5%), 354 as having moderate nicotine dependence (37.5%), and 95 as having severe nicotine dependence (10.0%).

Table 1 Sample Characteristics

Category	Subcategory	n / M $\pm$ SD	%
Age (years)	M $\pm$ SD	20.44 $\pm$ 1.49	

Sex	Male	706	74.7
	Female	239	25.3
Institution type	General undergraduate institution	722	76.4
	Higher vocational college	223	23.6
Only-child status	Yes	143	15.1
	No	802	84.9
Long-term residence	Urban	395	41.8
	Rural	550	58.2
Nicotine dependence severity	Mild	496	52.5
	Moderate	354	37.5
	Severe	95	10.0

Note. Age is presented as mean $\pm$ standard deviation; categorical variables are presented as frequency and percentage. Nicotine dependence severity was classified according to FTND scores: 0-3 = mild, 4-6 = moderate, and ≥ 7 = severe.

2.2 Measures

Demographic information. A self-designed demographic questionnaire was used to collect participants' basic information, including sex, age, type of institution, major category, only-child status, and long-term residence. In this study, sex, age, only-child status, and long-term residence were included as control variables in the statistical model. Sex was coded as male = 1 and female = 2; only-child status was coded as only child = 1 and non-only child = 2; long-term residence was coded as urban = 1 and rural = 2.

Self-control. The Chinese version of the Self-Control Scale (SCS) was used to assess participants' level of self-control. The scale contains 19 items scored on a 5-point Likert scale, with total scores ranging from 19 to 95. After reverse scoring relevant items, higher total scores indicate higher self-control. The scale measures individuals' ability to inhibit impulses, control behavior, delay gratification, and maintain goal-directed behavior. In the present sample, Cronbach's alpha for the SCS was 0.845, indicating good internal consistency.

Sleep quality problems. The Chinese version of the Pittsburgh Sleep Quality Index (PSQI) was used to assess participants' sleep quality problems. The PSQI consists of 19 self-rated items that are aggregated into seven components: subjective sleep quality, sleep latency, sleep duration, sleep efficiency, sleep disturbances, use of sleep medication, and daytime dysfunction. The global score was calculated according to the standard PSQI scoring method, with higher total scores indicating more severe sleep quality problems (Buysse et al., 1989). In the present sample, Cronbach's alpha for the PSQI was 0.724, indicating acceptable internal consistency. Throughout this manuscript, the PSQI global score is consistently referred to as sleep quality problems. The term sleep disturbances is retained only when denoting the specific PSQI component.

Nicotine dependence. The Chinese version of the Fagerström Test for Nicotine Dependence (FTND) was used to assess participants' nicotine dependence. The FTND consists of six items and was scored according to the original FTND scoring method. It assesses physiological dependence characteristics such as morning smoking, daily cigarette consumption, and difficulty refraining from smoking. Total scores range from 0 to 10, with higher scores indicating more severe nicotine dependence (Heatherton et al., 1991). The FTND is a commonly used brief assessment tool in smoking and nicotine dependence research and is often used to distinguish

mild, moderate, and severe levels of nicotine dependence (Fagerström, 2012). According to established criteria, scores of 0–3 indicate mild dependence, scores of 4–6 indicate moderate dependence, and scores of 7 or above indicate severe dependence. In the present sample, Cronbach's alpha for the FTND was 0.625. Because the FTND contains few items and different items reflect different aspects such as smoking timing, smoking quantity, and control over withdrawal-related smoking, its internal consistency is relatively limited, and the results should be interpreted cautiously in light of the scale characteristics.

2.3 Data Processing and Statistical Analysis

SPSS 26.0 was used for statistical analysis. First, descriptive statistics were conducted for demographic variables and main study variables. Categorical variables were presented as frequencies and percentages, and continuous variables were presented as means and standard deviations. Pearson correlation analysis was then used to examine the preliminary relationships among self-control, sleep quality problems, and nicotine dependence. Finally, PROCESS macro Model 4 was used to test the statistical mediating role of sleep quality problems between self-control and nicotine dependence (Hayes, 2022).

In the mediation model, self-control was specified as the independent variable, sleep quality problems as the mediator, and nicotine dependence as the dependent variable. Sex, age, only-child status, and long-term residence were included as control variables. The indirect effect and its 95% confidence interval were estimated using 5,000 bootstrap samples. If the 95% Bootstrap confidence interval did not include 0, the indirect effect was considered statistically significant (Preacher & Hayes, 2008). Because all variables were measured at the same time point through self-report questionnaires, the results of this study should only be interpreted as cross-sectional statistical mediation and not as causal relationships or temporal ordering. For cross-sectional

mediation analysis, methodological research has noted that without longitudinal data, researchers should not directly interpret statistical pathways as true causal processes (Maxwell & Cole, 2007).

3 Results

3.1 Descriptive Statistics and Correlation Analysis

Descriptive statistics showed that the self-control score was 55.50 ± 10.21 , the sleep quality problems score was 8.59 ± 4.00 , and the nicotine dependence score was 3.30 ± 2.29 . Self-control scores ranged from 24.00 to 90.00, sleep quality problems scores ranged from 0.00 to 23.00, and nicotine dependence scores ranged from 0.00 to 10.00. Correlation analysis showed significant correlations among self-control, sleep quality problems, and nicotine dependence. Specifically, self-control was significantly negatively correlated with sleep quality problems, $r = -0.333$, $p < 0.001$; self-control was significantly negatively correlated with nicotine dependence, $r = -0.099$, $p = 0.002$; and sleep quality problems were significantly positively correlated with nicotine dependence, $r = 0.122$, $p < 0.001$. These results indicate that lower self-control was associated with more severe sleep quality problems and higher nicotine dependence among college student smokers, and that more severe sleep quality problems were associated with higher nicotine dependence. It should be noted that the correlations between self-control and nicotine dependence and between sleep quality problems and nicotine dependence were small, indicating that nicotine dependence is influenced by multiple factors and that this study focuses on one statistically meaningful but limited psychological and behavioral pathway.

Table 2 Descriptive Statistics and Correlations Among Main Variables

Variable	M	SD	1	2	3
1. Self-control	55.50	10.21	1		
2. Sleep quality problems	8.59	4.00	-0.333***	1	
3. Nicotine dependence	3.30	2.29	-0.099**	0.122***	1

Note. N = 945. M = mean; SD = standard deviation. ** $p < 0.01$, *** $p < 0.001$.

3.2 Testing the Mediating Effect of Sleep Quality Problems

After controlling for sex, age, only-child status, and long-term residence, PROCESS macro Model 4 was used to test the mediating role of sleep quality problems between self-control and nicotine dependence. The β values reported in the following regression results are standardized regression coefficients; the corresponding unstandardized coefficients (B), SEs, and 95% CIs are provided in Tables 3a and 3b. The results showed that, in the model with sleep quality problems as the dependent variable, self-control significantly negatively predicted sleep quality problems, $\beta = -0.330$, $t = -10.465$, $p < 0.001$. The overall model was significant, $R^2 = 0.119$, $F(5, 939) = 25.403$, $p < 0.001$. Among the control variables, age significantly positively predicted sleep quality problems, $\beta = 0.084$, $p = 0.007$, indicating that older participants in this sample reported slightly more sleep quality problems; sex, only-child status, and long-term residence were not significant predictors.

In the model with nicotine dependence as the dependent variable, both self-control and sleep quality problems were significant predictors. Specifically, self-control significantly negatively predicted nicotine dependence, $\beta = -0.119$, $t = -3.494$, $p < 0.001$; sleep quality problems significantly positively predicted nicotine dependence, $\beta = 0.103$, $t = 3.100$, $p = 0.002$. The overall model was significant, $R^2 = 0.082$, $F(6, 938) = 13.948$, $p < 0.001$. Among the control

variables, sex significantly negatively predicted nicotine dependence, $\beta = -0.242$, $p < 0.001$. Because sex was coded as male = 1 and female = 2, the result indicates that male college student smokers had higher nicotine dependence scores than female smokers. Only-child status also significantly negatively predicted nicotine dependence, $\beta = -0.066$, $p = 0.041$. Because only-child status was coded as only child = 1 and non-only child = 2, the result suggests that only children had higher nicotine dependence scores than non-only children. Age and long-term residence did not reach statistical significance in predicting nicotine dependence.

Bootstrap mediation analysis showed that the completely standardized indirect effect of sleep quality problems between self-control and nicotine dependence was significant (effect = -0.0341, BootSE = 0.0118, 95% bootstrap CI [-0.0579, -0.0116]). Because the confidence interval did not include 0, this indicates that the indirect effect of sleep quality problems between self-control and nicotine dependence was significant. Meanwhile, the standardized regression coefficient for the direct path from self-control to nicotine dependence remained significant ($\beta = -0.119$), indicating that sleep quality problems served as a partial statistical mediator. Given the cross-sectional design of this study, no causal direction among the variables can be inferred, and the mediation result should be understood as a statistical mediation relationship.

Table 3a Regression Results With Sleep Quality Problems as the Dependent Variable

Predictor	B	SE	β	t	p	95% CI
Self-control	-0.129	0.012	-0.330	-10.465	<0.001	[-0.153, -0.105]
Sex	0.118	0.289	0.013	0.409	0.683	[-0.450, 0.686]

Age	0.226	0.084	0.084	2.710	0.007	[0.062, 0.390]
Only-child status	-0.035	0.354	-0.003	-0.099	0.921	[-0.729, 0.659]
Long-term residence	-0.335	0.260	-0.041	-1.286	0.199	[-0.845, 0.176]

Note. N = 945. B = unstandardized regression coefficient; SE = standard error; β = standardized regression coefficient; CI = confidence interval. The overall model was significant, $R^2 = 0.119$, $F(5, 939) = 25.403$, $p < 0.001$.

Table 3b Regression Results With Nicotine Dependence as the Dependent Variable

Predictor	B	SE	β	t	p	95% CI
Self-control	-0.027	0.008	-0.119	-3.494	0.0005	[-0.042, - 0.012]
Sleep quality problems	0.059	0.019	0.103	3.100	0.002	[0.022, 0.097]
Sex	-1.274	0.169	-0.242	-7.518	<0.001	[-1.606, - 0.941]
Age	-0.001	0.049	-0.001	-0.015	0.988	[-0.097, 0.096]
Only-child status	-0.423	0.207	-0.066	-2.045	0.041	[-0.829, - 0.017]
Long-term residence	0.277	0.153	0.060	1.818	0.069	[-0.022, 0.576]

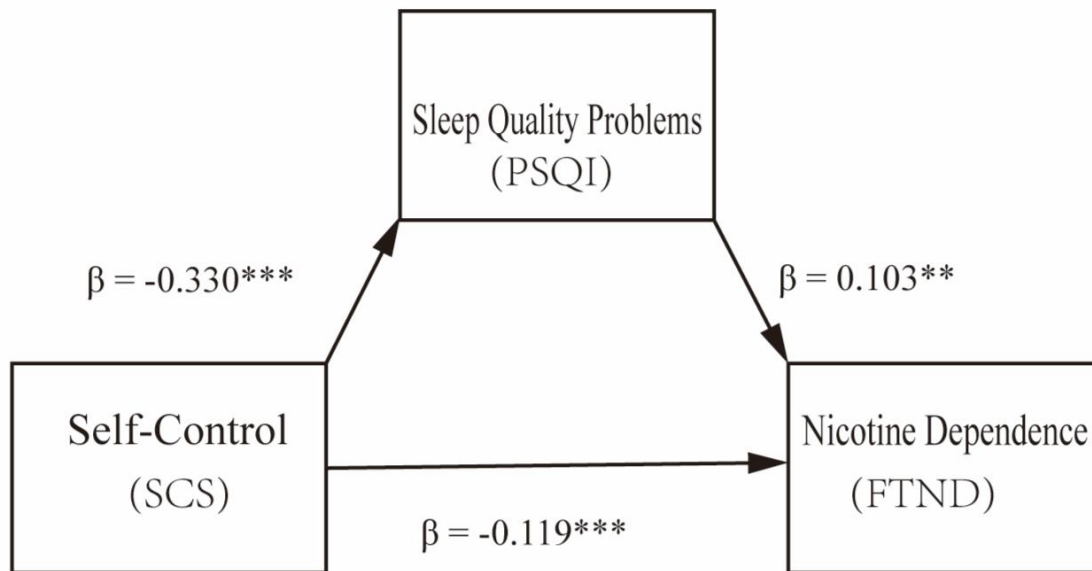
Note. N = 945. B = unstandardized regression coefficient; SE = standard error; β = standardized regression coefficient; CI = confidence interval. The overall model was significant, $R^2 = 0.082$, $F(6, 938) = 13.948$, $p < 0.001$.

Table 4 Direct and Indirect Effects of Sleep Quality Problems Between Self-Control and Nicotine Dependence

Effect type	Path	Estimate type	Estimate	SE/ BootSE	95% CI
Direct effect	Self-control → Nicotine dependence	Unstandardized direct effect (B)	-0.0267	0.0076	[-0.0416, -0.0117]
	Self-control → Sleep quality problems → Nicotine dependence	Unstandardized indirect effect (ab)	-0.0076	0.0026	[-0.0130, -0.0026]
Indirect effect	Self-control → Sleep quality problems → Nicotine dependence	Completely standardized indirect effect	-0.0341	0.0118	[-0.0579, -0.0116]

Note. The model controlled for sex, age, only-child status, and long-term residence. The direct effect is reported as an unstandardized regression coefficient (B). The indirect effect is reported both as an unstandardized indirect effect (ab) and as a completely standardized indirect effect. For the direct effect, SE and the conventional 95% CI are reported; for the indirect effects, BootSE and 95% bootstrap CIs based on 5,000 bootstrap samples are reported. An indirect effect was considered statistically significant when its 95% bootstrap CI did not include zero.

Figure 1 Mediation Model of Self-Control, Sleep Quality Problems, and Nicotine Dependence



Note. The model controlled for sex, age, only-child status, and long-term residence. Path coefficients are standardized regression coefficients (β); β is not used to label the indirect effect. ** $p < 0.01$, *** $p < 0.001$. This model is a cross-sectional statistical mediation model; arrows represent statistical regression paths and should not be interpreted as causal effects.

4 Discussion

This study examined cross-sectional associations among self-control, sleep quality problems, and nicotine dependence in 945 Chinese college student smokers, and further tested whether sleep quality problems played a statistical mediating role between self-control and nicotine dependence. The results showed that self-control was significantly negatively correlated with both sleep quality problems and nicotine dependence, whereas sleep quality problems were significantly positively correlated with nicotine dependence. Mediation analysis further indicated that, after controlling for sex, age, only-child status, and long-term residence, self-control was directly associated with nicotine dependence and indirectly associated with nicotine dependence

through sleep quality problems. Overall, sleep quality problems partially statistically explained the relationship between self-control and nicotine dependence.

This study found that lower self-control was associated with higher nicotine dependence among college student smokers. This result is consistent with self-control theory and previous research showing that higher self-control is associated with better behavioral adjustment, fewer maladaptive behaviors, and better health-related outcomes (Ridder et al., 2012; Tangney et al., 2004) . It also accords with prior evidence suggesting that individual differences in self-control are related to dimensions of nicotine dependence among smokers (Wilson & Maclean, 2013). Self-control is an important psychological regulatory resource that helps individuals inhibit impulses, manage behavior, delay gratification, and maintain long-term goals. Smoking has an obvious immediate reward component, and nicotine intake can provide subjective experiences of stimulation, relaxation, craving reduction, or discomfort relief within a short period; such immediate reinforcement and habit-related motives have also been observed among college student smokers (Piasecki et al., 2007). In cross-sectional terms, lower self-control may reflect greater difficulty resisting immediate smoking impulses and maintaining stable choices between long-term health goals and short-term rewards. In college life, students encounter peer smoking, social settings, academic pressure, nighttime entertainment, and flexible daily schedules, all of which require stronger self-control to maintain healthy behavior. Therefore, lower self-control may be associated with higher nicotine dependence, although the present design cannot establish a developmental causal process.

The effect size of the association between self-control and nicotine dependence should be interpreted cautiously. The zero-order correlation between self-control and nicotine dependence was small, $r = -0.099$, and the standardized regression coefficient for the direct path from self-

control to nicotine dependence was also relatively limited, $\beta = -0.119$. Nicotine dependence, as an addiction-related outcome, is influenced by multiple factors, including smoking duration, daily cigarette consumption, age at first smoking, peer smoking, family smoking, e-cigarette use, quit attempts, social environment, and individual biological sensitivity. Therefore, this study does not claim that self-control is the sole or primary determinant of nicotine dependence. Rather, it suggests that self-control may constitute one upstream psychological and behavioral factor worthy of attention. In a large college population, even small associations may warrant further evaluation as potential markers for risk stratification, but their predictive and preventive utility requires prospective validation.

This study also found that lower self-control was associated with more severe sleep quality problems. Sleep behavior is not determined entirely by physiological need; it is also influenced by daily choices, time management, and environmental cues. Many college students know the harms of insufficient sleep and have basic conditions for sleep, yet they still find it difficult to stop current activities in time when facing smartphones, games, social media, short videos, or nighttime socializing. This pattern reflects self-regulation difficulty in sleep behavior. Consistent with this interpretation, problematic smartphone use has been linked to poorer sleep quality in systematic review evidence and in studies of Chinese college students (Huang et al., 2020; Yang et al., 2020). For college student smokers, insufficient self-control may be reflected not only in difficulty controlling smoking impulses, but also in difficulty maintaining regular routines, reducing bedtime stimulation, and avoiding smoking-related coping when fatigued or stressed.

Sleep quality problems were also positively associated with nicotine dependence and remained a significant predictor in the regression model. Multiple links may exist between sleep quality problems and nicotine dependence. First, nicotine has stimulant effects and may delay sleep

onset, reduce sleep continuity, or alter sleep structure. Prior research has shown that smokers report poorer sleep quality and shorter sleep duration than non-smokers, and that higher nicotine dependence and smoking intensity are associated with shorter sleep duration (Cohrs et al., 2014). Systematic review evidence also suggests that smoking increases risk of sleep quality problems (Amiri & Behnezhad, 2020). Second, insufficient sleep may be accompanied by daytime fatigue, reduced attention, and lower learning efficiency, making individuals more likely to use smoking for brief stimulation or fatigue relief. Third, reduced sleep quality may weaken emotion regulation and impulse control, making individuals more likely to choose smoking as an immediate coping strategy under stress or discomfort. In cigarette smokers, poorer sleep quality has also been associated with stronger withdrawal, craving, and smoking urges (Purani et al., 2019). These processes may jointly form a cycle of sleep quality problems, increased fatigue or discomfort, smoking as coping, and worsened nicotine dependence, but such a cycle requires longitudinal verification.

The mediating result further suggests that sleep quality problems may serve as a concrete lifestyle-related link between self-control and nicotine dependence. Lower self-control was associated with more sleep quality problems, and sleep quality problems were further associated with higher nicotine dependence. This indirect association does not mean that sleep quality problems are the only pathway connecting self-control and nicotine dependence. Rather, it indicates that the abstract construct of self-control can be partly reflected in observable daily routines such as delayed sleep onset, bedtime smartphone use, nighttime smoking, and daytime fatigue. In this sense, sleep quality problems are not merely an ancillary variable in nicotine dependence research, but a behavioral indicator that helps situate nicotine dependence within broader lifestyle dysregulation.

Because sleep quality problems only partially explained the association between self-control and nicotine dependence, other pathways should also be considered. Individuals with lower self-control may be more susceptible to peer smoking influence and may find it harder to refuse cigarettes in social situations. They may also be more likely to experience academic procrastination, internet addiction, impulsive consumption, or emotional coping, all of which may further increase smoking frequency. In addition, self-control may be associated with persistence in quitting goals, the ability to avoid smoking cues, and tolerance of withdrawal discomfort. Future research can build on this model by including daily cigarette consumption, smoking duration, age at first smoking, peer smoking, willingness to quit, e-cigarette use, internet addiction, and emotion-regulation strategies to construct more complete multiple mediation or chain mediation models.

Regarding control variables, male college student smokers had significantly higher nicotine dependence scores than female smokers. This result is broadly consistent with tobacco epidemiological evidence from China showing that smoking prevalence among college students is substantially higher among males than females (Mingxin et al., 2026). Only-child status also significantly predicted nicotine dependence; under the coding scheme used in this study, only children had higher nicotine dependence than non-only children. This finding should be interpreted cautiously, because only-child status may be intertwined with family structure, parental monitoring, social support, economic conditions, and individual lifestyle. Long-term residence was close to but did not reach statistical significance in predicting nicotine dependence, indicating that urban-rural background may show a certain trend but has limited explanatory power after controlling for other variables.

Finally, this study used a cross-sectional statistical mediation model; therefore, all pathways should be interpreted as statistical associations rather than causal mechanisms. Although it is theoretically possible to propose that insufficient self-control may be associated with sleep quality problems, which are then associated with nicotine dependence, cross-sectional data cannot establish the temporal order among variables, and cross-sectional mediation models may produce biased estimates of longitudinal mediation processes (Maxwell & Cole, 2007). Reverse pathways may also exist: students with higher nicotine dependence may experience reduced sleep quality due to nighttime smoking, withdrawal discomfort, or changes in sleep structure, and sleep quality problems may in turn weaken self-control. Third variables, such as stress, depression, peer smoking, or internet addiction, may also simultaneously affect self-control, sleep quality problems, and nicotine dependence. Therefore, the more accurate interpretation of this study is that sleep quality problems play a cross-sectional statistical mediating role between self-control and nicotine dependence, rather than serving as a causal psychological mechanism.

5 Practical Implications

Given the cross-sectional design and the small completely standardized indirect effect, the practical implications of this study should be regarded as preliminary and hypothesis-generating. The observed association between sleep quality problems and nicotine dependence suggests that sleep quality assessment could be considered in future campus tobacco-control and student health programs. However, the present data do not show that screening or addressing sleep quality problems will reduce nicotine dependence.

Self-control and sleep-related behaviors may be considered candidate targets for the development of future interventions rather than established treatment components. Potential

strategies, including goal management, smoking-cue identification, bedtime behavior management, reduced bedtime smartphone use, avoidance of smoking before sleep, exercise, relaxation, and peer support, require prospective and experimental evaluation before conclusions can be drawn about their effectiveness.

A tiered support model could also be evaluated in future studies. Students with different levels of nicotine dependence and sleep quality problems may require different levels of assessment, health education, psychological support, smoking-cessation counseling, or medical referral. Nevertheless, this cross-sectional study cannot determine which components are effective, whether any component is sufficient, or how services should be sequenced.

6 Limitations and Future Directions

This study has several limitations. First, the cross-sectional design limits the ability to determine the temporal order and causal relationships among self-control, sleep quality problems, and nicotine dependence. Future studies should employ longitudinal designs, ecological momentary assessment, or intervention approaches to further examine the dynamic relationships among these variables. Cross-lagged models may also help clarify whether sleep quality problems predict subsequent changes in nicotine dependence or whether nicotine dependence contributes to later sleep deterioration.

Second, this study primarily relied on self-report questionnaires, which may introduce common method bias and social desirability effects (Podsakoff et al., 2003). Moreover, although self-control and sleep quality problems were identified as important correlates of nicotine dependence, other relevant factors, such as smoking behaviors, emotional symptoms, social influences, and biological indicators, were not included in the current model. Future research should combine

objective measures (e.g., wearable sleep monitoring and biochemical indicators), behavioral records, and more comprehensive models to better capture the multifactorial nature of nicotine dependence. In addition, the relatively low internal consistency of the FTND in this sample (Cronbach's $\alpha = 0.625$) may have affected the stability of observed associations. Future studies should consider using multiple measures of nicotine dependence to improve assessment reliability.

Third, the sample was limited to college student smokers, which restricts the generalizability of the findings to other populations, including non-smokers, older adults, and individuals with different smoking patterns. Future research should include more diverse samples and comparison groups to examine whether the relationships among self-control, sleep quality problems, and nicotine dependence vary across different populations. Furthermore, although the indirect effect through sleep quality problems was statistically significant, the completely standardized indirect effect was relatively small (effect = -0.0341), suggesting that sleep represents only one component of a broader risk pathway. Therefore, sleep-related interventions should be integrated with comprehensive smoking cessation strategies rather than considered as a standalone approach.

7 Conclusion

Based on a sample of 945 Chinese college student smokers, this study identified cross-sectional associations among self-control, sleep quality problems, and nicotine dependence. Lower self-control was associated with more severe sleep quality problems and higher nicotine dependence, and the indirect association through sleep quality problems was statistically significant but small. These findings support further investigation of self-control, sleep health, and nicotine

dependence within longitudinal and experimental designs. They should not be interpreted as establishing temporal ordering, a causal mechanism, or the effectiveness of self-control training, sleep-focused education, or other intervention components.

Declarations

Ethics Approval and Consent to Participate

This study was approved by the Human Research Ethics Committee of Zunyi Medical University (Approval No. ZMU[2025]3-009) and was conducted in accordance with the Declaration of Helsinki and its subsequent amendments. All participants provided informed consent prior to participation.

Competing Interests

The authors declare that they have no competing interests.

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Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Author Contributions

B.H., W.Q., and T.B. contributed to the conception and development of the study. B.H. and W.Q. contributed to data collection, data processing, and statistical analysis. B.H. drafted the initial manuscript. T.B. supervised the study and critically revised the manuscript for important intellectual content. All authors reviewed and approved the final version of the manuscript.

References

- Akbari, M., Hasani, J., & Seydavi, M. (2020). Negative affect among daily smokers: A systematic review and meta-analysis. *Journal of Affective Disorders*, 274, 553–567. <https://doi.org/10.1016/j.jad.2020.05.063>
- Amiri, S., & Behnezhad, S. (2020). Smoking and risk of sleep-related issues: A systematic review and meta-analysis of prospective studies. *Canadian Journal of Public Health*, 111(5), 775–786. <https://doi.org/10.17269/s41997-020-00308-3>
- Baker, T. B., Piper, M. E., McCarthy, D. E., Majeskie, M. R., & Fiore, M. C. (2004). Addiction motivation reformulated: An affective processing model of negative reinforcement. *Psychological Review*, 111(1), 33–51. <https://doi.org/10.1037/0033-295X.111.1.33>
- Becker, S. P., Jarrett, M. A., Luebbe, A. M., Garner, A. A., Burns, G. L., & Kofler, M. J. (2018). Sleep in a large, multi-university sample of college students: Sleep problem prevalence, sex differences, and mental health correlates. *Sleep Health: Journal of the National Sleep Foundation*, 4(2), 174–181. <https://doi.org/10.1016/j.sleh.2018.01.001>
- Benowitz, N. L. (2009). Pharmacology of nicotine: Addiction, smoking-induced disease, and therapeutics. *Annual Review of Pharmacology and Toxicology*, 49, 57–71. <https://doi.org/10.1146/annurev.pharmtox.48.113006.094742>
- Boehm, M. A., Lei, Q. M., Lloyd, R. M., & Prichard, J. R. (2016). Depression, anxiety, and tobacco use: Overlapping impediments to sleep in a national sample of college students. *Journal of American College Health*, 64(7), 565–574. <https://doi.org/10.1080/07448481.2016.1205073>
- Busse, D. J., Reynolds, C. F., 3rd, Monk, T. H., Berman, S. R., & Kupfer, D. J. (1989). The Pittsburgh Sleep Quality Index: A new instrument for psychiatric practice and research. *Psychiatry Research*, 28(2), 193–213. [https://doi.org/10.1016/0165-1781\(89\)90047-4](https://doi.org/10.1016/0165-1781(89)90047-4)
- Cohrs, S., Rodenbeck, A., Riemann, D., Szagun, B., Jaehne, A., Brinkmeyer, J., Gründer, G., Wienker, T., Diaz-Lacava, A., Mobascher, A., Dahmen, N., Thürauf, N., Kornhuber, J., Kiefer, F., Gallinat, J., Wagner, M., Kunz, D., Grittner, U., & Winterer, G. (2014). Impaired sleep quality and sleep duration in smokers—results from the German Multicenter Study on Nicotine Dependence. *Addiction Biology*, 19(3), 486–496. <https://doi.org/10.1111/j.1369-1600.2012.00487.x>
- DiFranza, J. R., Savageau, J. A., Rigotti, N. A., Fletcher, K., Ockene, J. K., McNeill, A. D., Coleman, M., & Wood, C. (2002). Development of symptoms of tobacco dependence in youths: 30 month follow up data from the DANDY study. *Tobacco Control*, 11(3), 228–235. <https://doi.org/10.1136/tc.11.3.228>

- Etter, J.-F., Le Houezec, J., & Perneger, T. V. (2003). A self-administered questionnaire to measure dependence on cigarettes: the cigarette dependence scale. *Neuropsychopharmacology*, 28(2), 359–370. <https://doi.org/10.1038/sj.npp.1300030>
- Fagerström, K. (2012). Determinants of tobacco use and renaming the FTND to the Fagerström Test for Cigarette Dependence. *Nicotine & Tobacco Research*, 14(1), 75–78. <https://doi.org/10.1093/ntr/ntr137>
- Fluharty, M., Taylor, A. E., Grabski, M., & Munafò, M. R. (2017). The association of cigarette smoking with depression and anxiety: A systematic review. *Nicotine & Tobacco Research*, 19(1), 3–13. <https://doi.org/10.1093/ntr/ntw140>
- Geng, Y., Gu, J., Wang, J., & Zhang, R. (2021). Smartphone addiction and depression, anxiety: The role of bedtime procrastination and self-control. *Journal of Affective Disorders*, 293, 415–421. <https://doi.org/10.1016/j.jad.2021.06.062>
- Goldstein, A. N., & Walker, M. P. (2014). The role of sleep in emotional brain function. *Annual Review of Clinical Psychology*, 10, 679–708. <https://doi.org/10.1146/annurev-clinpsy-032813-153716>
- Hayes, A. F. (2022). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach (3rd ed.). The Guilford Press.
- Heatherton, T. F., Kozlowski, L. T., Frecker, R. C., & Fagerstrom, K.-O. (1991). The Fagerström Test for Nicotine Dependence: A revision of the Fagerstrom Tolerance Questionnaire. *British Journal of Addiction*, 86(9), 1119–1127. <https://doi.org/10.1111/j.1360-0443.1991.tb01879.x>
- Huang, Q., Li, Y., Huang, S., Qi, J., Shao, T., Chen, X., Liao, Z., Lin, S., Zhang, X., Cai, Y., & Chen, H. (2020). Smartphone use and sleep quality in Chinese college students: A preliminary study. *Frontiers in Psychiatry*, 11, Article 352. <https://doi.org/10.3389/fpsy.2020.00352>
- Jaehne, A., Loessl, B., Bárkai, Z., Riemann, D., & Hornyak, M. (2009). Effects of nicotine on sleep during consumption, withdrawal and replacement therapy. *Sleep Medicine Reviews*, 13(5), 363–377. <https://doi.org/10.1016/j.smrv.2008.12.003>
- Kroese, F. M., De Ridder, D. T. D., Evers, C., & Adriaanse, M. A. (2014). Bedtime procrastination: Introducing a new area of procrastination. *Frontiers in Psychology*, 5, Article 611. <https://doi.org/10.3389/fpsyg.2014.00611>
- Kühnel, J., Syrek, C. J., & Dreher, A. (2018). Why don't you go to bed on time? A daily diary study on the relationships between chronotype, self-control resources and the phenomenon of bedtime procrastination. *Frontiers in Psychology*, 9, Article 77. <https://doi.org/10.3389/fpsyg.2018.00077>

- Leventhal, A. M., & Zvolensky, M. J. (2015). Anxiety, depression, and cigarette smoking: A transdiagnostic vulnerability framework to understanding emotion-smoking comorbidity. *Psychological Bulletin*, 141(1), 176–212. <https://doi.org/10.1037/bul0000003>
- Lund, H. G., Reider, B. D., Whiting, A. B., & Prichard, J. R. (2010). Sleep patterns and predictors of disturbed sleep in a large population of college students.. *Journal of Adolescent Health*, 46(2), 124–132. doi:10.1016/j.jadohealth.2009.06.016.
- Maxwell, S., & Cole, D. (2007). Bias in Cross-Sectional Analyses of Longitudinal Mediation. *Psychological Methods*, 12, 23–44. <https://doi.org/10.1037/1082-989X.12.1.23>
- Mingxin, Q., Xinying, Z., Liu, S., Ying, L., & Xiao, L. (2026). Smoking Prevalence and Initiation Reasons Among College Students — China, 2025. *China CDC Weekly*, 8, 673–678. <https://doi.org/10.46234/ccdcw2026.109>
- Moffitt, T. E., Arseneault, L., Belsky, D., Dickson, N., Hancox, R. J., Harrington, H., Houts, R., Poulton, R., Roberts, B. W., Ross, S., Sears, M. R., Thomson, W. M., & Caspi, A. (2011). A gradient of childhood self-control predicts health, wealth, and public safety. *Proceedings of the National Academy of Sciences*, 108(7), 2693–2698. <https://doi.org/10.1073/pnas.1010076108>
- Palmer, C., & Alfano, C. (2016). Sleep and emotion regulation: An organizing, integrative review. . *Sleep Medicine Reviews*, 31. <https://doi.org/10.1016/j.smrv.2015.12.006>
- Piasecki, T., Richardson, A., & Smith, S. (2007). Self-monitored motives for smoking among college students. *Psychology of Addictive Behaviors*, 21, 328–337. <https://doi.org/10.1037/0893-164X.21.3.328>
- Piper, M. E., Piasecki, T. M., Federman, E. B., Bolt, D. M., Smith, S. S., Fiore, M. C., & Baker, T. B. (2004). A multiple motives approach to tobacco dependence: the Wisconsin Inventory of Smoking Dependence Motives (WISDM-68). *Journal of Consulting and Clinical Psychology*, 72(2), 139–154. <https://doi.org/10.1037/0022-006x.72.2.139>
- Podsakoff, P., MacKenzie, S., Lee, J.-Y., & Podsakoff, N. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88, 879–903. <https://doi.org/10.1037/0021-9010.88.5.879>
- Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, 40(3), 879–891. <https://doi.org/10.3758/BRM.40.3.879>
- Purani, H., Friedrichsen, S., & Allen, A. M. (2019). Sleep quality in cigarette smokers: Associations with smoking-related outcomes and exercise. *Addictive Behaviors*, 90, 71–76. <https://doi.org/10.1016/j.addbeh.2018.10.023>
- Ridder, D., Lensvelt-Mulders, G., Finkenauer, C., Stok, M., & Baumeister, R. (2012). Taking Stock of Self-Control A Meta-Analysis of How Trait Self-Control Relates to a Wide

- Range of Behaviors. *Personality and Social Psychology Review*, 16, 76–99.
<https://doi.org/10.1177/1088868311418749>
- Shiffman, S., Waters, A., & Hickcox, M. (2004). The nicotine dependence syndrome scale: a multidimensional measure of nicotine dependence. *Nicotine & Tobacco Research*, 6(2), 327–348. <https://doi.org/10.1080/1462220042000202481>
- Tangney, J. P., Baumeister, R. F., & Boone, A. L. (2004). High self-control predicts good adjustment, less pathology, better grades, and interpersonal success. *Journal of Personality*, 72(2), 271–324. <https://doi.org/10.1111/j.0022-3506.2004.00263.x>
- Wetter, D. W., & Young, T. B. (1994). The relation between cigarette smoking and sleep disturbance. *Preventive Medicine*, 23(3), 328–334.
<https://doi.org/10.1006/pmed.1994.1046>
- Wilson, S. J., & Maclean, R. R. (2013). Associations between self-control and dimensions of nicotine dependence: a preliminary report. *Addictive Behaviors*, 38(3), 1812–1815.
<https://doi.org/10.1016/j.addbeh.2012.11.004>
- Yang, J., Fu, X., Liao, X., & Li, Y. (2020). Association of problematic smartphone use with poor sleep quality, depression, and anxiety: A systematic review and meta-analysis. *Psychiatry Research*, 284, 112686. <https://doi.org/10.1016/j.psychres.2019.112686>
- Zhang, M. X., & Wu, A. M. S. (2020). Effects of smartphone addiction on sleep quality among Chinese university students: The mediating role of self-regulation and bedtime procrastination. *Addictive Behaviors*, 111, 106552.
<https://doi.org/10.1016/j.addbeh.2020.106552>



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AI-Enabled Learning Support and Student Learning Performance in Malaysian Higher Education: The Mediating Roles of Self-Regulated Learning and Academic Engagement

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Abstract

Objective: To develop a conceptual model examining the relationships between AI learning support, digital competence, teacher AI guidance, and learning performance among students in Malaysian higher education institutions. **Methods:** The proposed study adopts a quantitative cross-sectional design. Data will be collected through a survey of Malaysian university students, and the hypothesised relationships will be tested using structural equation modelling. The model includes academic engagement and self-regulated learning as sequential mediators and academic integrity concern as a moderator of the relationship between academic engagement and learning performance. **Results:** Drawing on self-regulated learning theory, student engagement theory, social cognitive theory, AI literacy, digital competence, and academic integrity literature, the proposed model suggests that AI learning support does not automatically improve students' learning performance. Its effectiveness depends on students' ability to use AI strategically, critically, and ethically, together with appropriate guidance from lecturers. **Conclusion:** The proposed model contributes to the AI education literature by shifting attention from students' intention to adopt AI towards the learning mechanisms through which AI use may influence academic outcomes. It also provides a framework for understanding the roles of academic engagement, self-regulated learning, teacher guidance, digital competence, and academic integrity in AI-supported learning.

Keywords: Artificial intelligence, AI learning support, digital competence, self-regulated learning, academic engagement, academic integrity

Introduction

AI is a significant player in reshaping the higher education landscape. AI is being researched in universities globally for its potential in teaching and learning, assessment and

feedback, student advising, research and academic administration (Bond et al., 2024; Holmes et al., 2019; Luckin, 2017). The education sector in Malaysia is also witnessing a fast-paced digital transformation, following the increased demand for flexible, tech-enabled and future-oriented learning. The importance of AI readiness, education through technology, and AI in education cannot be overstated, as it is increasingly focus of Malaysia's national agenda in relation to AI-enabled learning in higher education (Jamaluddin, 2025; UNESCO, 2023).

AI-powered learning tools offer a number of educational advantages. They can be used to aid students in comprehending challenging concepts, creating examples, getting prompt explanation, enhancing writing, arranging learning material and preparing for examinations, etc. (Chan & Hu, 2023; Kasneci et al., 2023; Zawacki-Richter et al., 2019). AI technologies can serve as personal assistants for students needing extra learning support, available outside of class time. This is particularly important in higher education in Malaysia, where students have a varied academic, linguistic, cultural and technological background.

But using AI tools does not equal better learning. Technology powered by artificial intelligence can be used actively and responsibly by students, or passively and unethically by students. Some students may seek to clarify concepts and enhance learning strategies by using AI (Cotton et al., 2024; Eaton, 2023; Perkins, 2023) while others use AI tools to copy content without understanding or acknowledging the work (Cotton et al., 2024; Eaton, 2023; Perkins, 2023). The question is not just whether students employ AI tools, but how they employ them and when—under what learning conditions—is the use of AI tools contributing to true learning?

In the past, there were many studies that specifically concentrated on acceptance of technology, perceived usefulness, ease of use, and behavioural intention (Davis, 1989; Venkatesh et al., 2003; Venkatesh et al., 2012). While this is true, it is not all of the factors that account for

how AI tools affect academic outcomes. A student can use AI and accept it in more ways than one, but that doesn't necessarily mean that this is having an impactful effect on learning. Hence, the present paper suggests a learning mechanism-based model instead of a mere technology adoption.

Specifically, the proposed model investigates the effects of AI learning support, digital competence, and teacher AI guidance on students' learning performance by way of self-regulated learning and academic engagement. Self-regulated learning also is crucial because the learning behaviour needs to be planned, monitored, evaluated and controlled by the learners (Pintrich, 2000; Zimmerman, 2002). Academic engagement also is critical as students need to be actively involved in learning activities in order for AI support to lead to positive academic outcomes (Fredricks et al., 2004; Kahu, 2013; Kuh, 2009).

Academic Integrity Concern is also included as a moderating variable in this paper. Ethical awareness is key in the context of AI in education, as students can employ AI for learning support or as a tool to expedite academic work. Academic integrity concern is linked to greater likelihood to confirm AI-generated information, not plagiarize, and recognize AI assistance as required (Bretag, 2016; Eaton, 2023; McCabe et al., 2012). So academic integrity issue can boost the connection between academic involvement and real academic outcomes.

Literature Review

Artificial Intelligence in Malaysian Higher Education

AI in education is the application of intelligent systems to assist in learning, teaching, feedback, prediction, assessment, and academic decision making (Holmes et al., 2019; Luckin, 2017). Some tools that make use of AI can encompass intelligent tutoring systems, automated

writing support, adaptive learning platforms, learning analytics systems, and generative AI applications. They can facilitate students' flexible and independent learning and assist teachers in creating more responsive learning settings (Ifenthaler & Yau, 2020; Zawacki-Richter et al., 2019).

In Malaysia, the relevance of AI comes in the wake of the digital transformation of universities in higher education. The use of online learning, blended learning, digital platforms and data-driven academic support have increased. AI tools can help with these changes by providing students with academic support outside of the classroom. The effective application of AI requires digital competence of students, guidance from lecturers, institutional preparedness, and ethical awareness (Bond et al., 2024; Jamaluddin, 2025; UNESCO, 2023).

AI must not be perceived as a replacement for teachers and students' work. Instead, it should be seen as a learning support mechanism. Holmes et al. (2019) proposed that in education the use of AI must be to assist human learning and human judgement, not to replace them. UNESCO (2023) also highlighted the importance of using generative AI in education in ways that are shaped by human-centered principles and values, inclusion, transparency and ethical protection. These viewpoints are particularly crucial for integration of AI into Malaysian universities, as it should contribute to enhancing the educational experience while simultaneously promoting academic integrity.

AI Learning Support

AI learning support is students' perception of how they use AI to support their academic learning activities. Such support can encompass aiding students in comprehending complex ideas, offering illustrative examples, guiding writing, offering feedback, creating practice questions, organizing ideas, and guiding the revision process. AI learning support is different from general digital technology use, as it specifically addresses the learning support that is offered by AI-

based systems (Kasneci et al., 2023; Ng et al., 2021).

Students might be able to overcome learning obstacles with AI learning support. If they have difficulty understanding the academic language, students can ask AI to explain it in simpler terms; if they have difficulty with a topic, students can ask AI to give examples or explain it in other ways. These functions can be especially beneficial in multilingual and heterogeneous contexts like Malaysia in higher education. Learning support, on the other hand, can only be useful if students apply it critically with the help of AI support. When students copy the AI-generated responses, learning quality can be decreased by AI. When they use AI to brainstorm ideas, track their comprehension, and edit their work, AI can enhance their learning journey (Chan & Hu, 2023; Kasneci et al., 2023).

Digital Competence

Digital competence is the complex ability of students to use digital tools effectively, critically, creatively and responsibly. It contains skills like information searching, digital communication, online collaboration, problem solving, privacy awareness and evaluation of digital information (Carretero et al., 2017; Ferrari, 2013). Digital competence in the age of AI also encompasses how to interact with AI systems, how to evaluate AI-generated content, and how to understand the ethical issues that arise from the use of AI (Long & Magerko, 2020; Ng et al., 2021).

Higher levels of digital competence are correlated with greater strategic use of AI tools by students. They can refine their prompts, compare AI-generated content to academic texts, recognize incorrect information, and leverage AI to help achieve specific learning objectives. However, learners with less digital competence might be misled or misinterpret digital responses, accept information that is not accurate, or rely too heavily on generated content. This is

especially so for digital competence in Malaysian Higher Education as universities are expected to produce graduates who can function in digital and AI driven environments.

Teacher AI Guidance

Teacher AI guidance involves lecturers giving direction, support and instruction on how to use the AI tools appropriately for learning. This guidance might involve the communication of acceptable uses of AI, the creation of exemplar prompts, prompting students to reflect on the outputs of AI, and the rules concerning plagiarism and academic integrity (Boud & Molloy, 2013; McDonald et al., 2024).

Lecturers have a pivotal role in influencing students' learning behaviour in relation to AI. Students might be more inclined to utilize artificial intelligence tools as learning aids when they receive clear and constructive guidance from lecturers. When lecturers give clear and constructive guidance, students are more likely to use AI tools as learning supports. But when lecturers do not take any action on AI usage or only ban it without any justification, students may resort to using AI surreptitiously without comprehending the ethics. Teacher guidance can lower the uncertainty and help students to be more responsible regarding learning strategies (Dotan et al., 2024; UNESCO, 2023).

Self-Regulated Learning

Self-regulated learning is the ability of students to plan, monitor, control and evaluate their own learning. It involves goal setting, time management, learning strategy use, self-monitoring, reflection, and help seeking (Boekaerts, 1999; Pintrich, 2000; Zimmerman, 2002). Self-regulated learning is particularly significant in the setting of an AI-supported learning environment. Students can have access to powerful tools that may give them answers that will immediately

appear.

A self-regulated student can leverage AI to verify comprehension, create practice questions, share explanations, and identify knowledge gaps. A student who is not supervised may use AI to simply hand in work without learning. In this regard, self-regulated learning, which is one of the mechanisms that influence academic engagement, is proposed here as an important pathway by which AI learning support and digital competence, as well as the teacher's guidance on the use of AI, exert their effects.

Academic Engagement

Academic engagement is defined as students' active participation in the academic learning process. It consists of behavioural engagement, emotional engagement, and cognitive engagement (Fredricks et al., 2004). Behavioural engagement is manifested in participation, effort, and task completion. Emotional engagement consists of interest, motivation and positive learning feelings. Cognitive engagement is characterized by complex learning strategies, persistence and deep thinking (Kahu, 2013; Kuh, 2009).

AI tools can enhance engagement through interactive and personalized learning experiences. Students will be better able to have instant explanations. Additionally, they can be more cognitively involved when utilizing AI to investigate concepts and contrast point of views. Furthermore, they can be more intellectually engaged when moving on the ideas and contrasting points of view with AI. But AI doesn't mean engagement. Cognitive passivity means that learners may engage with the AI on a regular basis without questioning or judging the content created by the AI, as this would require additional cognitive effort and skills (Bond et al., 2024; Selwyn, 2022).

Learning Performance

Learning performance are defined as the students' learning results, such as learning improvements as perceived by students, academic task performance, learning achievement of the course, students' grades, and students' satisfaction with learning. The model doesn't make the assumption that AI will directly enhance performance. Instead, it suggests that AI can enhance performance when used to facilitation SRL and academic engagement. Because student behaviour, motivation, and effort, as well as ethical use, will influence learning outcomes, this is important, not only technology (Kuh, 2009; Pintrich, 2000; Zimmerman, 2002).

Academic Integrity Concern

Academic integrity concern is the student's concern and awareness for academic honesty, originality, responsibility, fairness and appropriate acknowledgment in academic work. This is a critical concern in AI-supported learning as generative AI can generate text that may be submitted as student work. Cotton et al. (2024), Eaton (2023), and Perkins (2023) stated that AI poses new academic integrity challenges due to the difficulties in distinguishing between assistance and academic dishonesty.

Students who have high academic integrity concern are more likely to use AI responsibly. They can confirm AI-generated content, refrain from copying AI-generated content, note when AI has been used and as required, follow institutional guidelines. Based on this, academic integrity concern is thus proposed as a moderator between academic engagement and learning performance.

Theoretical Foundation

This study is based on the integrated theoretical framework of self-regulated learning theory,

student engagement theory, social cognitive theory, AI literacy theory, digital competence literature, teacher scaffolding and academic integrity scholarship. The proposed model presents the claim that the adoption of AI-based LSU in Malaysian Higher Education institutions does not necessarily lead to improved learning outcomes. Rather, AI supports students' learning when they have adequate digital competence, are guided by their teacher in a meaningful way, take charge of their own learning, are actively involved in learning-related tasks, and are mindful of what is expected with respect to academic integrity.

Self-Regulated Learning Theory

The concept of SRL theory is a conceptual model that describes how students plan, monitor, use strategies and reflect on their learning process. According to Zimmerman (2002), SRLs are students who are metacognitively, motivationally, and behaviourally engaged in learning. In the same way, Pintrich (2000) stated that self-regulation is consisting of goal-setting, self-monitoring, control of learning strategies, and reflection on learning progress. The other important research that was mentioned was Boekaerts' (1999) formulation that SRL is a function of student motivation, cognitive strategies, and learning context.

Self-regulated learning is an important concept in AI-enabled learning because while AI tools can offer students the necessary support, they must learn to use this support in the right manner. Students can use AI to gain a deeper understanding of complex topics, create examples, proofread grammar, summarise information, and get instant explanations. However, if students are not self-regulated, they might passively or dependently use AI tools (Kasneci et al., 2023; Selwyn, 2022).

Self-regulated students are better able to strategic use AI. They can ask AI to present the concept in other ways, compare the answers from the AI with academic sources, adjust their

understanding and track their own learning. Based on this view, AI learning support does not contribute to learning unless it enhances the students' capacity to self-manage their learning. The authors Schunk and Greene (2018) pointed out that self-regulation is not a personal attribute but a learning ability that can be developed through learning environments, feedback and instructional support.

Student Engagement Theory

The proposed model also draws on the theory of student engagement. Academic engagement is the level of students' emotional, cognitive and behavioral participation in learning. Fredricks et al. (2004) found three key aspects of engagement: behavioural engagement, emotional engagement, and cognitive engagement. There is extensive research on how engagement relates to learning success in higher education. Kuh (2009) asserted that student engagement is a measure of "time and effort spent on educationally purposeful activity". Kahu (2013) went on to explain that engagement is the link between student motivation, institutional conditions, learning behaviour, and outcomes.

Engagement is even more crucial in AI-supported learning environments as the presence of AI tools could foster engagement but can also lead to shallow tasks. By making learning more interactive, responsive, and personalised, AI tools can help boost engagement. But AI use is not always a sure thing for engagement. If students use generated answers without reflection, they might have frequent opportunities to talk with AI, but lack the opportunity for cognitive engagement (Bond et al., 2024; Selwyn, 2022).

Social Cognitive Theory

According to social cognitive theory, learning is influenced by the interplay between

personal characteristics, behaviour and environment. Bandura (1986) stated that human learning is a result of reciprocal determinism, which is an interaction between personal cognition, behaviour, and environment. From the perspective of the usage of AI in education, students' digital competency is a personal competency, teacher AI guidance is an environmental support, and self-regulated learning is a learning behaviour.

This is especially helpful to consider when talking about the adoption of AI in Malaysian higher education as students are not using AI alone. They are shaped by their own confidence and competence, digital learning environment, lecturer expectations, the norms of peers and institutional policies. A student who has good digital competence might feel more confident in being able to leverage AI tools properly. Providing clear guidance on the proper use of AI by a lecturer can foster a responsible environment for using AI. These can influence students' SRL behaviour and thereby student engagement and learning performance.

AI Literacy and Digital Competence Perspective

AI literacy is defined as the awareness and proficiency needed to understand, utilize, assess and engage with AI systems in a responsible manner. AI literacy is a collection of abilities that enable people to critically analyze AI technologies and effectively interact with them, according to Long and Magerko (2020). Ng et al. (2021) also added the four components of AI literacy, which are concept of AI, application of AI, assessment of AI output and ethical consideration related to AI. More recent debates on AI literacy also highlight the importance of understanding of AI systems at a functional, critical, and sociocultural level (Gu & Ericson, 2025).

Digital competence is closely related to AI literacy. In the proposed model, digital competence becomes a predictor of SRL due to its ability to effectively utilize AI tools by students for academic purposes. They can ask more precise questions, evaluate the pertinence of

the AI-generated answers, confirm the information, and prevent inappropriate usage. This is particularly relevant for the Malaysian educational sector as the students are required to be able to function in a learning environment that is rich in technology.

Teacher Guidance and Scaffolding Perspective

The other critical theoretical factor in this research is the teacher's AI guidance. AI tools can be directly used by students, but lecturers play a crucial role in how these tools are applied. The teacher guidance can be explained with the term scaffolding, which is a support given by the teacher so that the learner can do something that he or she cannot do alone (Boud & Molloy, 2013).

Scaffolding can involve clarifying ethical and responsible use of AI, providing models of good prompting, teaching students how to recognize the use of AI, or summarizing academic integrity guidelines. Uncertainty can also be minimized through teacher AI guidance. Students might not know if they're permitted to use AI or if they can use too much, or whether they have to cite AI-generated ideas. Good lecturer guidance can support students in their safe and responsible use of AI (Dotan et al., 2024; McDonald et al., 2024).

Academic Integrity and Ethical AI Use

Academic integrity is defined as honesty, responsibility, fairness, trust and respect in academic work (Bretag, 2016; McCabe et al., 2012). AI in education brings academic integrity into focus as students might be tempted to complete assignments using generative AI-generated content as their own. Cotton et al. (2024) stated that ChatGPT and other AI tools present significant ethical and academic integrity concerns that must be addressed, as they offer a range of possibilities for academic cheating that are hard to distinguish from academic support and

collaboration. Bittle et al. (2025) also noted the positive and negative implications generative AI has had for academic integrity in higher education.

In this model, academic integrity concern is considered as a moderator between academic engagement and performance in learning. The answer is that engagement can't always ensure that learning is authentic. Even if a student is very active in using AI tools, they could still be misusing them if they are not aware of academic integrity. On the other hand, students of high academic integrity worry more about using AI tools to enhance their real learning. However, students with high academic integrity are more likely to be concerned about using AI for authentic learning. It aligns with the recent calls for a multi-layered approach to assessment, encompassing not just the use of AI detection tools but also the creation of assessment designs, policies, and learning cultures that foster responsible use of AI (Eaton, 2023; Perkins, 2023; UNESCO, 2023).

Hypotheses Development

AI Learning Support and Self-Regulated Learning

AI learning support is the perception that the student has about the usefulness of the use of AI tools to support their academic learning. This can involve clarifying complex ideas, generating examples, offering guidance with writing, offering feedback, supporting revision and independent study. The idea that self-regulated learning works best when students can plan, monitor and assess their learning activities (Pintrich 2000; Zimmerman, 2002) is supported by research. AI tools can assist this process by enabling pupils to ask questions, identify gaps in knowledge and be given instant answers.

But AI learning support does not necessarily lead to self-regulation. Students will be

required to intentionally and critically use AI tools. The use of AI for rapid answers could undermine SRL. However, if AI is used as a learning aid, it can motivate students to establish learning goals, practice their learning, and refine their learning products. AI in education research indicates that when used correctly, AI tools can contribute significantly to personalised learning and feedback (Holmes et al., 2019; Kasneci et al., 2023; Luckin, 2017).

H1: AI learning support positively influences self-regulated learning among Malaysian higher education students.

Digital Competence and Self-Regulated Learning

Digital competence is defined as student's ability to utilize digital technologies effectively, critically and responsibly. It covers aspects of information search, assessing online resources, solving digital problems, using e-learning platforms, as well as the ethical implications of digital tools (Carretero et al., 2017; Ferrari, 2013). Digital competence is particularly relevant in AI-supported education as it involves students engaging with intricate systems, assessing suggestions created by AI, and defending academic integrity.

There is a positive correlation between students' digital competence and the strategic use of AI tools. They can develop more effective prompts, detect misleading information, compare AI-generated answers to academic resources, and use digital tools to assist learning objectives. Such behaviours are highly similar to the SRL behaviors. Ng et al. (2021) suggested that AI literacy is required so that the learners can be aware of applications of AI and use them responsibly. The importance of being able to critically assess AI systems is also highlighted by Long and Magerko (2020), who call for AI literacy.

H2: Digital competence positively influences self-regulated learning among Malaysian higher education students.

Teacher AI Guidance and Self-Regulated Learning

The concept of teacher AI guidance is how much direction, explanation and support teachers give their students with the proper use of AI tools. Lecturers can guide students from the use of unstructured AI tools to meaningful AI-assisted learning from a scaffolding point of view. Boud and Molloy (2013) proposed that students' feedback should contribute to the development of evaluative judgement. With AI-assisted learning, lecturers can assist students in evaluating the accuracy and relevance of AI-generated answers and decide whether they are academically suitable.

AI policies for higher education institutions could vary from university to faculty, making teacher guidance especially critical in the Malaysian context. Lecturers can guide students to control their use of AI according to academic standards when they give clear guidance. In the absence of guidance, students can turn to peer norms or personal judgement which may lead to increased risk of misuse (Dotan et al., 2024; McDonald et al., 2024).

H3: Teacher AI guidance positively influences self-regulated learning among Malaysian higher education students.

Self-Regulated Learning and Academic Engagement

Self-regulated learning is expected to positively influence academic engagement as students who manage their learning positively are expected to be active in academic tasks. The 4 components of SRL are setting goals, monitoring progress, adjusting strategies, and reflecting on outcomes (Boekaerts, 1999; Schunk & Greene, 2018; Zimmerman, 2002). These behaviours are closely related to behavioural and cognitive engagement.

Student engagement theory proposes that student engagement is a three-part process that includes behavioral, emotional and cognitive engagement in learning (Fredricks et al., 2004). All

three dimensions are nurtured by SFL. Self-regulation may be even more critical in an AI-supported learning environment, as students are presented with vast quantities of information generated by AI. If they aren't self-regulated, students can get distracted or rely too heavily on AI. Self-regulation enables students to utilize AI resources to promote active learning.

H4: Self-regulated learning positively influences academic engagement among Malaysian higher education students.

Academic Engagement and Learning Performance

Academic involvement is known to be one of the factors that predicts learning performance. Engaged students are more likely to invest in learning activities by spending time, effort and attention. In the case of engagement, Kuh (2009) said that it means students are involved in educationally relevant activities, which helps to achieve learning success. Kahu (2013) also highlighted that engagement is the link between institutional support, student motivation, student learning behaviour and outcomes.

Engagement is the key to whether students leverage AI tools meaningfully in AI-supported education. For engaged students, AI can help them brainstorm ideas, refine their writing, practice their comprehension and critically analyze feedback. These activities can enhance learning performance as they are active cognitive processes. On the other hand, students who are just using AI to get the work done might finish tasks swiftly, but they might not grasp the content thoroughly (Selwyn, 2022).

H5: Academic engagement positively influences learning performance among Malaysian higher education students.

Sequential Mediation of Self-Regulated Learning and Academic Engagement

The model proposed in this study suggests that the impact of factors related to AI on learning performance is mediated by self-regulated learning and academic engagement. This implies that the initial effects of AI learning support, digital competence and teacher AI guidance are to enhance the ability of students to regulate their learning. Increased academic engagement results in increased learning performance, while increased self-regulated learning increases academic engagement.

This sequence of mediation logic is in line with the concept of learning outcome being generated through learning processes, and not just through technology access. AI tools can be used as resources, and students should be able to control how they utilize the assistance. Engagement in academic activities is more likely when students have a successful regulation of their learning. Engagement is then linked to enhanced performances (Fredricks et al., 2004; Kahu, 2013; Pintrich, 2000).

H6: Self-regulated learning and academic engagement sequentially mediate the relationship between AI learning support and learning performance.

H7: Self-regulated learning and academic engagement sequentially mediate the relationship between digital competence and learning performance.

H8: Self-regulated learning and academic engagement sequentially mediate the relationship between teacher AI guidance and learning performance.

Moderating Role of Academic Integrity Concern

Academic Integrity Concern indicates students' understanding and interest in academic integrity, including the use of AI responsibly, avoiding plagiarism, and giving proper credit. Academic integrity concern plays a crucial role in AI-powered learning, as students can choose

to employ AI either as a learning aid or to avoid effort. Cotton et al. (2024), Eaton (2023) and Perkins (2023) emphasized that generative AI presents problems for academic integrity due to the potential for students to generate content that could be considered theirs, but may not be.

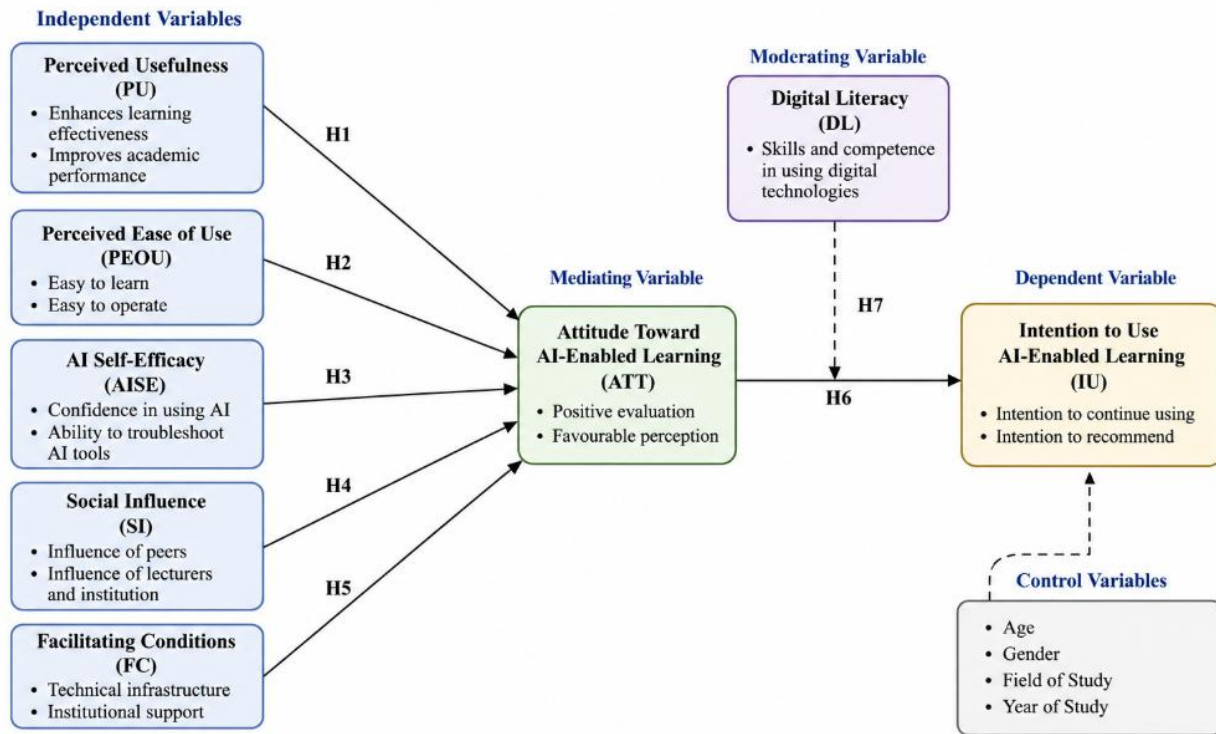
Based on this idea, this study argues that academic integrity concern is a moderator between academic engagement and learning performance. With high academic integrity concerns, engaged students are more apt to make responsible use of AI. They can confirm AI-generated work, refrain from plagiarizing AI-generated content, cite the use of AI if necessary, and ensure that their work is their own. In such a situation, students' engagement in an academic activity will increase the likelihood of achieving actual academic performance.

H9: Academic integrity concern moderates the relationship between academic engagement and learning performance, such that the relationship is stronger when academic integrity concern is high.

Proposed Conceptual Framework

The proposed conceptual framework comprises of three independent variables, namely AI learning support, digital competence, and teacher AI guidance. These variables are hypothesized to have an effect on self-regulated learning. The roles of self-regulated learning in influencing academic engagement and learning performance are expected. It is suggested that self-regulated learning and academic engagement are sequential mediators. Academic integrity concern is suggested as a mediating factor between academic engagement and academic performance.

The proposed model can be summarized in figure 1:

Figure 1. Research Model

Proposed Methodology

Research Design

The research design in this study is quantitative research with a cross-sectional survey type. The study seeks to test hypothesized relationships between measurable constructs; a quantitative design is appropriate. The cross-sectional study method is suitable for asking answers from a large number of students from universities for a certain period of time. The study of educational technology and AI adoption often relies on quantitative survey designs, as they enable researchers to analyze the relationship among perceptions, learning processes and learning outcomes (Hair et al., 2022; Zawacki-Richter et al., 2019).

Research Context

The study will be focusing the Malaysian higher education sector. The study setting can be public or private universities in Malaysia. The context of this Malaysia is appropriate as various higher education institutions are also implementing digital and AI-based learning tools with concurrent challenges of digital readiness, lecturer readiness, and academic integrity (Jamaluddin, 2025; UNESCO, 2023).

Population and Sample

The target population will be the undergraduate students who are studying in Malaysia higher education institutions. The selection of undergraduate students is driven by the increasingly common use of digital learning platforms by students and the possibility that they may be more dependent on AI tools for academic support. For structural equation modelling, it is recommended to have 400-500 students. The sample size is appropriate for testing a model with multiple predictors, mediators and a moderator (Hair et al., 2022; Kline, 2023).

Sampling Technique

Purposive sampling and convenience sampling may be used for the study. Purposive sampling involves a sampling of university students that have awareness/experience using AI-enabled learning tools. The researcher can use convenience sampling to make the questionnaire available on university networks, on-line student groups, learning management systems and email invitations. To increase the variety of the samples, the researcher should consider collecting data from both public and private universities with students from a range of year level.

Data Collection Procedure

Data will be collected using a structured online questionnaire. Ethical approval must be

granted by the appropriate University ethics committee prior to data collection. Participants will be told the purpose of the study, the voluntary nature of participation, the conditions of confidentiality, anonymity and right to withdraw. The questionnaire will start with screening questions to make sure that the respondents are current university students and have some knowledge about AI learning tools.

Measurement of Constructs

Multi-item scales adapted from previous literature will be used to measure all constructs. This will be measured on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). The learning support items used in AI can be modified based on AI-supported learning and educational technology studies (Holmes et al., 2019; Kasneci et al., 2023). Digital competence items can be chosen from various digital competence or AI literacy frameworks (Carretero et al., 2017; Ng et al., 2021; Ferrari, 2013). Some self-regulated learning items are adapted from Pintrich (2000), Schunk and Greene (2018), and Zimmerman (2002). Academic engagement items can be adapted from Fredricks et al. (2004), Kahu (2013) and Kuh (2009). Items for concern regarding academic integrity may be modified from Breitg and Eaton (2016), Eaton (2023), and McCabe et al. (2012).

Data Analysis

The data will be analysed by SPSS and SmartPLS or AMOS. Firstly, a data screening will be performed to look out for missing data, outliers, incomplete answers and careless answers. The profiles and patterns of usage of the AI will be summarized using descriptive statistics. Secondly, reliability and validity will be measured. Cronbach's alpha and composite reliability will be used to assess internal consistency. Convergent validity will be tested by using Average

Variance Extracted (AVE). The Fornell-Larcker criterion and heterotrait-monotrait ratio will be used to test the discriminant validity (Hair et al., 2022). Thirdly, the hypotheses will be tested using structural equation modelling. Mediation and moderation will be tested using a bootstrapping procedure.

Ethical Considerations

Ethical research principles will be adhered to in the study. Participation will be voluntary and informed consent will be obtained prior to answering the questionnaire. The survey will not request personal information that would not be useful to the researcher. Responses will be anonymous and confidential. The study will require academic integrity and use of AI, which might cause some participants to be hesitant to report their true behaviour. The purpose of the questionnaire should therefore be clearly specified to exclude investigation of individual misconduct. The intent is to gain a general idea of learning experiences and perceptions.

Research Implications

This study offers several important research implications for the field of AI-enabled education, particularly within the Malaysian higher education context. First, the proposed model extends existing research by shifting the focus from students' general intention to use AI tools toward the learning processes through which AI may influence academic outcomes. While many previous studies have examined technology acceptance and AI adoption, this study highlights that AI learning support contributes to learning performance mainly through self-regulated learning and academic engagement. This provides a more learning-centred explanation of AI's role in higher education.

Second, the study contributes to self-regulated learning literature by positioning AI learning

support, digital competence, and teacher AI guidance as important antecedents of students' self-regulated learning. This suggests that self-regulated learning in AI-supported environments is not only an individual ability but also a process shaped by technological support, students' digital capability, and lecturer guidance. Future researchers may further examine how different forms of AI tools influence students' planning, monitoring, reflection, and learning strategy use.

Third, this study strengthens the connection between student engagement theory and AI-enabled learning. By proposing academic engagement as a mediator between self-regulated learning and learning performance, the model explains how AI-supported learning may become meaningful only when students are behaviourally, emotionally, and cognitively involved in academic tasks. This provides a useful direction for future studies to explore whether AI tools promote deep engagement or merely increase surface-level task completion.

Fourth, the inclusion of academic integrity concern as a moderating variable adds an ethical dimension to AI education research. The model suggests that the positive effect of academic engagement on learning performance may depend on students' awareness of responsible AI use, plagiarism, originality, and proper acknowledgement. This implication is important because AI-related learning performance should not be assessed only in terms of grades or productivity, but also in terms of authentic and ethical learning.

Finally, this study provides a foundation for future empirical research in Malaysian higher education. Researchers may test the proposed model across public and private universities, different academic disciplines, and different student groups. Future studies may also compare AI usage patterns between undergraduate and postgraduate students or examine whether institutional AI policies influence the relationships proposed in this model. Overall, the study contributes to the development of a more comprehensive research agenda on responsible,

student-centred, and performance-oriented AI integration in higher education.

Practical Implications

The proposed model offers several practical implications for Malaysian higher education institutions. First, universities should move beyond simple access to AI tools and focus on meaningful learning support. Students need to understand how AI can be used to support explanation, revision, feedback, and reflection. Second, universities should strengthen digital competence. AI literacy should be included in student development programmes. Students should learn how to write effective prompts, verify AI-generated information, protect privacy, and avoid academic misconduct.

Third, lecturers should receive training on AI-supported teaching. Lecturer guidance is important because students need clear expectations about acceptable and unacceptable AI use. Lecturers should also redesign assessments to encourage reflection, application, originality, and critical thinking. Fourth, academic integrity policies should be updated. Universities should clarify whether students may use AI for brainstorming, grammar checking, translation, coding, or drafting. Students should also be taught how to disclose AI assistance when required. Finally, Malaysian higher education institutions should promote a culture of responsible innovation. AI should be used to enhance human learning, not replace student effort or lecturer judgement.

Conclusion

This paper proposed a new conceptual model for examining AI-enabled learning in Malaysian higher education. Unlike technology acceptance models that focus mainly on intention to use, this model focuses on learning mechanisms. It proposes that AI learning support, digital competence, and teacher AI guidance influence learning performance through self-

regulated learning and academic engagement. Academic integrity concern is proposed as a moderator that strengthens the relationship between engagement and genuine learning performance.

The proposed study is important because AI tools are becoming increasingly common in higher education. However, their educational value depends on how students use them. AI can support learning when students are digitally competent, self-regulated, engaged, and ethically aware. For Malaysian universities, the challenge is not only to adopt AI but also to guide its responsible and meaningful use.

Declarations

Ethical Considerations

The present article develops a conceptual framework and proposes an empirical research design for examining AI-enabled learning in Malaysian higher education. No participant data were collected for the present paper. Prior to the implementation of the proposed empirical study, ethical approval will be obtained from the appropriate institutional ethics committee.

Participation will be voluntary, and informed consent will be obtained from all participants. The proposed survey will also ensure anonymity, confidentiality, and participants' right to withdraw.

Data Availability

No empirical dataset was generated or analysed for this article. The study presents a conceptual model and proposed methodology intended to guide subsequent empirical investigation.

Competing Interests

The authors declare that they have no competing interests.

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Author Contributions

All authors contributed to the conceptual development of the study, review and synthesis of the relevant literature, development of the proposed research framework, and preparation and revision of the manuscript. All authors reviewed and approved the final manuscript.

References

- Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice-Hall.
- Bittle, K., Sadowski, C., & Nguyen, H. (2025). Generative AI and academic integrity in higher education: A systematic review and research agenda. *Information, 16*(4), 296.
- Bond, M., Khosravi, H., De Laat, M., Bergdahl, N., Negrea, V., Oxley, E., Pham, P., Chong, S. W., & Siemens, G. (2024). A meta systematic review of artificial intelligence in higher education: A call for increased ethics, collaboration, and rigour. *International Journal of Educational Technology in Higher Education, 21*, Article 4.
- Boekaerts, M. (1999). Self-regulated learning: Where we are today. *International Journal of Educational Research, 31*(6), 445–457.
- Boud, D., & Molloy, E. (2013). Rethinking models of feedback for learning: The challenge of design. *Assessment & Evaluation in Higher Education, 38*(6), 698–712.
- Bretag, T. (Ed.). (2016). *Handbook of academic integrity*. Springer.
- Carretero, S., Vuorikari, R., & Punie, Y. (2017). *DigComp 2.1: The digital competence framework for citizens*. Publications Office of the European Union.
- Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education, 20*, Article 43.

- Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2024). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. *Innovations in Education and Teaching International*, 61(2), 228–239.
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340.
- Dotan, R., Parker, L. S., & Radzilowicz, J. G. (2024). Responsible adoption of generative AI in higher education: Developing a points-to-consider approach based on faculty perspectives. *arXiv*. <https://arxiv.org/abs/2406.01930>
- Eaton, S. E. (2023). Postplagiarism: Transdisciplinary ethics and integrity in the age of artificial intelligence and neurotechnology. *International Journal for Educational Integrity*, 19, Article 23.
- Ferrari, A. (2013). *DIGCOMP: A framework for developing and understanding digital competence in Europe*. Publications Office of the European Union.
- Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of Educational Research*, 74(1), 59–109.
- Gu, X., & Ericson, B. J. (2025). AI literacy in K–12 and higher education in the wake of generative AI: An integrative review. *arXiv*. <https://arxiv.org/abs/2503.00079>
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). SAGE.
- Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign.
- Ifenthaler, D., & Yau, J. Y. K. (2020). Utilising learning analytics to support study success in higher education: A systematic review. *Educational Technology Research and Development*, 68, 1961–1990.
- Jamaluddin, F. (2025). Malaysia's AI-driven education landscape: Policies, applications, and comparative insights for a digital future. *arXiv*. <https://arxiv.org/abs/2509.21858>
- Kahu, E. R. (2013). Framing student engagement in higher education. *Studies in Higher Education*, 38(5), 758–773.

- Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, 102274.
- Kline, R. B. (2023). *Principles and practice of structural equation modeling* (5th ed.). Guilford Press.
- Kuh, G. D. (2009). The national survey of student engagement: Conceptual and empirical foundations. *New Directions for Institutional Research, 2009*(141), 5–20.
- Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1–16). Association for Computing Machinery.
- Luckin, R. (2017). Towards artificial intelligence-based assessment systems. *Nature Human Behaviour, 1*, Article 0028.
- McCabe, D. L., Butterfield, K. D., & Treviño, L. K. (2012). *Cheating in college: Why students do it and what educators can do about it*. Johns Hopkins University Press.
- McDonald, N., Johri, A., Ali, A., & Hingle, A. (2024). Generative artificial intelligence in higher education: Evidence from an analysis of institutional policies and guidelines. *arXiv*. <https://arxiv.org/abs/2402.01659>
- Miao, F., & Holmes, W. (2023). *Guidance for generative AI in education and research*. UNESCO.
- Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). Conceptualising AI literacy: An exploratory review. *Computers and Education: Artificial Intelligence, 2*, 100041.
- Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. *Science, 381*(6654), 187–192.
- Perkins, M. (2023). Academic integrity considerations of AI large language models in the post-pandemic era: ChatGPT and beyond. *Journal of University Teaching and Learning Practice, 20*(2), 1–24.

- Pintrich, P. R. (2000). The role of goal orientation in self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 451–502). Academic Press.
- Schunk, D. H., & Greene, J. A. (2018). *Handbook of self-regulation of learning and performance* (2nd ed.). Routledge.
- Selwyn, N. (2022). *Education and technology: Key issues and debates* (3rd ed.). Bloomsbury Academic.
- UNESCO. (2023). *Guidance for generative AI in education and research*. United Nations Educational, Scientific and Cultural Organization.
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478.
- Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, 36(1), 157–178.
- Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education. *International Journal of Educational Technology in Higher Education*, 16, Article 39.
- Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory Into Practice*, 41(2), 64–70.



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Factors Influencing ChatGPT Utilisation in Higher Education: A Proposed Empirical Study Based on the UTAUT Framework

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Abstract

Objective: To examine the effects of performance expectancy, effort expectancy, social influence, and facilitating conditions on university students' behavioural intention to use and actual use of ChatGPT in higher education, while assessing the moderating role of ethical awareness. **Methods:** The proposed study adopts a quantitative cross-sectional survey design. Data will be collected from university students and analysed using structural equation modelling. Guided by the Unified Theory of Acceptance and Use of Technology, the model evaluates the technological, social, institutional, and ethical factors influencing students' adoption and use of ChatGPT. **Results:** The proposed model suggests that students' behavioural intention and actual use of ChatGPT are influenced by its perceived usefulness, ease of use, social influence, and the availability of institutional and technological support. Ethical awareness is expected to moderate these relationships because ChatGPT use may raise concerns related to academic integrity, plagiarism, overreliance, privacy, fairness, and reduced critical thinking. **Conclusion:** The study contributes to the literature by integrating technology acceptance with responsible AI use in higher education. It provides a framework for examining ChatGPT adoption patterns, students' motivations for using the technology, and its implications for academic integrity, while offering practical guidance for universities, educators, and policymakers in developing AI literacy programmes and responsible-use policies.

Keywords: ChatGPT, higher education, generative artificial intelligence, UTAUT, student adoption, academic integrity, ethical awareness

Introduction

AI has emerged as a significant part of modern-day higher education. Digital learning platforms are increasingly used, automated feedback systems are widely deployed, intelligent tutoring software is everywhere, learning analytics dashboards are in use, and virtual

communication tools are now being utilized in universities to aid teaching and learning. This change has been exacerbated by the rise of generative AI, which can create new materials instead of just storing, sharing, and organising existing ones. One of the most prominent examples of this is ChatGPT. It can create explanations, summaries, outlines, examples, codes, translations, and academic style text when prompted by the user. This has made it an increasingly popular learning support tool for students and a subject of discussion for educators, as cited by Kasneci et al. (2023) and Strzelecki (2023).

The use of ChatGPT in higher education is no surprise. The academic demands, consultation time, language difficulties and complexity of the theoretical concepts are often obstacles that students encounter. ChatGPT can give instant responses, break down complex information, offer ideas for how to organize assignments, and feedback on writing. The tool can also be used as a private and low-burden aid for students who might not be inclined to pose questions in class. ChatGPT can also be helpful for educators in preparing lessons, generating questions, designing feedback, and creating examples or cases. The possibilities demonstrated above indicate that generative AI can play a role in personalised and flexible learning, provided it is used wisely (Archibald & Clark, 2023; Kim, 2023).

Meanwhile, ChatGPT has raised major concerns on the definition of learning and academic honesty. Students might be tempted to submit AI-generated work as their own as it can produce fluent text in seconds. This poses a challenge to educators, who are required to identify student originality and separate it from writing produced by AI. Generative AI poses a threat to traditional assessment practices, particularly to the emphasis on final products over learning processes in take-home assignments and written work (Cotton et al., 2024; Rudolph et al., 2023). Students using ChatGPT without critical evaluation can also inadvertently be exposed to

inaccurate information, fabricate references, be influenced by social biases or engage in superficial learning (Fecher et al., 2023; Li et al., 2023).

This is because the introduction of ChatGPT can't be attributed solely to technology. The usefulness of the tool, ease to use, encouragement from peers and lecturers, and policies, infrastructure and training from the institution all affect students' utilisation. The dimensions are similar to Unified Theory of Acceptance and Use of Technology (UTAUT) explaining technology acceptance in terms of performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). UTAUT has been employed in many studies of educational technology adoption and offers a suitable theoretical underpinning for the investigation of ChatGPT adoption as it links individual perceptions with social and organisational support.

But the introduction of ChatGPT is unlike some previous innovations in the field of education. LMS, video conferencing and digital libraries are primarily used to facilitate access to learning materials or communication. The use of ChatGPT is more ethically complex when it comes to creating academic content. A student can use ChatGPT to learn something, or he or she can use it to write an assignment, but no learning occurs. Thus, it is necessary to incorporate acceptance factors and ethical awareness into a model of ChatGPT use. UNESCO's recommendations for the use of generative AI in education highlight the importance of developing human-centred policies, safeguarding learners, transparency, and governance before widespread adoption of generative AI in learning environments (Miao & Holmes, 2023).

This paper presents an empirical study to explore the factors which influence the utilization of ChatGPT by students in higher education. In particular, it explores how performance expectancy, effort expectancy, social influence, and facilitating conditions influence the

behavioural intention and actual use. It also suggests the ethical awareness as moderator to increase responsible use. The paper is designed to offer a framework for research that can be tested quantitatively and will be applicable to universities in creating programmes on AI literacy, academic integrity policies, and supportive learning environments.

Literature Review

Generative AI: AI systems that generate content like text, images, code, audio, and summaries from user input. ChatGPT is a large language model-based generative AI text-based tool. It can be trained using a massive amount of text, and can be used to generate or predict text patterns and interact with users via natural language prompts. The ability to engage in conversations makes ChatGPT appealing in higher education, allowing students to ask questions using natural language and get instant answers. Unlike conventional search engines, ChatGPT isn't just about listing sources, it arranges information into explanatory text. It is a very useful feature, but at the same time, it can be dangerous as the answer might be incomplete or wrong (Kasneci et al., 2023; Yan et al., 2023).

The potential benefits of ChatGPT in education have been identified through research. The first is ChatGPT's ability to offer tailored learning experiences based on the learner's input and comprehension level. The first is that ChatGPT can help with personalized learning by adjusting its responses to the prompt and understanding of the learner. A student can request a simple explanation, a detailed comparison or a practical scenario. Second, ChatGPT can be used to offer support right away, thus benefiting students when they're studying independently or outside of standard office hours. Third, it could be more helpful for students who require language support, writing help, and/or more explanation. Fourth, It can be used to create teaching materials, discussion points, and formative feedback for educators (Ali et al., 2024; Sandu et al., 2024).

Although these advantages are notable, there are also significant drawbacks which are discussed in the literature. ChatGPT does not comprehend information as humans do, but rather produces responses that are likely based on language patterns. This can result in mistakes, inaccurate facts, speculative statements, and bogus citations. Students who are not digitally and information literate may take such responses for granted without checking. Furthermore, ChatGPT can produce entire essays or parts of assignments, making it a topic of discussion about who is the author, where did the information come from, and the distinction between helping and cheating. Due to the shortcomings of traditional plagiarism detection, Cotton et al. (2024) suggested a paradigm shift in the practice of assessment and academic honesty in universities.

Ethics are particularly critical in educational institutions of higher learning. Acosta-Enriquez et al. (2024) found that students' knowledge, attitudes, and perceived ethics are important in understanding how they use ChatGPT. Students' integrity is also key to the adoption of generative AI, as Bouteraa et al. (2024) agreed. Students who don't know what they can and cannot do may be using ChatGPT in a manner that is contrary to the academic rules. However, when students know what is expected of them ethically, they can use ChatGPT to brainstorm, provide feedback on, or revise their own writing, but they will still be responsible for their own content.

Another big problem is the institution's response. At first, some universities were thinking of banning or using tools to detect ChatGPT. But many academics today believe that prohibition is a non-starter as students can use AI tools outside of university environments. Rather, institutions must establish clear policies, provide training on AI literacy, disclose requirements, and design assessment systems to emphasize process, reflection, and real-life application (Miao & Holmes, 2023; Wang et al., 2023). Using ChatGPT is not only a student behaviour, but also an

indicator of institutional readiness.

Theoretical Foundation: UTAUT

Venkatesh et al. (2003) created the Unified Theory of Acceptance and Use of Technology (UTAUT) that explains why people accept and adopt new technologies. The model was developed based on a combination of the theories, Technology Acceptance Model (TAM), Theory of Planned Behaviour (TPB), Motivational Model, and Innovation Diffusion Theory. Performance expectancy, effort expectancy, social influence and facilitating conditions are proposed by UTAUT to impact both behavioural intention and use behaviour. The theoretical approach has been used extensively in education, as it helps to understand the attitudes of students and teachers towards the introduction of new learning technologies.

Performance expectancy is the extent to which an individual thinks that a technology will help performance. In relation to ChatGPT, this means that students think that the tool can benefit learning effectiveness, learning productivity, comprehension of course material and writing quality. Effort expectancy is the perceived ease of use of the technology. The conversational interface of ChatGPT could raise the effort expectancy as students do not require advanced technical expertise to engage with it. The social influence is the degree of influence of important persons like classmates, lecturers and institutions on students' choice of the tool. Facilitating conditions are the resources, knowledge, support, and infrastructure that are available to effectively use technology.

The UTAUT model is appropriate for the proposed study as it encompasses both attitudes of individuals and the environmental support. While most students might think that ChatGPT is helpful and convenient, its adoption can still hinge on the attitudes of lecturers, peers and the university's policies. Recent research based on the UTAUT or UTAUT2 has demonstrated that

social influence, habit, learning value and performance-related beliefs can influence students' intentions for using ChatGPT (Benard et al., 2024; GC & Bhatta, 2024). These results indicate that UTAUT is still relevant to the understanding of adopting generative AI.

However, UTAUT cannot completely cover the ethics of generative AI. Previous technologies were mostly not the ones that completed students' academic work as measured by UTAUT. ChatGPT does. Thus, the proposed study makes an extension to the UTAUT with including the construct of ethical awareness as a moderating construct. Ethical awareness is the students' knowledge of academic honesty, disclosure of AI use, privacy, responsible prompting, and verifying AI-generated information. This addition means that the study can analyze whether students are using ChatGPT, as well as if they are likely to do so in an appropriate way.

Hypotheses Development

Performance expectancies are likely to be important factors in explaining students' behavioural intentions to use ChatGPT. The tool is likely to be adopted when students think it can enhance their academic achievements or learning effectiveness. In higher education, performance expectancy can encompass quicker concept understanding, enhanced writing clarity, better assignment planning, more efficient revision, and higher confidence. ChatGPT can assist with these outcomes by offering explanations, examples, outlines and feedback. Strzelecki (2023) determined that students' acceptance of ChatGPT is closely related to the perceived usefulness, and other research revealed that perceived academic benefits are key factors in the adoption of generative AI (Bouteraa et al., 2024; GC & Bhatta, 2024). For this reason, students who endorse that ChatGPT improves academic performance should be more inclined to use ChatGPT. For this reason, students that think ChatGPT improves academic performance are supposed to have a stronger intention to use ChatGPT.

H1: Performance expectancy positively influences students' behavioural intention to use ChatGPT.

Effort expectancy is also expected to influence behavioural intention. Technology that is easy to use will be more likely to be accepted, including among students of varying digital competency. Because the user can speak to ChatGPT using natural language, it's relatively easy to access and use. It is not such a specialised software that it needs to be trained in a complex way to use it. But good and mature use does still need fast literacy, source checking and knowledge of the limits of the sources. The interactive and accessible design of AI chatbots has educational potential as mentioned by Kim (2023). If students think ChatGPT is easy to use and easy to understand, they are more likely to plan to use it to learn.

H2: Effort expectancy positively influences students' behavioural intention to use ChatGPT.

Another factor that matters is social influence. Students are likely to experience digital tools from their fellow students, friends, lecturers or online academic communities. Peer usage of ChatGPT for study support can lead to other students using it as well. Students can feel more confident if they are encouraged to use the material responsibly and are told that there are boundaries beyond which it should not be used. However, if lecturers are not clear or negative, students may choose not to use the tool or use it covertly. Benard et al. (2024) noted that there is a possibility of herd behavior affecting the use of ChatGPT in the academic environment. One can therefore assume that social influence would have an impact on students' intention.

H3: Social influence positively influences students' behavioural intention to use ChatGPT.

Facilitating conditions are the resources, infrastructure, and support that empower students to use ChatGPT effectively. They can be internet access, digital device, training workshops, institutional AI policies, lecturer guidance, and technical support. Students may be more inclined

to use ChatGPT if they are aware of its proper usage and when the expectations of the institution are defined. Alshammari and Alshammari (2024) discovered that the facilitation of conditions influences the adoption of ChatGPT in higher education. Furthermore, policies and resources within the university can decrease uncertainty and promote clear usage (Wang et al., 2023).

H4: Facilitating conditions positively influence students' behavioural intention to use ChatGPT.

Behavioural intention is expected to influence actual utilisation. According to UTAUT, individuals who intend to use a technology are more likely to engage in actual use (Venkatesh et al., 2003). In this study, ChatGPT utilisation refers to the frequency and purposes of use, including concept explanation, writing support, brainstorming, grammar checking, assignment planning, coding assistance, and revision. Students with stronger intention are expected to use ChatGPT more frequently for academic tasks.

H5: Behavioural intention positively influences ChatGPT utilisation among higher education students.

The relationships between the UTAUT factors and utilisation can also be mediated using behavioural intention. In other words, performance expectancy does not directly lead to use, but it instead increases intention to use. Likewise, ease of use, social influence and facilitating conditions can lead to the students' intention, and the intention can cause the actual behaviour. This mediation process is in line with the technology acceptance theory.

H6: Behavioural intention mediates the relationships between performance expectancy, effort expectancy, social influence, facilitating conditions, and ChatGPT utilisation.

Lastly, ethical awareness is suggested as a moderator. While students are eager to use ChatGPT, their usage and ethical awareness could be influenced by their understanding of

academic integrity and the limitations of AI. Ethical awareness involves comprehension of the ethical implications of using AI tools, such as: Avoiding plagiarism by not submitting AI-generated content as self-authored work; Citing AI sources; Fact-checking; Safeguarding privacy and confidential information; Using AI for learning purposes, rather than as a replacement for thinking. Academic integrity, data protection, and assessment fairness continue to be key ethical issues highlighted in the research of ChatGPT ethics (Acosta-Enriquez et al., 2024; Li et al., 2023).

H7: Ethical awareness moderates the relationship between behavioural intention and ChatGPT utilisation, such that students with higher ethical awareness are more likely to use ChatGPT responsibly.

Proposed Conceptual Framework

In the conceptual framework proposed, the factors of performance expectancy, effort expectancy, social influence and facilitating conditions are considered to be independent variables. Behavioural intention is considered a mediator and ChatGPT utilisation is the outcome variable. Ethical awareness is incorporated as a moderating variable between the behavioural intention and utilisation. The model proposes that the students' intention to use ChatGPT is influenced by their expectations of academic gains, perceived ease of use, social encouragement, and institutional support. But, from intention to the responsible use requires ethical awareness.

This framework is beneficial because it acknowledges how ChatGPT is both a beneficial tool in higher education and a potentially harmful one. ChatGPT, on the other hand, is a learning technology that has the potential to enhance academic support and productivity. On the other side, it is a system of content production, which poses threat to the academic integrity and quality of learning. The model's adoption of UTAUT along with ethical awareness offers a more balanced

explanation of the adoption of ChatGPT. It enables researchers to examine the context in which uses are initiated as well as the context in which uses become responsible and educationally valuable. Figure 1 shows the conceptual model.

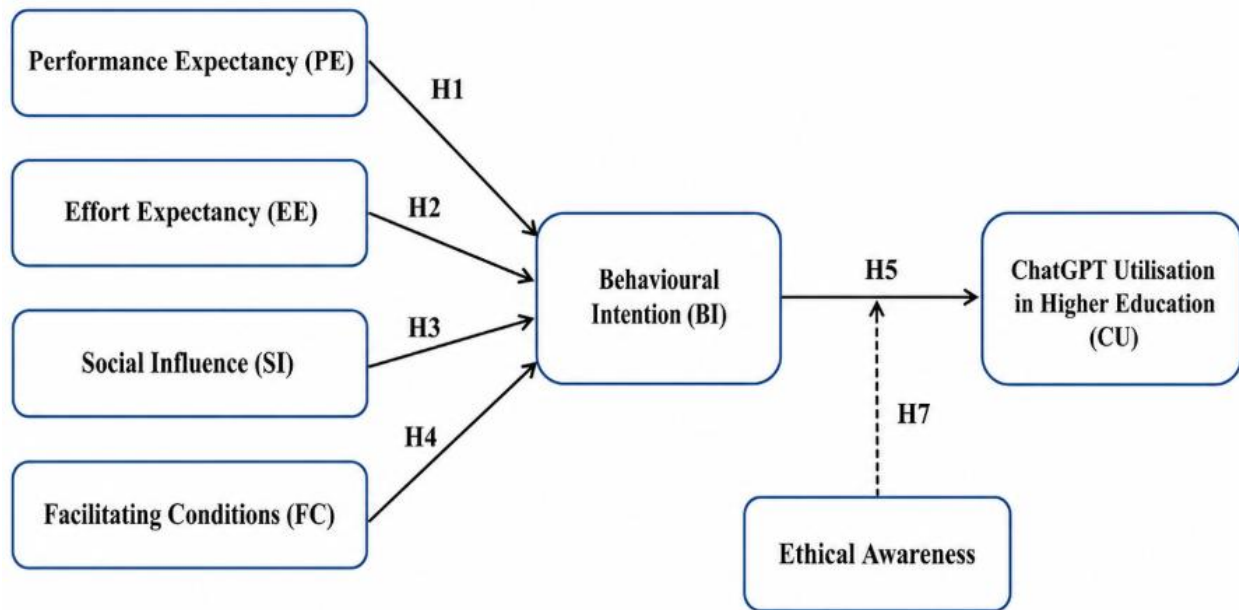


Figure 1: Conceptual Model

Proposed Methodology

The type of research design in this study is Quantitative with cross sectional survey method. A quantitative design is the type of design that can be used in this study because the study has hypotheses which are relationships between clearly defined variables. The variables include performance expectancy, effort expectancy, social influence, facilitating conditions, behavioural intention, ethical awareness, and ChatGPT utilisation. Survey method enables the data to be collected from a relatively large number of university students and can enable statistical analysis of the technology acceptance patterns. The cross-sectional design is appropriate for this study since the research wants to find out the students' perceptions and behaviors at a particular time.

The research will take deductive approach. The hypotheses are derived from the UTAUT model and drawn from the literature on generative AI and educational technology. In the deductive method, the method starts with theory, formulate hypothesis, gather empirical data, and test the relations proposed. The approach is appropriate for studying the adoption of ChatGPT as it is grounded in the existing technology acceptance theory and presents a fresh domain for its application and extension.

The target group will be the students in the undergraduate and postgraduate level from Higher Education Institutions. Students have been chosen because they make ChatGPT a significant part of their academic lives. Students have been chosen because they use ChatGPT for academic tasks. The sample should comprise students from a variety of subject areas including business, education, social studies, engineering, computing, health sciences and humanities. It's important to include different disciplines, as the use of ChatGPT could differ depending on the type of academic task. In the language programmes, for instance, students could use ChatGPT to support them with writing, while in the computing programmes they could be supported with explanations on coding.

Purposive and convenience sampling may be used in the study. Using purposive sampling will guarantee that the respondents are university students who know about ChatGPT or have used it previously. Students are able to be accessed online, via university mailing lists, learning management systems and student groups; this may lead to the use of convenience sampling. Probability sampling would enhance generalisability but may not be feasible to have a complete sampling frame of all university students. The researcher should ensure that different universities, different levels of study, different faculties, different demographic groups respond to the research to minimize sampling bias.

It is recommended that at least 300 respondents be used for structural equation modelling. However, a greater number of valid responses (400 to 500) would be desirable due to the greater statistical power, greater model stability, and more reliable testing of mediation and moderation effects. If PLS-SEM is applied, the sample size should also meet the statistical power criteria as a function of the highest number of predictors that feed into the construct. A larger number of samples will also help to reduce missing data and unusable responses.

Data will be gathered by a structured questionnaire. The questionnaire can be sent via online platforms such as Google Forms, Microsoft Forms, or Qualtrics or other secure survey platform. The survey will include informed consent statements that describe the purpose of the study, voluntary participation, anonymity and confidentiality, and the right to withdraw. The screening questions will ensure that all respondents are current students and know about ChatGPT. The main questionnaire will consist of the measurement items for each construct, followed by the items of the demographics such as gender, age, study level, discipline, year of study, type of university, and the frequency of ChatGPT usage.

Multiple item scales adapted from the existent technology acceptance research and recent studies on ChatGPT will be used to measure all constructs. The Likert scale could be from 1 = strongly disagree to 5 = strongly agree. Performance expectancy may encompass elements like: ChatGPT contributes to my scholarly productivity, ChatGPT assists me successfully finish scholarly tasks, and ChatGPT improves my knowledge of the content of my course. Effort expectancy can involve elements like: The ChatGPT interface is user-friendly, I find it easy to learn how to use ChatGPT, and I can easily understand my interactions with ChatGPT. Items that represent social influence include peer influence, lecturer influence, and institutional encouragement.

Access, resources, training, and institutional support are possible measures of facilitating conditions. They can be: I can access ChatGPT, I know a lot about how to use it for academic purposes, or my university does provide guidelines on how to use AI responsibly. To represent the concept of behavioral intention, the following items have been included: I would like to use ChatGPT for academic learning in the future, I would continue to use ChatGPT for academic-related tasks, and I would recommend ChatGPT as a learning support tool. The use of ChatGPT can be tracked by inquiring about the frequency with which students utilize the technology to explain concepts, brainstorm ideas, use for writing, grammar corrections, planning assignments, coding, and revising.

Items pertaining to academic integrity, disclosure, verification, and privacy will be used to measure ethical awareness. Some examples: I know that AI-generated content must not be submitted as my own work, I check information that ChatGPT has provided, I understand when to cite my use of ChatGPT, and I do not provide confidential information to AI tools. The items are significant as part of the study of not only adoption but responsible utilisation.

The questionnaire should be reviewed by experts in educational technology, research methods and academic integrity prior to the main survey. Then a pilot test (of 30-50 students) should be done to test clarity, length and reliability. Unclear wording can be revised based on feedback from the pilot test. Cronbach's alpha may be used to test for reliability, and item-total correlation and expert judgment may be used to test for preliminary validity.

Data Screening will be the initial step in data analysis. The researcher needs to look for missing values, duplicate responses, straight line responses, outliers and normality. The characteristics of the respondents and use patterns of ChatGPT will be summarised using descriptive statistics. Validity and reliability will thereafter be evaluated. The Cronbach's alpha

and composite reliability should exceed 0.70. Average variance extracted will be used to evaluate convergent validity on which values above 0.50 will be acceptable. Fornell-Larcker criterion and heterotrait-monotrait ratio can be used to study discriminant validity.

Structural equation modelling will be used to test the hypotheses. The study is prediction based involving mediation and moderation relationship, therefore partial least squares structural equation modelling is recommended. The significance of path coefficients, indirect effects and interaction effects can be tested using 5,000 resamples. Path coefficients, t-values, p-values, coefficient of determination, effect size, predictive relevance and model fit indicators will be used where appropriate to evaluate the model.

Ethics are a must. All study data should be collected with approval from the relevant institutional ethics committee. Participation must be voluntary and no personally identifiable information be collected unless necessary. Data is to be safely stored and used by the research team. The study is about academic integrity and the survey should explain that it will not be examining specific instances of academic dishonesty. Rather, it is looking for an overall impression and preferences. This statement can help answerers to be candid.

Expected Results and Discussion

It is anticipated that the proposed study will yield a positive relationship between performance expectancy and behavioural intention that is strong and positive. Students will use ChatGPT if they think that it enhances academic outcomes and learning efficiency. Students will be more inclined to use ChatGPT if they feel it will improve their academic outcomes and learning efficiency. This finding was anticipated and aligned with the UTAUT as well as the recent findings by Strzelecki (2023) and Bouteraa et al. (2024) that perceived usefulness is a crucial factor influencing acceptance of ChatGPT. If performance expectancy is the most

important, then it is crucial for universities to demonstrate the ways in which ChatGPT can be used to enhance legitimate learning activities, such as clarifying concepts, providing formative feedback, and planning for revision.

It is also expected that effort expectancy will have a positive impact on intention. The ease of use of ChatGPT is due to its conversational nature. But findings could indicate that ease of simple use doesn't equal ease of responsible use. Students may be able to pose a question but not know how to assess an answer, paraphrase correctly, cite the information correctly, or recognize false information. Attention should be given, therefore, to the importance of effort expectancy, and university training should go beyond teaching access to the technical aspects of the Internet, and emphasize timely literacy, source verification and responsible academic practice.

Social influence is likely to be a key factor. Students can be affected by fellow pupils who are using ChatGPT regularly, teachers who talk openly about AI, and messages from the institution about AI. However, if social influence is important, it will imply that universities should not consider the use of ChatGPT as a private student behavior. Rather, responsible use must be nurtured through discussion in the classroom, lecturer modeling, peer mentoring and clear communication of the policy. Over time, fostering a positive academic culture that treats AI as a tool for learning, not a shortcut, is a goal that can be achieved. Over time, a positive academic culture can be created which views AI as a learning tool and not a shortcut.

Conditions to facilitate are expected to affect the intention to behave and presumably utilization. Students must have access, guidance and support. If there are not specific rules outlined in the institutions, they may be unsure if they are allowed to use ChatGPT. They may accidentally use it for the wrong purpose if not trained. When facilitating conditions are important, it is important for institutions to invest in AI literacy modules, policy documents,

academic integrity guidance and educator development. This type of support can help minimise faculty and course inconsistency.

It is hypothesized that the relationship between UTAUT factors and ChatGPT utilisation will be mediated by behavioural intention. This would support the notion that students' perceptions influence their desire to use ChatGPT and this desire translates into actual behaviour. The intention-use relationship is expected to be mediated by ethical awareness. Students with high ethical awareness can use ChatGPT more responsibly, and students with low ethical awareness can use ChatGPT in ways that result in academic risks. If this is the outcome to be expected, it is imperative that ethics be part of the model for adopting AI.

It is important to mention that the use of ChatGPT doesn't always have a positive impact. If used regularly and with the intent of asking questions, comparing explanations, and refining drafts, then students can benefit from using the tool while learning. But overuse can be detrimental to learning if they use it to escape reading, thinking, and writing. Future empirical research is therefore needed to provide a distinction between responsible use and problematic use. Frequency might be insufficient; other factors to consider include purpose, transparency, verification, and learning engagement.

Practical Implications

This proposed study has several practical implications to the higher education institutions. The first is to establish clear and transparent AI policies at universities. Acceptable and unacceptable use of ChatGPT should be outlined in policies. If students use ChatGPT to brainstorm, to clarify ideas, to improve grammar, or to get feedback, this can be OK, but it should never be used to write their own original work. Policies should also clarify when AI assistance will be required to be disclosed by students.

Secondly, AI education for students and professors should be offered in universities. It is important that students are aware of how ChatGPT works and what its limitations are and how to check sources. Lecturers require support in assignment design, communicating expectations, and instructions in responsible use. Consider using examples to make it more real for training as abstract warnings alone might not be sufficient to shift behavior.

Third, some rethinking is needed in the design of assessment. While traditional written assignments can still be useful, they need to be complemented with process-based and authentic evaluation. Students may be asked to provide outlines, drafts, reflection notes, oral explanations or statements that they have used AI. Alternatively, assessment tasks may be based on personal experience, local cases, problem-solving or in-class application. The following strategies can make it more difficult for students to use AI purely without human involvement, while also supporting their use of AI.

Fourth, universities should not solely depend on AI detection systems. Detection systems can yield false-positive results and can be inaccurate when it comes to telling the difference between writing done by humans and writing done by AI tools. This fixation on detection can also lead to a lack of trust between students and teachers. The best strategy is to integrate clear rules, open communication, new assessment design, and academic support. This resonates with the perspective that generative AI needs to be adapted to education in one way or another, not via a single technical solution (Cotton et al., 2024; Miao & Holmes, 2023).

Lastly, an ethical culture should be encouraged in institutions regarding AI. Students should be aware that academic honesty is not just about avoiding punishment, it is about fostering intellectual honesty, independent judgment, and professional responsibility. ChatGPT is a helpful tool, but it shouldn't take the place of the learner's thinking. It is, therefore, crucial that the use of

AI is integrated into the development of responsibility into the competences of graduates and digital citizenship.

Limitations and Future Research

There are a number of limitations for this proposed study. First, cross sectional design can only determine relations between variables, but not prove the cause of the variables. Longitudinal designs could be utilized in future studies to explore patterns in students' ChatGPT usage within the context of changing institutional policies and AI tools over time. Second, the study is based on self-reported data and thus may suffer from social desirability bias particularly since academic integrity is a delicate issue. The combination of survey, interview, focus group, learning analytics, or assignment analysis could also be incorporated into future studies.

Third, the selected UTAUT variables and ethical awareness are the ones in the proposed model. Other constructs like habit, trust, perceived risk, AI anxiety, digital literacy, academic self-efficacy and perceived policy clarity can be included in future research. These factors could offer a more holistic view of the factors driving the adoption of ChatGPT. Fourth, the study can take place in one country or institutional setting, thus restricting generalisability. It would be useful to make comparative studies across countries, disciplines and university types.

In addition to frequency, future studies could also explore how well ChatGPT is being used. For instance, the researchers can identify surface-level use (e.g., copying answers created by the AI) and deep learning use (e.g., comparing explanations and revising drafts with reflection). Research can also focus on how lecturers have adapted their assessment of the use of AI, and how students understand policies on the use of AI. With the ongoing development of Generative AI, the focus in higher education research needs to shift from what to how, and from what to why. The focus in higher education research needs to shift from what to how and what to why.

with the ongoing development of Generative AI.

Conclusion

ChatGPT has become a significant tool in higher education because it can support personalised learning, provide immediate assistance, improve academic productivity, and help students engage with complex material. However, its adoption also raises serious concerns about academic integrity, overreliance, misinformation, fairness, and privacy. Therefore, understanding why students use ChatGPT and how they can use it responsibly is an important research issue.

This paper proposed an empirical study based on the UTAUT framework. Performance expectancy, effort expectancy, social influence, and facilitating conditions are proposed as predictors of behavioural intention, while behavioural intention is proposed as a predictor of ChatGPT utilisation. Ethical awareness is included as a moderator because responsible use depends on students' understanding of academic integrity and AI limitations. The proposed methodology uses a quantitative cross-sectional survey design and structural equation modelling to test the research model.

The central argument of the paper is that ChatGPT should not be viewed simply as a threat or a solution. It is a powerful educational tool whose value depends on the conditions of use. When supported by clear policies, ethical awareness, AI literacy, and appropriate assessment strategies, ChatGPT can enhance learning. Without such support, it may undermine academic standards and student development. The future of ChatGPT in higher education therefore depends on responsible integration, institutional readiness, and a continued commitment to the core values of higher learning.

Declarations

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Competing Interests

The authors declare that they have no competing interests.

Data Availability

No empirical data were generated or analysed for this article. The paper develops a theoretical framework and proposed empirical research design for future investigation.

Author Contributions

All authors contributed to the conceptualization of the study, development of the theoretical framework, review of the relevant literature, and preparation of the manuscript. All authors reviewed and approved the final version of the manuscript.

References

- Abdaljaleel, M., Barakat, M., Alsanafi, M., Salim, N. A., Abazid, H., Malaeb, D., Mohammed, A. H., Hassan, B. A. R., Wayyes, A. M., & Farhan, S. S. (2024). A multinational study on the factors influencing university students' attitudes and usage of ChatGPT. *Scientific Reports*, 14(1), 1983. <https://doi.org/10.1038/s41598-024-52549-8>
- Acosta-Enriquez, B. G., Arbulú Ballesteros, M. A., Arbulu Perez Vargas, C. G., Orellana Ulloa, M. N., Gutiérrez Ulloa, C. R., Pizarro Romero, J. M., Gutiérrez Jaramillo, N. D., Cuenca Orellana, H. U., Ayala Anzoátegui, D. X., & López Roca, C. (2024). Knowledge, attitudes, and perceived ethics regarding the use of ChatGPT among generation Z university students. *International Journal for Educational Integrity*, 20, Article 10. <https://doi.org/10.1007/s40979-024-00157-4>

- Ali, D., Fatemi, Y., Boskabadi, E., Nikfar, M., Ugwuoke, J., & Ali, H. (2024). ChatGPT in teaching and learning: A systematic review. *Education Sciences*, 14(6), 643. <https://doi.org/10.3390/educsci14060643>
- Alshammari, S. H., & Alshammari, M. H. (2024). Factors affecting the adoption and use of ChatGPT in higher education. *International Journal of Information and Communication Technology Education*, 20(1), 1-16.
- Archibald, M. M., & Clark, A. M. (2023). ChatGPT: What is it and how can nursing and health science education use it? *Journal of Advanced Nursing*, 79(10), 3648-3651. <https://doi.org/10.1111/jan.15643>
- Benard, K., Moses, K., Arina, S., Jackson, A., & Leslie, O. A. (2024). ChatGPT usage in academia: Extending the Unified Theory of Acceptance and Use of Technology with herd behavior. *International Journal of Social Science and Human Research*, 7(7), 5213-5227. <https://doi.org/10.47191/ijsshr/v7-i07-69>
- Bouteraa, M., Bin-Nashwan, S. A., Al-Daihani, M., Dirie, K. A., Benlahcene, A., Sadallah, M., Zaki, H. O., Lada, S., Ansar, R., Fook, L. M., & Chekima, B. (2024). Understanding the diffusion of AI-generative ChatGPT in higher education: Does students' integrity matter? *Computers in Human Behavior Reports*, 14, 100402. <https://doi.org/10.1016/j.chbr.2024.100402>
- Consuegra-Fernández, M., Sanz-Aznar, J., Burguera-Serra, J. G., & Caballero Molina, J. J. (2024). ChatGPT: The dilemma of the authorship of graded assignments in higher education. *Revista de Investigación Educativa*, 42(2). <https://doi.org/10.6018/rie.565391>
- Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2024). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. *Innovations in Education and Teaching International*, 61(2), 228-239. <https://doi.org/10.1080/14703297.2023.2190148>
- Fecher, B., Hebing, M., Laufer, M., Pohle, J., & Sofsky, F. (2023). Friend or foe? Exploring the implications of large language models on the science system. *AI & Society*. Advance online publication. <https://doi.org/10.1007/s00146-023-01791-1>
- GC, S. B., & Bhatta, K. D. (2024). Examining the role of social influence, learning value and habit in students' intention to use ChatGPT: The moderating effect of information

- accuracy. *Cogent Education*, 11(1), 2403287.
<https://doi.org/10.1080/2331186X.2024.2403287>
- Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., Stadler, M., Weller, J., Kuhn, J., & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, 103, 102274. <https://doi.org/10.1016/j.lindif.2023.102274>
- Kim, T. W. (2023). Application of artificial intelligence chatbots, including ChatGPT, in education, scholarly work, programming, and content generation and its prospects: A narrative review. *Journal of Educational Evaluation for Health Professions*, 20, Article 38. <https://doi.org/10.3352/jeehp.2023.20.38>
- Li, M., Enkhtur, A., Cheng, F., & Yamamoto, B. A. (2023). Ethical implications of ChatGPT in higher education: A scoping review. *arXiv*. <https://arxiv.org/abs/2311.14378>
- Miao, F., & Holmes, W. (2023). Guidance for generative AI in education and research. UNESCO. <https://unesdoc.unesco.org/ark:/48223/pf0000386693>
- Rudolph, J., Tan, S., & Tan, S. (2023). ChatGPT: Bullshit spewer or the end of traditional assessments in higher education? *Journal of Applied Learning & Teaching*, 6(1), 342-363. <https://doi.org/10.37074/jalt.2023.6.1.9>
- Sandu, R., Gide, E., & Elkhodr, M. (2024). The role and impact of ChatGPT in educational practices: Insights from an Australian higher education case study. *Discover Education*, 3, Article 71.
- Strzelecki, A. (2023). To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology. *Interactive Learning Environments*. Advance online publication. <https://doi.org/10.1080/10494820.2023.2209881>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425-478. <https://doi.org/10.2307/30036540>

- Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, 36(1), 157-178. <https://doi.org/10.2307/41410412>
- Wang, H., Dang, A., Wu, Z., & Mac, S. (2023). Generative AI in higher education: Seeing ChatGPT through universities' policies, resources, and guidelines. arXiv. <https://arxiv.org/abs/2312.05235>
- Yan, L., Sha, L., Zhao, L., Li, Y., Martinez-Maldonado, R., Chen, G., Li, X., Jin, Y., & Gašević, D. (2023). Practical and ethical challenges of large language models in education: *A systematic scoping review*. arXiv. <https://arxiv.org/abs/2303.13379>



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Mobile-Assisted English-Speaking Practice and Speaking Fluency among Malaysian University Students: The Mediating Role of Speaking Anxiety Reduction and the Moderating Role of Trust in AI Feedback

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Abstract

Objective: To examine the relationship between mobile-assisted English-speaking practice and self-perceived speaking fluency among Malaysian university students, with speaking anxiety reduction as a mediator and trust in AI feedback as a moderator. **Methods:** A cross-sectional quantitative survey was conducted among 428 undergraduate students from Malaysian higher education institutions who used smartphones or mobile applications to practice English speaking at least once a week during the semester. Partial least squares structural equation modelling was used to assess the measurement model, direct effects, mediation effects, moderation effects, and conditional indirect effects. **Results:** Mobile-assisted English-speaking practice was positively associated with self-perceived speaking fluency and speaking anxiety reduction. Speaking anxiety reduction was also positively related to speaking fluency and partially mediated the relationship between mobile-assisted English-speaking practice and speaking fluency. Trust in AI feedback positively moderated the relationship between mobile-assisted English-speaking practice and speaking anxiety reduction, indicating that the relationship was stronger among students with higher levels of trust in AI feedback. The indirect effect of mobile-assisted English-speaking practice on speaking fluency through speaking anxiety reduction was also stronger at higher levels of trust in AI feedback. **Conclusion:** Mobile-assisted English-speaking practice can improve students perceived speaking fluency partly by reducing speaking anxiety. Trust in AI feedback strengthens this affective mechanism. The study contributes to the technology-assisted language learning literature by explaining how mobile and AI-supported speaking practice can enhance English-speaking outcomes in Malaysian higher education.

Keywords: Mobile-assisted English-speaking practice; Speaking fluency; Speaking anxiety reduction; Trust in AI feedback; Malaysian university students; PLS-SEM

Introduction

The ability to communicate in English fluently is a critical skill necessary for academic achievement and workability for Malaysian university students. Malaysia is a multilingual country with Bahasa Malaysia being the national language, and English being used extensively in higher education, professional communication, international business, tourism, research and international collaboration. While many Malaysian students are taught English throughout their school life, there are some who continue to struggle with the language, especially when they must communicate proficiently in formal presentations, discussions in groups, job interviews, workplace and international settings.

The development of English-speaking fluency is not only a matter of vocabulary and grammar knowledge. Practice opportunities, confidence, managing anxiety, feedback, monitoring pronunciation and willingness to communicate also play a part. There are many dimensions of fluency including smoothness, speed, automaticity, pausing patterns, and the ability to produce speech without excessive hesitation (De Jong & Perfetti, 2011; Segalowitz, 2010; Skehan, 2009; Tavakoli & Skehan, 2005). The students who have limited opportunities to practise their speech may experience hesitation, pauses, fears of mistakes and self-consciousness when speaking English. Students in multilingual classrooms can also make comparisons with more fluent students, thereby causing more speaking anxiety.

Mobile-Assisted English-Speaking Practice Provides New Opportunities for Enhancing Oral Fluency. Students can practice pronunciation, record and replay speech, converse with AI chatbots, perform speaking drills and get immediate speech recognition feedback, and engage in low-pressure speaking practice outside of class on a smartphone and mobile application. Mobile assisted language learning (MALL) is particularly relevant to Malaysia since learners are already

accustomed to using the mobile technology for communication, learning, translation and academic support (Burston, 2015; Chen, 2017; Kukulska-Hulme, 2020; Stockwell & Hubbard, 2013).

The advent of Artificial Intelligence has also transformed Mobile Assisted Speaking Practice. Speaking Apps are applications that use AI technology to give pronunciation feedback, fluency suggestions, grammar correction, simulation of conversations, vocabulary support, and automated scoring. Students may have exposure to repeated and private speaking opportunities with the use of these tools, not possible in large classrooms. One further benefit of AI-powered mobile practice is that it can help to minimise the reliance on teachers by offering instant feedback and self-paced learning opportunities (Godwin-Jones, 2023; Kim et al., 2021; Kohnke et al., 2023).

But speaking practice via mobile does not necessarily enhance speaking fluency. Even though students are using mobile tools often, they can also continue to struggle and not make progress if they do not learn meaningfully, believe in the feedback, or manage their learning. Furthermore, some students' fears of speaking may hinder them from maximizing their speaking experiences. Language anxiety has the potential to impair cognitive processing, oral participation, willingness to communicate and speaking performance (Horwitz, 1986; MacIntyre & Gardner, 1994; Teimouri et al., 2019). While a student can gain access to the mobile speaking tools, it may not improve fluency if the student is still worried about speaking, has not yet developed an appetite for oral production, or is not comfortable with feedback generated by the AI.

This study thus suggests a model that combines mobile-assisted English-speaking practice and reducing speaking anxiety to enhance the level of speaking fluency. The model also suggests that the process of using AI feedback to enhance communication (speaking) practice is enhanced

by trust in AI feedback, which in turn contributes to a reduction in speaking anxiety. That is, students' emotional benefit from MLP will improve if they feel that feedback from AI is credible, useful, fair and reliable (Jian et al., 2000; Lee & See, 2004; Nazaretsky et al., 2025).

The study is based on Social Cognitive Theory and the Affective Filter Hypothesis. Social Cognitive Theory provides the lens on how learning takes place in the interaction between behaviour, personal factors, feedback and environment (Bandura, 1986, 1991). Mobile-assisted speaking practice offers a technology-based learning environment, in which students have the opportunity to practice, review their performance, and receive feedback on speaking repeatedly. The Affective Filter Hypothesis suggests that anxiety could interfere with language performance, and that lower anxiety facilitates language performance (Krashen, 1982). These theories help support the argument that mobile assisted speaking practice can benefit in reducing speaking anxiety which will directly and indirectly improve speaking fluency.

To investigate the relationship between mobile-assisted English speaking practice and speaking fluency in university students in Malaysia; To investigate the relationship between mobile-assisted English speaking practice and reduction of speaking anxiety; To investigate the relationship between reduction of speaking anxiety and speaking fluency; To test the mediation of reduction of speaking anxiety; To investigate the moderating role of trust in AI feedback; and To test the conditional indirect effect of mobile-assisted English speaking practice on speaking fluency through reduction of speaking anxiety at different levels of trust in AI feedback.

Literature Review

Mobile-Assisted English-Speaking Practice

Mobile-assisted English-speaking practice involves using the students' mobile phones and mobile apps to practise oral English in the form of pronunciation exercises, recorded speaking

tasks, dialogue simulation, AI conversation, speech recognition, and feedback-based oral exercises. The flexibility, portability, accessibility and situated and self-paced learning (Burston, 2015; Kukulska-Hulme, 2020; Stockwell & Hubbard, 2013) of mobile-assisted language learning (MALL) have been well-documented. Mobile-assisted speaking practice differs from traditional classroom speaking tasks by enabling students to repeat speaking tasks independently, to self-monitor their own performances, and to practise their speaking skills when and where they wish to.

Mobile-assisted speaking practice can be implemented in Malaysian universities to complement the limited classroom speaking time. Students can record their oral writing outputs, communicate with AI chatbots, practise pronunciation, and rehearse their presentation using mobile applications, and have their spoken output automatically corrected. Such practices can assist the students' autonomy and their SLL as they can plan, monitor their own speaking process, and evaluate their performance independently (Zimmerman, 2002; Oxford, 2017). Previous studies have revealed that when MALL tools are used actively and purposefully, their effects on the motivation, engagement, vocabulary acquisition, pronunciation, and speaking self-confidence are positive (Chen, 2017; Hwang & Fu, 2019; Tai & Chen, 2023).

Speaking Fluency

Speaking fluency is characterized by the ease, continuity and comprehensibility of speech, coupled with few hesitations and pauses. It involves speed, automaticity, continuity, and ideas to be expressed without too much searching for words. In order to develop fluency, students need to have repeated speech production and greater automaticity in the retrieval, encoding, and articulation of their words (De Jong & Perfetti, 2011; Segalowitz, 2010; Skehan, 2009).

The measurement of speaking fluency in this study is based on the procedure of survey

design, which is self-perceived speaking fluency. Self-perceived speaking fluency matters because personal perception can have a positive or negative effect on a student's confidence, desire to communicate and future use of the language in speaking. But self-perceived fluency does not necessarily stand in for objective measures of fluency (e.g., speech rate, pause frequency, pronunciation accuracy, and teacher-rated oral performance). Hence, this study defines fluency in speaking as students' self-efficacy in their ability to speak English easily in an academic and daily communication situation.

Speaking Anxiety Reduction

Speaking anxiety is a most important affective obstacle to the second-language oral communication. It includes nervousness, anxiety, concern, apprehension, self-consciousness and worry about being evaluated negatively in the target language (Horwitz et al., 1986; MacIntyre & Gardner, 1994). Language anxiety has detrimental impacts on cognitive processing, oral participation, willingness to communicate and speaking performance (MacIntyre & Charos, 1996; Teimouri et al., 2019). Anxiety can lead to increased hesitation, pauses, avoidance of interaction and decreased fluency in speaking situations.

Speaking anxiety reduction means reducing students' fear, nervousness and uneasiness in speaking English. In this study, speaking anxiety reduction is viewed as positive and the higher scores represent less anxiety level or more anxiety reduction. Theoretically, the construct is supported by the Affective Filter Hypothesis that was proposed by Krashen (1982), stating that anxiety may inhibit language learning and language performance. Mobile-assisted speaking practice can help to lower speaking anxiety since it offers chances for private speaking, repeated speaking, and low-pressure speaking. Student can practice without immediate feedback from peers, repeat tasks until comfortable, and get feedback in a less threatening environment.

Trust in AI Feedback

Trust in AI feedback is the students' confidence in the accuracy, usefulness, fairness, understandability, and utility of AI generated comments, scores and suggestions. When using AI for speech input training, students can receive feedback on pronunciation, fluency, grammar, vocabulary, intonation, and overall speech performance. But students may not take such feedback for granted. They might wonder if the AI system is able to recognize their accents, variations of English, context of speech, or the purpose of their utterances.

Research on human-AI interaction has demonstrated that users' trust influences their acceptance, dependence, and action on recommendation offered by an automated system (Jian et al., 2000; Lee & See, 2004). Trust in AI is particularly crucial in educational settings, as learners need to evaluate the credibility of AI-provided feedback and determine if it is reliable enough to influence their learning actions (Kohnke et al., 2023; Nazaretsky et al., 2025). If students believe that the AI feedback is accurate, they may feel more confident using mobile speaking tools and this could reduce their anxiety because it's not as threatening as actual feedback.

Theoretical Foundation and Hypotheses Development

Social Cognitive Theory

According to the Social Cognitive Theory, learning is the process that involves personal factors, behaviour, and environment interacting. Bandura (1986, 1991) states that people learn by observing, practicing, receiving feedback, monitoring themselves and regulating their own behavior. In mobile-assisted English-speaking practice students are involved in repeated speaking acts, are provided feedback from mobile or AI technology, self-monitor their performance and modify future speaking acts.

This theory is applicable because the use of mobile assisted speaking practice will provide

an environment conducive to repeated speaking behaviour. Students can practice pronunciation, repeat tasks, track progress and utilize AI feedback to adjust future learning. Schunk and DiBenedetto (2020) also pointed to the importance of motivation and self-regulation in relation to learning, which provides further support for the idea that mobile-assisted practice may help to facilitate speaking fluency if the students are actively involved in using the feedback.

Affective Filter Hypothesis

According to the Affective Filter Hypothesis (Krashen, 1982), emotional state like anxiety, fear or lack of confidence can obstruct language acquisition and performance. Under high anxiety, students might have difficulties to comprehend language input and make language output. A decreased anxiety level may allow the student to be more willing and able to communicate and speak more fluently.

In this study speaking anxiety reduction is suggested as a mediation variable. Spoken practice (using mobile) might create a less intimidating setting for speaking, thus alleviating anxiousness. This will, in turn, help to improve fluency in speech. This theoretical reasoning is especially relevant in Malaysia when students feel uncomfortable when speaking English in public because they fear making mistakes, comparing themselves with others, and not having enough opportunities to practice oral speech.

Hypotheses Formulation

The use of mobile-assisted English-speaking practice is expected to have positive association with speaking fluency as it provides more opportunities for the students to use their voice, repeat, monitor, and provide feedback on the output. Mobile applications can facilitate these processes as students can practise their speaking skills beyond the classroom and have their automatic speech recognition or AI systems provide immediate feedback (Godwin-Jones, 2018;

Kukulska-Hulme, 2020; Tai & Chen, 2023). Thus, it is expected that students who practice mobile-assisted English-speaking practice more often will have more fluent reports.

H1: Mobile-assisted English-speaking practice is positively associated with speaking fluency among Malaysian university students.

Using mobile to assist in English speaking practice is also anticipated to alleviate speaking anxiety. Students may be even more anxious when facing others in the classroom, since they are concerned about making errors, being judged by others, or being negatively evaluated (Horwitz et al., 1986; MacIntyre & Gardner, 1994). Mobile apps offer private and repeated speaking opportunities, enabling students to practice, make mistakes, and get better before it's time to speak in public. Such practice can lead to lowering the affective filter which in turn can reduce nervousness in oral communication (Krashen, 1982; Teimouri et al., 2019).

H2: Mobile-assisted English-speaking practice is positively associated with speaking anxiety reduction among Malaysian university students.

It is predicted that speaking anxiety will have a positive relationship with speaking fluency. It can be predicted that speaking anxiety will be positively correlated to speaking fluency. If students do not have to worry about making errors or being criticized for their mistakes, they can devote more cognitive resources to delivering the message, pronunciation and interaction (MacIntyre & Gardner, 1994; Teimouri et al., 2019). Reduced anxiety can help to promote more fluid speech, less hesitation and increased communication readiness (Dewaele & MacIntyre, 2014; Tavakoli & Skehan, 2005).

H3: Speaking anxiety reduction is positively associated with speaking fluency among Malaysian university students.

The relationship between mobile assisted English-speaking practice and fluency is expected

to be mediated by speaking anxiety reduction. Mobile assisted practice may directly contribute to fluency by providing more practice and indirectly by decreasing anxiety. Practice in a mobile context in low-stress may decrease students' nervousness and they might be more open to speaking, which may in turn improve their perceived fluency. The mediation model is consistent with the Affective Filter Hypothesis and previous studies on language anxiety (Horwitz et al., 1986; Krashen, 1982; MacIntyre & Gardner, 1994; Teimouri et al., 2019).

H4: Speaking anxiety reduction mediates the relationship between mobile-assisted English-speaking practice and speaking fluency among Malaysian university students.

The level of trust in AI feedback is predicted to moderate the link between English speaking practice with mobile technologies and reduction in speaking anxiety. Student acceptance of constructive feedback is likely to be higher if they trust the AI feedback and will follow the suggestions to practice again and again, and feel supported by the AI system. Trust helps to minimize uncertainty and boost learners' trust in automated feedback (Jian et al., 2000; Lee & See, 2004). Low trust can, on the other hand, diminish the emotional and teaching advantages of AI-driven speaking practice.

H5: Trust in AI feedback positively moderates the relationship between mobile-assisted English-speaking practice and speaking anxiety reduction, such that the relationship is stronger when trust in AI feedback is higher.

Finally, the indirect effect of mobile-assisted English-speaking practice on speaking fluency via reducing speaking anxiety is predicted. If the trust is high, students can engage more with AI feedback, feel less anxious, and finally be more satisfied with their progression in fluency. Low trust = lower emotional and fluency benefits from same mobile-assisted practice. It is a conditional indirect logic that aligns with moderated mediation and trust-based human-AI

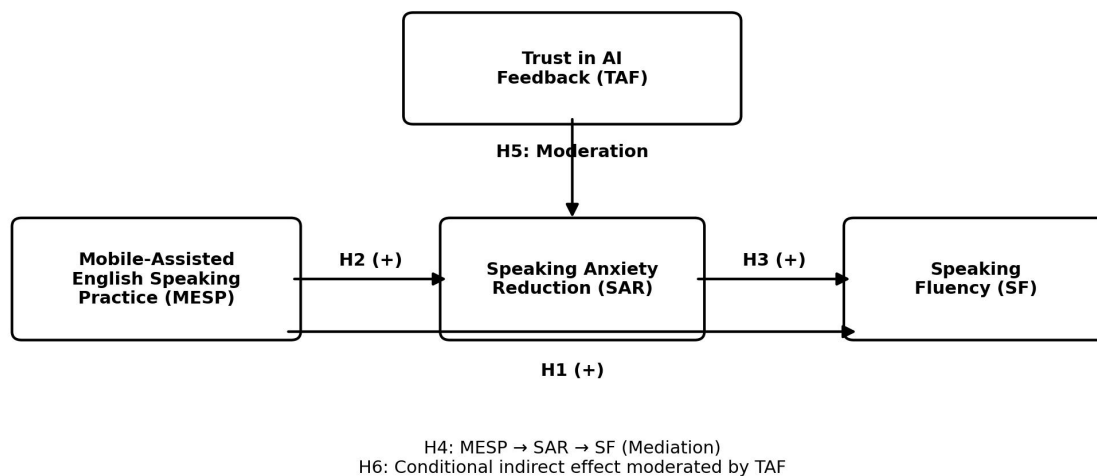
learning interaction (Hayes, 2018; Kohnke et al., 2023; Nazaretsky et al., 2025).

H6: Trust in AI feedback moderates the indirect relationship between mobile-assisted English-speaking practice and speaking fluency through speaking anxiety reduction, such that the indirect relationship is stronger when trust in AI feedback is higher.

Research Model

The moderated-mediation model is shown in Figure 1. Mobile-assisted English-speaking practice is proposed to have a direct and indirect (via reduction of speaking anxiety) effect on the learner's fluency in speaking. According to the proposed conditional indirect effect, trust in AI feedback would moderate the relationship between mobile-assisted English-speaking practice and reduction of speaking anxiety, which would yield a conditional indirect effect.

Figure 1
Research Model



Methodology

Research Design

This study adopted a cross-sectional quantitative survey design. The design was suitable given that the study was designed to examine a moderated mediation model that comprised of three variables: namely, mobile-assisted English-speaking practice, reduction of English-speaking anxiety, trust in AI feedback, and fluency in speaking. Partial least squares structural equation modelling was used because the model comprised of both direct, mediation, moderation, and conditional indirect relationships. The PLS-SEM can be used for prediction-oriented models involving multiple latent constructs with indirect effects (Hair et al., 2022).

Respondents and Study Context

The participants were undergraduate students at the Malaysian higher education institutions. Three inclusion criteria were used to select the respondents. In the first place they were to be undergraduate students. Secondly, they were required to be taking an English related course or an English course that involved oral communication activities. Third, they ought to practice English speaking at least once a week in the current semester by using mobile applications or their smartphones.

Students in Malaysian universities in Kuala Lumpur/Selangor, Penang, Johor and in Sabah/Sarawak were chosen as data subjects. The regions were chosen, so that there is a mix of contextual diversity in the urban, North, South and East Malaysian higher education environment. Students from public universities, private universities and university colleges were included in the sample.

Data Collection Procedure

An online questionnaire was used to gather data. The survey link was sent out via learning platforms, class networks, social media and groups of university students. The respondents were made aware that their responses would be anonymous and confidential and participation was

voluntary. The respondents were screened first to make sure they have been included in the questionnaire according to the inclusion criteria. We received 487 questionnaires. Following the exclusion of incomplete responses, straight-line responses and responses missing screening criteria, 428 valid questionnaires were left for final analysis.

Measurement of Constructs

Adapted multi-item scales were used to measure all constructs. This was answered with a 5-point Likert scale, with 1 = strongly disagree and 5 = strongly agree. Items adapted from the mobile-assisted language learning studies were used to measure mobile-assisted English-speaking practice. Resources related to the number and frequency of using mobile applications for speaking practice, pronunciation exercises, listening and speaking activities, AI conversation and oral feedback. The assessment of speaking anxiety was carried out in terms of reverse coded speaking relevant items from the Foreign Language Classroom Anxiety Scale (Horwitz et al., 1986). Higher scores represented lower speaking anxiety and/or greater reduction of anxiety. Items were adapted from the trust in automation (Jian et al., 2000) and trust in AI feedback scales (Lee & See, 2004) to measure trust in AI feedback. The speaking fluency was assessed with the use of the items of speaking fluency and literature on speaking performance (De Jong & Perfetti, 2011; Segalowitz, 2010; Skehan, 2009).

Data Analysis

The collected data was analysed using SPSS and Smart_PLS 4. Descriptive statistics and demography analysis were carried out using SPSS. For the assessment of the measurement model and the structural model, the Smart_PLS was applied. Cronbach's alpha, rho_A and composite reliability were used to test the reliability. Outer loadings and average variance extracted were used to check the convergent validity. The Fornell-Larcker criterion and

heterotrait-monotrait ratio were used to test for discriminant validity. Bootstrapping with 5,000 resample was used to test the structural relationships.

Results

Sample Characteristics

A total of 487 questionnaires were received from the Malaysian undergraduate students initially. Of the 63 questionnaires that were screened, 59 were excluded due to various reasons such as lack of information, straight-line answers or not meeting the inclusion criteria. Thus, 428 complete responses were used for the final analyses. Since this final sample was sufficient for PLS-SEM as it is the minimum sample size required for testing a moderated mediation model with multiple latent constructs, it was deemed adequate for PLS-SEM.

Table 1
Sample Socio-Demographic Profile (N = 428)

Characteristic	Category	Frequency	Percentage
Region	Kuala Lumpur/Selangor	118	27.6%
	Penang	103	24.1%
	Johor	101	23.6%
	Sabah/Sarawak	106	24.8%
Institution Type	Public university	226	52.8%
	Private university	149	34.8%
	University college	53	12.4%
Gender	Male	187	43.7%
	Female	241	56.3%
Age	18-19 years	79	18.5%
	20-21 years	183	42.8%
	22-23 years	129	30.1%
	24 years or above	37	8.6%
Year of Study	First year	91	21.3%
	Second year	126	29.4%

	Third year	132	30.8%
	Fourth year or above	79	18.5%
Field of Study	Business and social sciences	151	35.3%
	English/language/education	139	32.5%
	STEM and other fields	138	32.2%

Table 1 indicates that the respondents were well-distributed according to the four regions of Malaysia. The highest percentage of respondents was from Kuala Lumpur/Selangor (27.6%), followed by Sabah/Sarawak (24.8%), Penang (24.1%) and Johor (23.6%). This regional distribution indicates that the sample was not highly skewed towards any single region and also reflects wider Malaysian higher education contexts.

From the point of view of the type of institution, 52.8% of the respondents attended public university, 34.8% public private university, and 12.4% university college. That distribution is helpful because students attending institutions may come from a variety of contexts with varying degrees of exposure to English speaking practices, mobile learning, and receiving feedback with the help of AI. There was also a slight female predominance in the sample, as the female students were 56.3% and the male students were 43.7%.

The majority of respondents were in the age range of 20-23 years, the average age of undergraduate students. The respondents were also spread over different years of studies, the highest percentage representing third year students and the second-year students. When it came to field, there were students from business/social science, English/language/education, STEM or other. This means that the study was not conducted on English majors only.

Descriptive Statistics

The researchers analyzed descriptive statistics to gain insights into the overall trends in

respondents' perception of mobile-assisted English-speaking practice, speaking anxiety reduction, trust in AI feedback, and speaking fluency. The values for mean and standard deviation are given in Table 2.

Table 2
Descriptive Statistics

Construct	Mean	Standard Deviation
Mobile-assisted English speaking practice	3.82	0.69
Speaking anxiety reduction	3.64	0.73
Trust in AI feedback	3.71	0.70
Speaking fluency	3.76	0.67

All mean values were above the midpoint value of 3.00, indicating that responses of Malaysian university students were generally positive. The mean value of mobile-assisted English-speaking practice was the highest among all other means, indicating that generally respondents were not disagreeing that they use mobile devices or applications in order to practice English speaking. This means that the respondents were relatively familiar with mobile based speaking activities including pronunciation drills, recorded speaking tasks, AI conversation practice, and mobile feedback.

Students had an average score of 3.76 for speaking fluency with a range of 1–5 indicating moderate positive level of English-speaking fluency. Students' mean score of trust in AI feedback was 3.71, which suggests a positive overall attitude toward AI-generated feedback. This indicates that students were receptive to AI-based feedback, although the level is not particularly high, which indicates that the trust in AI feedback might need to be further reinforced by teacher guidance and training on AI literacy.

Speaking anxiety recorded a mean score of 3.64, the lowest of all the four constructs, but

above the mid-point. This suggests that learners' English-speaking anxiety was reduced when using mobile-assisted speaking tools, although this anxiety might also remain to be a problem for some learners. The range of the standard deviations was between 0.67 and 0.73, which indicated moderate variation of students' responses. This is a normal variation as students from Malaysia have different levels of English proficiency and exposure to digital learning, exposure to AI-supported tools, and level of confidence.

Measurement Model Assessment

The measurement model was examined for reliabilities and validity of the hypotheses before they were tested. As each of the constructs was measured with several items adapted from the earlier studies, it was important to check whether the items were reliable to represent each construct in the higher education context of Malaysia. Cronbach's alpha, rho_A and composite reliability were used to measure reliability. Outer loadings and average variance extracted were used to test the convergent validity.

Table 3
Reliability and Convergent Validity

Construct	Items Retained	Loading Range	Cronbach's Alpha	rho_A	Composite Reliability	AVE
Mobile-assisted English speaking practice	8	0.724-0.851	0.879	0.886	0.908	0.553
Speaking anxiety reduction	7	0.741-0.866	0.898	0.904	0.921	0.625
Trust in AI feedback	6	0.756-0.872	0.861	0.868	0.895	0.588
Speaking fluency	6	0.729-0.859	0.834	0.841	0.881	0.598

Table 3 shows that all outer loadings were above the recommended level of 0.70. The range of the mobile-assisted English-speaking practice items was between 0.724 and 0.851, which meant that all the items were effective in measuring the construct. Anxiety reduction had item loadings between 0.741 and 0.866, and the trust in AI feedback had loadings between 0.756 and 0.872. The loadings for the speaking fluency were also satisfactory, from 0.729 to 0.859. These results indicate that the indicators had satisfactory reliability.

Cronbach's alpha values were between 0.834 and 0.898, which is more than 0.70. This indicates good internal consistency among the items in each construct. Construct reliability was also supported by the rho_A values, which ranged from 0.841 to 0.904 and were all > 0.70 . The internal consistency of the items that measured the constructs ranged from 0.881 to 0.921, suggesting that the items were internally consistent.

The AVE values for all constructs were above 0.50. The AVE values for mobile-assisted English-speaking practice, speaking anxiety reduction, trust in AI feedback, and speaking fluency were 0.553, 0.625, 0.588, and 0.598, respectively. The values show that each construct accounted for over half of the variance in its indicators. Thus, convergent validity was achieved.

The results of the measurement model overall support the reliability and validity of the measurement items adapted to evaluate the mobile-assisted English-speaking practice, speaking anxiety reduction, trust in AI feedback, and speaking fluency among Malaysian university students.

Discriminant Validity

Heterotrait-monotrait ratio was used to assess discriminant validity. The "empirical distinctness" of each construct is assessed through the use of HTMT. Discriminant validity is acceptable if the HTMT values are less than 0.85.

Table 4
HTMT Results

Construct	MESP	SAR	TAF	SF
Mobile-assisted English speaking practice	—			
Speaking anxiety reduction	0.614	—		
Trust in AI feedback	0.537	0.489	—	
Speaking fluency	0.646	0.681	0.512	—

All the HTMT values were below the recommended value of 0.85, and ranged from 0.489 to 0.681. The maximum value obtained from HTMT was 0.681 which was between the scales of Speaking anxiety reduction and Speaking fluency. This is well reasonable as it is theoretically linked to speaking fluency, but the value is still below the threshold, thus affirming that the two constructs are still empirically different.

There was a relatively high correlation between the two constructs, mobile-assisted English-speaking practice and speaking fluency, with a correlation value of HTMT = 0.646. The same applies to the HTMT value for mobile-assisted English-speaking practice and reduction of speaking anxiety which is 0.614, indicating that practice behaviour and affective change are two different constructs. The other constructs had lower HTMT values for trust in AI feedback, indicating that it is a separate evaluation variable related to AI. Thus, discriminant validity was achieved.

Structural Model Results

The reliability and validity of the measurement model were verified, and then the structural model was evaluated to test the hypotheses. The structural model focused on the direct

relationships between the three variables of mobile-assisted English-speaking practice, reduction of speaking anxiety, and speaking fluency.

Table 5
Direct Effects

Hypothesis	Relationship	Beta	t-value	p-value	Decision
H1	MESP → Speaking fluency	0.318	6.214	<0.001	Supported
H2	MESP → Speaking anxiety reduction	0.529	12.476	<0.001	Supported
H3	Speaking anxiety reduction → Speaking fluency	0.401	8.932	<0.001	Supported

Table 5 indicates that there was a significant positive correlation between mobile-assisted English-speaking practice and speaking fluency ($\beta = 0.318$, $t = 6.214$, $p < 0.001$). Hence, H1 is supported. The result indicated that students who showed more active attitude towards their use of mobile applications more frequently for learning English speaking skills had high rates in their self-evaluation of their English-speaking proficiency. Mobile-assisted practice can in practice be used to help students practise pronunciation, repeat oral tasks, practise presentations, interact with AI tools, and get feedback on their speech, which can be beneficial for smoother oral production.

The relationship between mobile-assisted English-speaking practice and reduction of English-speaking anxiety was also significant and positive ($\beta = 0.529$, $t = 12.476$, $p < 0.001$). As a result, H2 got the support. This finding suggests that the more students used the technology to practice their speaking, the more their speaking anxiety decreased. It can be seen that the beta

value of the mobile-assisted practice is relatively high, which indicates that the use of mobile devices in practice has a significant influence on the students' nervousness and discomfort in speaking English. This might be because there is little peer judgement when using mobile tools, students can repeat challenging speech skills, and receive feedback in private.

The findings of this study support H3, which was speaking anxiety reduction positively related to speaking fluency ($\beta = 0.401$, $t = 8.932$, $p < 0.001$). That is, those with less speaking anxiety were more likely to feel they were fluent English speakers. This discovery corroborates the notion of emotional readiness as an important factor in oral fluency development. Students are able to concentrate more on the delivery of the message, on pronunciation, on the links etc. than on making mistakes, if they feel less anxious.

R-square value of speaking anxiety reduction was 0.342. This suggests that the variance in reduction of speaking anxiety can be accounted for by 34.2% of this mobile-assisted English-speaking practice and trust in the AI feedback. In behavioural or educational studies, this amount of explanation is satisfactory because there are so many other factors that could contribute to the anxiousness of students, including their personality, previous English learning experiences, classroom environment, comparison to others, and teacher support.

R-square for the speaking fluency was 0.517. This indicates that 51.7% of the variance in the level of fluency in English as a foreign language was explained by the mobile assisted speaking practice and the reduction of speaking anxiety. This is moderate to substantial level of explanatory power, indicating that the proposed model is able to offer students a meaningful explanation for their perception of fluency in speaking in the context of higher education in Malaysia.

Mediation Analysis

To see if the relationship between mobile-assisted English-speaking practice and speaking fluency is mediated by speaking anxiety reduction, a mediation analysis was performed. The indirect effect was tested significant using "bootstrapping".

Table 6
Mediation Effect

Hypothesis	Indirect Relationship	Beta	t-value	p-value	Decision
H4	MESP → Speaking anxiety reduction → Speaking fluency	0.212	7.384	<0.001	Supported

The result of the mediation revealed that the indirect effect of mobile-assisted English-speaking practice on English speaking fluency via reduction of speaking anxiety was significant ($\beta = 0.212$, $t = 7.384$, $p < 0.001$). Hence, H4 was advocated. The result suggests that speaking anxiety reduction is an important psychological mechanism between the mobile-assisted practice and speaking fluency.

After including the mediator, the direct effect of mobile-assisted English-speaking practice on the speaking fluency was still significant. Thus, the mediation is not complete, it is only partial. Mobile-assisted speaking practice is related to speaking fluency in two ways (Jafar, 2012). Firstly, it directly promotes fluency through opportunities for oral repetition, pronunciation practice, feedback use and self-monitoring. Second, it indirectly contributes to fluency by easing speaking anxiety. Pupils using mobile devices can be more relaxed about making mistakes, less nervous about taking part in speaking activities, and more confident in speaking English.

This finding is significant because it indicates that using mobile as a speaking tool is not just a technical or behavioural practice. In addition, it serves an affective purpose. Mobile-

assisted practice could be used to offer a safer environment for oral development, as in the Malaysian context, some students may not feel confident speaking in English for fear of making mistakes, peers judging them in English, or not having been exposed to English communication enough.

Moderation Analysis

The moderation analysis examined the moderating effect of trust in AI feedback on the relationship between mobile-assisted English-speaking practice and reduction of speaking anxiety. The interaction term of mobile-assisted English-speaking practice and trust in AI feedback was developed and tested with the help of bootstrapping method in Smart_PLS.

Table 7
Moderating Effect of Trust in AI Feedback

Hypothesis	Interaction Effect	Beta	t-value	p-value	Decision
H5	MESP × Trust in AI Feedback → Speaking anxiety reduction	0.146	3.518	<0.001	Supported

The interaction effect was significant and positive ($\beta = 0.146$, $t = 3.518$, $p < 0.001$), supporting H5. This suggests that English speaking confidence increases as the relationship between mobile assisted English speaking and reducing English speaking anxiety strengthens with trust in AI feedback. That is, high trust in the AI-generated feedback is associated with greater effectiveness of mobile-assisted speaking practice in reducing speaking anxiety.

The interaction effect is smaller than the direct effects but this is typical of moderation studies. The interaction effects tend to be small because they are seen as a change in a relationship when conditions are different, not main effects. The interaction between trust in AI

feedback and positive and significant, indicating that it is an important boundary in speaking practice with AI.

A high level of trust in AI feedback might incline students to accept pronunciation scores, fluency comments, grammar corrections, and suggestions for speaking. They feel less threatened and supported during practice since they believe the feedback they receive is credible and useful. Students not so confident with AI feedback, however, may not be convinced of the accuracy or fairness of the feedback, diminishing the anxiety reducing effect.

Conditional Indirect Effect

To investigate the indirect effect of mobile-assisted English-speaking practice on speaking fluency via reduction of the speaking anxiety, the moderated mediation analysis was conducted, in which the interaction between mobile-assisted English-speaking practice and trust in AI feedback was examined.

Table 8
Conditional Indirect Effects at Different Levels of Trust in AI Feedback

Level of Trust in AI Feedback	Indirect Effect	t-value	p-value
Low trust	0.153	4.927	<0.001
Mean trust	0.212	7.384	<0.001
High trust	0.268	8.641	<0.001

As detailed in Table 8, indirect effect was significant at low, mean, and high levels of trust in AI feedback. However, the strength of the indirect effect increased as trust in AI feedback increased. The indirect effect was 0.153 at low trust. The indirect effect grew to 0.212 at the average level of trust. The indirect effect was further increased to 0.268 at high trust.

The results for these are consistent with H6 and also validate the moderated mediation effect. The results show that mobile-assisted English-speaking practice is more strongly related

with speaking fluency when students have high trust in AI feedback in reducing speaking anxiety. This shows that trust in AI feedback has a direct impact on the emotional value of mobile practice, but also enhances the indirect pathway from practice to fluency.

This outcome is significant to education. While AI feedback can be used to aid the growth of English speaking, its usefulness can be partly dependent on students' trust in AI. If students think the AI feedback they've received is accurate, fair, and helpful, they are more likely to practise with confidence, less likely to experience anxiety, and likely to report an improvement in speaking fluency. Hence, the trustworthy feedback from AI is an essential element of effective AI-enhanced speaking practice.

Summary of Hypotheses Testing

Table 9
Summary of Hypotheses

Hypothesis	Statement	Result
H1	MESP positively relates to speaking fluency.	Supported
H2	MESP positively relates to speaking anxiety reduction.	Supported
H3	Speaking anxiety reduction positively relates to speaking fluency.	Supported
H4	Speaking anxiety reduction mediates the MESP-speaking fluency relationship.	Supported
H5	Trust in AI feedback moderates the MESP-speaking anxiety reduction relationship.	Supported
H6	Trust in AI feedback moderates the indirect effect of MESP on speaking fluency through anxiety reduction.	Supported

Table 9 summarizes the results of hypothesis testing. The hypotheses were all accepted. The result verifies the direct relationships between the mobile-assisted English-speaking practice and the reduction in speaking anxiety and the increase in fluency in speaking. Speaking anxiety

reduction is also positively related to speaking fluency and is a partial mediator. Moreover, the relationship between mobile-assisted English-speaking practice and speaking anxiety reduction was positively reinforced by the trust in AI feedback, and the relationship between practicing and speaking anxiety and speaking fluency was also positively mediated by reducing speaking anxiety.

The results overall confirm the proposed moderated mediation model. The results indicate that mobile-assisted English-speaking practice can help improve students' speaking fluency in both behavioral and affective ways. The direct relationship between mobile-assisted practice and speaking fluency reflects the behavioural pathway, and the mediation of the speaking anxiety reduction reflects the affective pathway. Finally, the moderating effect of trust in the AI feedback further demonstrates that AI-assisted learning is more effective when students think that the feedback is reliable, useful, and credible.

Discussion

The results offer empirical evidence in the form of positive relation between mobile-assisted English-speaking practice and English-speaking fluency of university students in Malaysia. This indicates that students who engage with mobile applications for pronunciation practice, recorded speaking, AI conversation, and oral feedback are more inclined to self-perceive as fluent English speakers. The discovery aligns with the concept that mobile-assisted language learning can create additional opportunities for students to speak beyond the classroom, and to provide multiple opportunities for learning, which is crucial for fluency acquisition (Burston, 2015; Kukulska-Hulme, 2020; Stockwell & Hubbard, 2013).

The study also revealed that speaking anxiety reduction is positively related to mobile assisted English-speaking practice. It implies that students who are more active in using mobile

tools might have less nervousness and self-consciousness in using English. Mobile-assisted practice can offer a less threatening context for oral rehearsal for students who speak a non-native language and/or have varying degrees of proficiency in English in Malaysia. This corresponds to the Affective Filter Hypothesis and the oral anxiety research findings by Horwitz et al. (1986), Krashen (1982), and Teimouri et al. (2019) that indicated anxiety had an impact on oral performance.

Speaking anxiety reduction was also found to be positively correlated with speaking fluency. Less nervous students will speak with less hesitation, pauses, and less continuity. Thus, reducing anxiety is a crucial affective process in the development of speaking fluency. The outcome implies that the speaking improvement process is not a cognitive or behavioural process alone, but also an emotional process.

The result of mediation indicates that speaking anxiety reduction partially mediate the relationship between mobile-assisted English-speaking practice and speaking fluency. This indicates that mobile-assisted practice is effective not only in enhancing the opportunities for practice, but also in minimizing anxiety. The mediation is partial however; other mechanisms may account for the relationship. These can include pronunciation, vocabulary recall, speaking confidence, feedback use, self-regulation and willingness to communicate.

The moderation result indicates that the relationship between the use of mobile-assisted English-speaking practice and reduction of speaking anxiety is strengthened by trust in AI feedback. This is particularly significant because having AI feedback doesn't mean it is useful. Students need to believe in the feedback before believing it and applying it. To maintain the confidence of students, reduce their anxiety, and assist them with speaking abilities, mobile speaking practice should be provided with the assistance of AI feedback that is credible,

understandable, and useful, as these factors can boost their confidence and alleviate anxiety (Jian et al., 2000; Lee & See, 2004; Nazaretsky et al., 2025).

Lastly, the moderated mediation result shows that the indirect effect of mobile-assisted English-speaking practice on fluency through a decrease in anxiety is more evident when there is high trust in the feedback provided by the AI. This implies that building trust is a crucial boundary condition for using AI in language learning. It is essential that in the context of Malaysia, lecturers and institutions give students insights into how AI feedback is generated so that they can confidently and responsibly use AI feedback.

Theoretical Implications

The study has a number of implications for theory. Firstly, it continues the research of mobile assisted language learning in that it explores the direct relationship between mobile assisted speaking practice and fluency of speaking as well as the affective pathway on which the reduction of speaking anxiety took place. The following gives a more comprehensive account of the role of mobile tools in oral development.

Second, the study extends to the field of Social Cognitive Theory by showing that mobile-assisted speaking practice offers a technology-supported environment in which repeated speaking practice, feedback, self-monitoring and behavioural regulation take place. These conditions are related to students' perceived fluency. Thirdly, the study is related to the Affective Filter Hypothesis in which speaking anxiety reduction is considered as the mediator. The findings indicated that one possible factor for the correlation between mobile assisted speaking practice and speaking fluency is the fact that the practice reduces the anxiety that students experience in their speaking activities.

First, it is a new study that adds trust in AI feedback to the Human-AI interaction research

field in education. This underscores that AI-powered learning relies on a combination of technology availability and students' faith in the suggestions given. Lastly, the Malaysian context contributes in providing insight of how mobile-assisted speaking practice can be applicable in the context of a multilingual higher education setting.

Practical Implications

This study provides implications for the implementation in Malaysian HEIs. To begin with, universities should adopt tasks in language courses which are suitable to be taught through the use of mobile devices. Additional speaking opportunities can be given through weekly mobile speaking activities, recorded oral summaries, AI dialogue practice and pronunciation drills.

Second, the lecturer should adopt mobile assisted practice to alleviate students' anxiety in speaking. Speaking tasks that have low stakes can be used to help students practise their performance before class. It can be particularly beneficial for learners who are shy, anxious or less confident. Third, universities must enhance the students' ability to read feedback in the form of AI. Pupils should be made aware of the process for creating AI feedback, what it can and can't assess, and how to interpret pronunciation scores or fluency ratings. This can help build trust in AI feedback and foster responsible AI use.

Fourth, AI feedback needs to be supplemented by human feedback. While useful for immediate feedback, teachers play an essential role in clarifying errors, interpreting feedback, and assisting students in making meaningful use of suggestions in a meaningful conversation. Lastly, universities must be able to provide access to mobile-assisted speaking tools that is inclusive. Students of diverse socio-economic statuses should be provided with an equal opportunity to utilize digital speaking resources.

Limitations and Future Research

There are some limitations to this study. First of all, the cross-sectional design is not suitable for causal interpretation. Longitudinal and/or experimental designs are needed to investigate the development of speaking anxiety and fluency over time in future studies. Second, fluency was assessed by the self-perception. The teacher ratings, oral performance tasks, speech recordings and acoustic measures (speech rate, number of pauses, mean length of run) should be included in future studies. Thirdly, the study was limited to the Malaysian undergraduate students. Future studies could be conducted to compare undergraduates and postgraduates, or to look at differences between the public and private universities. Fourth, trust in AI feedback was tested as a moderator, which could be investigated in future studies with other moderators like digital competence, English language proficiency, willingness to communicate with AI, lecturer support, or previous experience with AI tools.

Conclusion

The present study is an empirical study that focuses on the impact of mobile-assisted English-speaking practice on the speaking fluency of the Malaysia University students. Results indicate that mobile-assisted speaking practice is positively related to speaking fluency and speaking anxiety reduction. Speaking anxiety reduction partially mediates the relationship between mobile-assisted speaking practice and speaking fluency. The relationship between mobile-assisted speaking practice and anxiety reduction is enhanced by the trust in AI feedback, as is the indirect relationship with speaking fluency. The findings in the study identify that active use of mobile and AI mediated speaking practice could be useful for promoting English speaking fluency if students have low levels of speaking anxiety and high levels of trust in speaking feedback. Mobile assisted speaking practice can be a valuable means of boosting oral confidence and fluency in English in the multilingual higher education environment in Malaysia.

Declarations

Ethical Considerations

Informed consent was obtained from all respondents before participation. Respondents were informed that participation was voluntary, responses would remain anonymous and confidential, and they could withdraw from the study at any stage without penalty.

Use of Artificial Intelligence

The authors declare that generative AI tools may be used only for language editing and grammatical improvement. The use of AI does not influence the study design, data analysis, interpretation, results, or conclusions. The authors remain fully responsible for the manuscript content.

Conflict of Interest

The authors declare no conflict of interest.

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References

- Bandura, A. (1986). Social foundations of thought and action: A social cognitive theory. Prentice-Hall.
- Bandura, A. (1991). Social cognitive theory of self-regulation. *Organizational Behavior and Human Decision Processes*, 50(2), 248-287.
- Burston, J. (2015). Twenty years of MALL project implementation: A meta-analysis of learning outcomes. *ReCALL*, 27(1), 4-20.
- Chen, X. B. (2017). Tablets for informal language learning: Student usage and attitudes. *Language Learning & Technology*, 21(2), 20-36.

- De Jong, N. H., & Perfetti, C. A. (2011). Fluency training in the ESL classroom: An experimental study of fluency development and proceduralization. *Language Learning*, 61(2), 533-568.
- Derakhshan, A., Khalili, A. N., & Beheshti, F. (2016). Developing EFL learner's speaking ability, accuracy and fluency. *English Language and Literature Studies*, 6(2), 177-186.
- Dewaele, J. M., & MacIntyre, P. D. (2014). The two faces of Janus? Anxiety and enjoyment in the foreign language classroom. *Studies in Second Language Learning and Teaching*, 4(2), 237-274.
- Dizon, G. (2020). Evaluating intelligent personal assistants for L2 listening and speaking development. *Language Learning & Technology*, 24(1), 16-26.
- Ebadi, S., & Raygan, A. (2023). Investigating the role of mobile-assisted language learning in EFL learners' language development. *Computer Assisted Language Learning*, 36(5-6), 1032-1058.
- Gan, Z., Yan, Z., & An, Z. (2022). Development and validation of a self-efficacy scale for English as a foreign language speaking. *Language Teaching Research*. Advance online publication.
- Godwin-Jones, R. (2018). Using mobile devices in the language classroom. *Cambridge Papers in ELT*, 1-18.
- Godwin-Jones, R. (2023). Partnering with AI: Intelligent writing assistance and instructed language learning. *Language Learning & Technology*, 27(2), 1-15.
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). A primer on partial least squares structural equation modeling (PLS-SEM) (3rd ed.). SAGE.
- Hayes, A. F. (2018). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach (2nd ed.). Guilford Press.
- Horwitz, E. K., Horwitz, M. B., & Cope, J. A. (1986). Foreign language classroom anxiety. *The Modern Language Journal*, 70(2), 125-132.

- Hwang, G. J., & Fu, Q. K. (2019). Trends in the research design and application of mobile language learning: A review of 2007-2016 publications. *Interactive Learning Environments*, 27(4), 567-581.
- Jian, J. Y., Bisantz, A. M., & Drury, C. G. (2000). Foundations for an empirically determined scale of trust in automated systems. *International Journal of Cognitive Ergonomics*, 4(1), 53-71.
- Kim, N. Y., Cha, Y., & Kim, H. S. (2021). Future English learning: Chatbots and artificial intelligence. *Multimedia-Assisted Language Learning*, 24(1), 32-53.
- Kohnke, L., Moorhouse, B. L., & Zou, D. (2023). ChatGPT for language teaching and learning. *RELC Journal*, 54(2), 537-550.
- Krashen, S. D. (1982). Principles and practice in second language acquisition. Pergamon Press.
- Kukulska-Hulme, A. (2020). Mobile-assisted language learning. In C. A. Chapelle (Ed.), *The concise encyclopedia of applied linguistics* (pp. 1-6). Wiley.
- Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. *Human Factors*, 46(1), 50-80.
- MacIntyre, P. D., & Charos, C. (1996). Personality, attitudes, and affect as predictors of second language communication. *Journal of Language and Social Psychology*, 15(1), 3-26.
- MacIntyre, P. D., & Gardner, R. C. (1994). The subtle effects of language anxiety on cognitive processing in the second language. *Language Learning*, 44(2), 283-305.
- Nazaretsky, T., Mejia-Domenzain, P., Swamy, V., Frej, J., & Käser, T. (2025). Student trust in AI-based educational technologies: A multidimensional perspective. *Computers & Education*, 215, 105031.
- Oxford, R. L. (2017). Teaching and researching language learning strategies: Self-regulation in context (2nd ed.). Routledge.
- Papi, M., & Khajavy, G. H. (2023). Second language anxiety: Construct, effects, and sources. *Annual Review of Applied Linguistics*, 43, 127-139.
- Schunk, D. H., & DiBenedetto, M. K. (2020). Motivation and social cognitive theory. *Contemporary Educational Psychology*, 60, 101832.

- Segalowitz, N. (2010). Cognitive bases of second language fluency. Routledge.
- Skehan, P. (2009). Modelling second language performance: Integrating complexity, accuracy, fluency, and lexis. *Applied Linguistics*, 30(4), 510-532.
- Stockwell, G., & Hubbard, P. (2013). Some emerging principles for mobile-assisted language learning. *The International Research Foundation for English Language Education*, 1-15.
- Tai, T. Y., & Chen, H. H. J. (2023). The impact of mobile-assisted language learning on EFL learners' speaking performance and speaking anxiety. *Computer Assisted Language Learning*, 36(7), 1200-1226.
- Tavakoli, P. (2025). Fluency in second language speaking assessment: Developments and future directions. *Language Teaching*, 58(1), 1-18.
- Tavakoli, P., & Skehan, P. (2005). Strategic planning, task structure, and performance testing. In R. Ellis (Ed.), *Planning and task performance in a second language* (pp. 239-273). John Benjamins.
- Teimouri, Y., Goetze, J., & Plonsky, L. (2019). Second language anxiety and achievement: A meta-analysis. *Studies in Second Language Acquisition*, 41(2), 363-387.
- Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory Into Practice*, 41(2), 64-70.
- Zou, B., Wang, C., Du, X., Yan, Y., & Ji, Y. (2025). Exploring English as a foreign language learners' adoption and utilisation of ChatGPT for speaking practice through an extended Technology Acceptance Model. *International Journal of Applied Linguistics*, 35(2), 689-704.



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**Ethical Reflections on Nurse–Patient Communication in Obstetric Clinical Practice:
An Expanded Academic Revision**

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Abstract

Obstetric care involves the simultaneous safeguarding of maternal and neonatal well-being and is characterized by high risk, high emotional intensity, and persistent communication demands. In this context, nurse–patient communication is not merely a technical adjunct to nursing practice but a core ethical activity that shapes care quality, patient safety, emotional well-being, treatment adherence, and the overall climate of clinical trust. Pregnant and postpartum women constitute a distinctive patient group whose physical condition, psychological status, and decision-making needs shift dynamically across the antenatal, intrapartum, and postpartum continuum. Consequently, communication in obstetric settings requires a higher level of professional sensitivity, ethical discipline, and person-centered responsiveness than is often assumed in general inpatient care. Drawing on the four foundational principles of biomedical ethics—respect for autonomy, beneficence, nonmaleficence, and justice—this revised paper provides a more theoretically grounded and analytically rigorous examination of common communication problems in obstetric nursing. It argues that persistent weaknesses in informed communication, privacy protection, empathic engagement, language regulation, and equitable service delivery are not isolated behavioral lapses but manifestations of deeper structural tensions between efficiency-oriented care routines and the ethical demands of patient-centered maternity care. The paper further proposes a full-cycle ethical communication framework for obstetric practice, integrating graded informed consent, privacy-sensitive communication protocols, empathy-based psychological support, standardized low-harm language strategies, stratified yet equitable communication planning, and department-level quality governance. By strengthening

conceptual depth and practical applicability, this article aims to contribute to the construction of a more humane, ethically coherent, and clinically effective model of obstetric nursing communication.

Keywords: obstetric nursing; nurse–patient communication; biomedical ethics; respectful maternity care; humanistic nursing; clinical application

I. Introduction

With the continuing transition from a purely biomedical model to a biopsychosocial and person-centered paradigm, the quality of communication has become a central criterion for evaluating contemporary clinical care. In obstetrics, this shift is particularly consequential. Obstetric services concern not only disease management but also reproduction, embodiment, family transition, vulnerability, and the protection of two interrelated lives. Pregnancy and childbirth are therefore not routine physiological events alone; they are ethically charged, psychologically intensive, and socially embedded experiences that require careful communicative practice.

Compared with other hospital departments, obstetric units present a uniquely complex communication environment. Women receiving obstetric care may be planning pregnancy, experiencing antenatal hospitalization, undergoing labor, recovering from delivery, or coping with early postpartum adaptation. Across these stages, fear of pain, uncertainty about fetal health, changes in body image, concerns over maternal competence, and family expectations often converge. Such factors can heighten emotional sensitivity and reduce tolerance for ambiguity, making the quality, timing, and tone of communication clinically significant. In this setting, ineffective communication

may not only impair understanding but also intensify distress, weaken cooperation, delay intervention, and generate conflict.

Recent scholarship on respectful maternity care has further emphasized that communication is one of the defining components of dignified and rights-based obstetric practice. Systematic reviews have identified communication, privacy, informed consent, dignity, safety, and justice as overlapping dimensions of respectful maternity care, indicating that communication is simultaneously a relational process, an ethical obligation, and a determinant of care outcomes (Cantor et al., 2024; Kawish et al., 2023). Evidence also suggests that women's experiences of communication during childbirth strongly shape their sense of dignity, emotional security, and trust in caregivers (Collins et al., 2023). At the same time, large international studies have shown that mistreatment during facility-based childbirth remains a significant global problem, with poor communication and disrespectful treatment being recurrent features (Bohren et al., 2019; World Health Organization, 2019). These findings underscore that obstetric communication must be understood not as a soft skill peripheral to safety, but as a constitutive element of ethical and high-quality care.

From the perspective of biomedical ethics, nurse–patient communication in obstetrics must be anchored in four foundational principles: respect for autonomy, beneficence, nonmaleficence, and justice. These principles are especially relevant in obstetric care because the patient's needs are multidimensional and rapidly evolving. To respect autonomy is to ensure meaningful informed participation rather than ritualized consent; to practice beneficence is to support both physical and psychological well-being; to honor nonmaleficence is to avoid not only physical harm but also communicative injury; and to

uphold justice is to provide fair, comprehensible, and responsive communication across different social and clinical groups.

Against this background, the present paper revises and deepens the original discussion by moving beyond a descriptive account of communication defects. It seeks to show that common communication problems in obstetric nursing arise from the interaction of individual limitations, organizational routines, institutional metrics, and broader ethical blind spots. On this basis, the article develops a more systematic framework for improving communication quality in obstetric settings and for integrating ethical reasoning into everyday nursing practice.

II. The Ethical Foundations and Clinical Value of Nurse–Patient Communication in Obstetrics

2.1 Core Ethical Connotations of Obstetric Nurse–Patient Communication

The four principles of biomedical ethics provide a robust conceptual foundation for understanding communication in obstetric nursing, yet their application in this field requires contextual interpretation. Respect for autonomy in obstetrics extends beyond obtaining signatures on consent forms. It requires recognition of pregnant and postpartum women as moral agents entitled to dignity, bodily integrity, informed participation, and privacy. In practical terms, this means that communication should support understanding, not merely compliance; explain options, not merely announce decisions; and preserve confidentiality, especially regarding reproductive history, previous pregnancy loss, marital circumstances, and other highly sensitive information.

Beneficence, in turn, requires that communication actively promote the patient's overall good. In obstetric nursing, "benefit" should not be reduced to the successful completion of clinical procedures. Because pregnancy and childbirth are emotionally intense and identity-transforming experiences, beneficial communication also involves alleviating fear, enhancing coping capacity, strengthening trust, and facilitating adaptation to maternal role transition. Thus, communication is therapeutic when it supports both clinical safety and psychological resilience.

Nonmaleficence is traditionally associated with the avoidance of physical injury, but in communication-rich settings such as obstetrics, psychological and relational harms must also be taken seriously. A dismissive tone, shaming remark, coercive explanation, or abrupt disclosure of bad news can cause invisible but enduring injury. Such communicative harm may heighten labor distress, intensify postpartum vulnerability, and leave lasting negative memories of childbirth. Therefore, low-harm communication should be treated as an ethical minimum rather than an optional interpersonal refinement.

Justice requires fairness in both access to information and quality of interaction. In obstetric care, communication justice means that no woman should receive poorer explanations, less patience, or reduced emotional support because of age, educational background, socioeconomic position, marital status, language ability, or the perceived simplicity of her condition. At a deeper level, justice also requires equity-oriented adaptation: communication should be equal in moral worth yet responsive to differences in comprehension, risk, and psychosocial need.

2.2 The Clinical Significance of Ethical Communication

Ethically grounded communication contributes directly to maternal and neonatal safety. In obstetric emergencies and high-risk pregnancies, timely and comprehensible communication improves cooperation with monitoring, intervention, and symptom reporting. When women and their families understand risk trajectories and treatment rationales, adherence tends to improve and preventable complications may be reduced.

Ethical communication also plays a major role in mental health support. Pregnancy-related anxiety, fear of childbirth, and postpartum depressive symptoms are common concerns in maternity settings. A broader body of evidence indicates that high-quality patient-centered communication is associated with improved trust, satisfaction, and patient-centered outcomes (King & Hoppe, 2013; Oliveira et al., 2012; Sharkiya, 2023). In obstetrics specifically, effective communication has been identified as central to women's sense of dignity and positive childbirth experience (Collins et al., 2023). This suggests that communication can function as a protective factor against emotional destabilization.

In addition, communication quality is closely linked to medico-legal and relational outcomes. Many conflicts in obstetric care arise not solely from technical error, but from misunderstanding, unmet expectations, perceived disrespect, insufficient explanation, or privacy violations. Ethical communication can therefore reduce disputes by clarifying uncertainty, acknowledging emotion, and demonstrating procedural fairness. Finally, it is a cornerstone of humanistic and high-quality nursing. It supports the broader transformation of care models from task completion to person-centered accompaniment, thereby aligning obstetric nursing with global movements toward respectful maternity

care (Cantor et al., 2024; White Ribbon Alliance, 2011; World Health Organization, 2018).

III. Common Ethical Problems in Obstetric Nurse–Patient Communication and Their Causes

3.1 Formalistic Respect: Weaknesses in Informed Communication and Privacy Protection

Although respect is widely endorsed in principle, it is often incompletely realized in daily obstetric practice. One common problem is the reduction of informed communication to administrative completion. Important issues such as labor analgesia, induction, monitoring of high-risk pregnancy, or changes in treatment planning may be explained briefly and in highly technical language, with limited assessment of whether the patient actually understands the information. Under these conditions, signed consent may exist without meaningful autonomy. Such practices become especially problematic for women facing complex risk profiles, who often require staged explanation, repeated clarification, and opportunities for questions.

A second problem concerns privacy. Obstetric care frequently involves deeply sensitive personal information, yet privacy breaches may occur through loud discussion of reproductive history, bedside disclosure in shared wards, careless placement of records, or insufficient shielding during examinations and procedures. These practices compromise dignity and may produce shame, embarrassment, or distrust. In ethical terms, the failure is not merely procedural; it reflects insufficient recognition that confidentiality and bodily privacy are integral to respectful care.

These weaknesses arise from several interacting causes. Some nurses receive limited systematic training in ethics and communication law, causing them to focus more on procedural completion than on substantive understanding. Departmental protocols may also lack graded communication pathways tailored to ordinary, high-risk, and critical cases. Furthermore, quality supervision often emphasizes technical performance and documentation accuracy more than communication adequacy or privacy-sensitive conduct.

3.2 Narrow Beneficence: Insufficient Empathy and Psychological Care

A second major problem is the overly narrow interpretation of patient benefit. In many settings, communication remains concentrated on physiological indicators and routine health education, while emotional suffering and existential concerns receive inadequate attention. Nurses may explain fetal heart monitoring, contractions, blood pressure, lactation, or wound care competently, yet devote far less time to listening to fears about labor pain, fetal abnormality, maternal role competence, or postpartum exhaustion.

This imbalance reveals a deeper conceptual issue: when benefit is understood primarily in biomedical terms, psychological care becomes secondary and often optional. However, obstetric patients frequently experience fluctuating anxiety, irritability, helplessness, and role insecurity. If these states are met with formulaic reassurance rather than empathic engagement, communication loses much of its therapeutic value. Women who struggle with breastfeeding, delayed recovery, infant-related stress, or unexpected clinical developments may then experience cumulative distress, which can interfere with recovery and adaptation.

The causes are partly structural. Obstetric units are often fast-paced, labor-intensive, and vulnerable to staffing shortages, leaving nurses with little discretionary time for in-depth emotional communication. Training systems may also prioritize technical competency over empathy, counseling, or trauma-informed interaction. In addition, institutional performance metrics frequently reward safety indicators and task completion more visibly than relational excellence, which can unintentionally marginalize humanistic communication.

3.3 Inadequate Nonmaleficence: Hidden Psychological Harm Caused by Language

Communication in obstetrics can cause harm even when no physical injury occurs. Under work pressure, fatigue, or frustration, nurses may resort to directive, impatient, comparative, or dismissive expressions, particularly when a laboring woman repeatedly asks questions, cries out in pain, or shows difficulty cooperating. Statements that minimize suffering or imply weakness can intensify fear, self-blame, humiliation, and isolation. Similarly, abrupt disclosure of negative news without emotional preparation may trigger acute distress.

The ethical significance of such language lies in its invisible consequences. Psychological harm may not be measurable like bleeding or infection, yet it can alter the woman's memory of childbirth, trust in caregivers, willingness to seek future care, and emotional recovery after delivery. Global evidence on mistreatment during childbirth has highlighted verbal abuse, neglect, and disrespectful interaction as widespread problems with serious consequences for women's experiences and rights (Bohren et al., 2019; World Health Organization, 2019).

These communicative harms are often sustained by limited emotional self-regulation among staff, the absence of scenario-based low-harm communication guidelines, and managerial underestimation of the ethical seriousness of verbal and nonverbal injury. Where only technical safety is monitored, harmful language may remain normalized or invisible.

3.4 Deviations from Justice: Uneven and Insufficiently Tailored Communication

A fourth problem concerns justice. In practice, communication resources are not always distributed evenly. Women with more family support, higher education, stronger advocacy capacity, or more obviously severe clinical conditions may receive more detailed explanations and more patient responses. By contrast, those who appear medically stable, socially isolated, older, less educated, or slower to understand may receive compressed or delayed communication. Such inequality is ethically problematic because it allows subjective valuation of patients to influence communicative attention.

At the same time, justice is undermined by rigidly uniform communication. Equal treatment does not mean identical wording for all patients. Younger first-time mothers, older gravidas, women with limited literacy, and those with high-risk pregnancies differ substantially in informational need, emotional concerns, and decision-making burden. Communication that is standardized without being adaptive may formally appear fair while functionally failing large groups of patients.

The causes include implicit bias, lack of tiered communication guidance, and staffing constraints that force prioritization under time pressure. Thus, injustice in communication is not always the result of deliberate discrimination; it may also emerge from institutional

scarcity and unexamined routines. Nevertheless, its effects on patient experience, trust, and informed participation remain significant.

IV. Strategies for Optimizing Obstetric Nurse–Patient Communication Under Biomedical Ethical Principles

4.1 Upholding Respect: Strengthening Informed Communication and Building Robust Privacy Protection

An ethically credible obstetric communication system should begin with graded informed communication rather than one-time generic instruction. Patients can be stratified into ordinary, high-risk, and critical categories, with communication checklists adapted to the level of clinical complexity and urgency. For ordinary cases, explanations should cover care pathways, routine procedures, common risks, and self-management expectations. For high-risk and rapidly changing cases, communication should occur at multiple nodes—admission, change in condition, therapeutic adjustment, and preparation for delivery—so that understanding develops progressively rather than being compressed into a single episode.

Respect for autonomy also requires that options such as labor analgesia and mode of birth be presented in balanced language that clarifies benefits, limitations, indications, and uncertainties without coercion. Documentation remains important, but the ethical endpoint is genuine understanding. To support this goal, visual aids, simplified written materials, and teach-back methods can be incorporated into routine practice.

Privacy protection must be treated as a full-scene management task. Curtains, doors, and visitor control should be consistently used during examinations and procedures. Sensitive

discussions should be conducted away from public circulation areas. Access to records should be restricted, and special one-to-one communication arrangements should be made for women with particularly sensitive personal histories. Such measures transform privacy from a symbolic principle into an operational norm.

4.2 Practicing Beneficence: Constructing a Full-Cycle Empathic Communication Model

To embody beneficence in a richer sense, communication should accompany the patient across the entire obstetric trajectory. During the antenatal stage, nurses should not limit education to routine instructions; they should actively assess fear, uncertainty, and informational confusion. Individualized explanations about fetal movement monitoring, hospitalization expectations, dietary concerns, and warning signs can reduce anxiety and improve self-efficacy.

During labor, communication should become more immediate, supportive, and process-oriented. Real-time explanation of labor progress, guidance in breathing and coping, and repeated emotional affirmation can help women maintain orientation and a sense of participation. Because labor pain often narrows cognitive processing, short, calm, and encouraging communication is especially important.

In the postpartum stage, emotional care becomes central. Early feedback about maternal and neonatal status, targeted support for wound pain, lactation difficulties, sleep deprivation, and adaptation stress, and timely identification of depressive risk can promote recovery. Where needed, nursing teams should collaborate with psychology or psychiatry services. In this way, communication becomes a continuous form of care that bridges information, emotion, and recovery.

Departmental training should therefore include empathy development, reflective listening, validation skills, and basic psychological first response. The aim is not to transform every nurse into a therapist, but to ensure that all nurses can provide emotionally safe and therapeutically useful interaction within the scope of practice.

4.3 Safeguarding Nonmaleficence: Standardizing Low-Harm Language and Regulating Emotional Expression

Nonmaleficence requires explicit attention to language. Obstetric departments should establish lists of prohibited expressions, especially those involving blame, ridicule, comparison, emotional dismissal, or unnecessarily alarming wording. In parallel, scenario-based communication templates should be developed for common high-stress situations, including pain reassurance, repeated questioning, poor cooperation, family anxiety, and disclosure of adverse developments.

When communicating bad news or uncertainty, a buffered approach is preferable: stabilize the interaction first, describe the current situation clearly, explain the next steps, and preserve realistic hope without deception. This approach reduces shock and fosters partnership. Equally important is the management of nonverbal communication. Tone, facial expression, posture, and pacing can either reduce or amplify distress.

Because harmful communication often arises when staff are exhausted or emotionally overloaded, departments should also invest in staff well-being and emotional regulation training. Debriefing after critical incidents, supportive supervision, and attention to burnout are not merely workforce issues; they are part of an ethical strategy to reduce preventable communicative harm.

4.4 Realizing Justice: Combining Standardized Baseline Service with Individualized Precision Communication

A just communication system in obstetrics should combine universal baseline rights with tailored adaptation. Every patient, regardless of social or educational background, should receive the same minimum standard of explanation, answering time, privacy protection, and respectful interaction. This baseline should be codified and auditable.

At the same time, communication methods should be adjusted to individual needs. Older women or those with complex comorbidities may need slower pacing and repeated risk clarification; women with limited health literacy may need plain-language explanation and demonstration; first-time mothers may need more anticipatory guidance and emotional reassurance; and high-risk patients may need more frequent updates. Such adaptation is not preferential treatment but substantive justice, because it seeks comparable understanding across unequal starting points.

4.5 Establishing a Long-Term Departmental Governance Mechanism

Improvements in communication cannot rely solely on individual goodwill. They require institutionalization through training, quality control, feedback, and accountability. First, obstetric units should provide regular education on biomedical ethics, respectful maternity care, communication skills, trauma-informed care, and privacy-sensitive practice. Case-based learning drawn from real clinical incidents can enhance practical relevance.

Second, communication quality should be included in routine supervision and performance evaluation. Audits can assess the adequacy of informed communication,

privacy compliance, interaction style, and patient-reported respect. Indicators such as patient satisfaction, complaint patterns, and communication-related adverse events may be incorporated into departmental quality dashboards.

Third, multiple feedback channels should be established, including discharge surveys, follow-up interviews, and confidential reporting pathways. Such feedback should be analyzed not only descriptively but also diagnostically, so that recurrent weaknesses can be linked to staffing, workflow, training gaps, or leadership issues. A closed-loop model of training, implementation, monitoring, feedback, and improvement is essential if ethical communication is to become an enduring feature of obstetric practice rather than a temporary campaign.

V. Conclusion

Nurse–patient communication in obstetric care is far more than the transmission of clinical information. It is a site where biomedical ethics, humanistic nursing, psychological support, and patient safety converge. Because obstetric patients experience dynamic physical risk and emotional vulnerability across the full reproductive continuum, communication in this field carries unusually high ethical weight.

This revised discussion has argued that current communication problems in obstetric settings can be interpreted through four recurrent ethical failures: formalistic respect, narrowed beneficence, inadequate nonmaleficence, and incomplete justice. These failures are sustained not only by individual deficiencies in skill or awareness, but also by time pressure, staffing limitations, protocol design, managerial priorities, and insufficient integration of ethical reasoning into nursing governance.

Accordingly, improving obstetric communication requires more than exhorting nurses to “be kinder.” It requires a systematic ethical infrastructure: meaningful informed communication, rigorous privacy protection, empathy-based full-cycle support, standardized low-harm language, equity-sensitive communication design, and organizational mechanisms for training, quality assessment, and patient feedback. Such reforms would align obstetric nursing more closely with the principles of respectful maternity care and the broader goals of person-centered healthcare.

Ultimately, when ethical reflection is translated into everyday communicative action—during admission, explanation, accompaniment, reassurance, and discharge guidance—obstetric nursing can better protect maternal and neonatal well-being, reduce conflict, and foster dignified clinical experiences. In this sense, communication is not secondary to care; it is one of care’s most essential ethical forms.

Declarations

Conflict of Interest

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References

Bohren, M. A., Mehrtash, H., Fawole, B., Maung, T. M., Balde, M. D., Maya, E., Thwin, S. S., Aderoba, A. K., Vogel, J. P., Irinyenikan, T. A., Adeyanju, A. O., Mon, N. O., Adu-Bonsaffoh, K., Landoulsi, S., Guure, C., Adanu, R., Diallo, B. A.,

- Gülmezoglu, A. M., Soumah, A.-M., ... Tunçalp, Ö. (2019). How women are treated during facility-based childbirth in four countries: A cross-sectional study with labour observations and community-based surveys. *The Lancet*, 394(10210), 1750–1763. [https://doi.org/10.1016/S0140-6736\(19\)31992-0](https://doi.org/10.1016/S0140-6736(19)31992-0)
- Cantor, A. G., Jungbauer, R. M., Skelly, A. C., Hart, E. L., Jorda, K., Davis-O'Reilly, C., Caughey, A. B., & Tilden, E. L. (2024). Respectful maternity care: A systematic review. *Annals of Internal Medicine*, 177(1), 50–64. <https://doi.org/10.7326/M23-2676>
- Collins, B., Hall, J., Hundley, V., & Ireland, J. (2023). Effective communication: Core to promoting respectful maternity care for disabled women. *Midwifery*, 116, 103525. <https://doi.org/10.1016/j.midw.2022.103525>
- Kawish, A. B., Umer, M. F., Arshed, M., Khan, S. A., Hafeez, A., & Waqar, S. (2023). Respectful maternal care experience in low- and middle-income countries: A systematic review. *Medicina*, 59(10), 1842. <https://doi.org/10.3390/medicina59101842>
- King, A., & Hoppe, R. B. (2013). “Best practice” for patient-centered communication: A narrative review. *Journal of Graduate Medical Education*, 5(3), 385–393. <https://doi.org/10.4300/JGME-D-13-00072.1>
- Oliveira, V. C., Refshauge, K. M., Ferreira, M. L., Pinto, R. Z., Beckenkamp, P. R., Negrao Filho, R. F., & Ferreira, P. H. (2012). Communication that values patient autonomy is associated with satisfaction with care: A systematic review. *Journal of Physiotherapy*, 58(4), 215–229. [https://doi.org/10.1016/S1836-9553\(12\)70123-6](https://doi.org/10.1016/S1836-9553(12)70123-6)

- Sharkiya, S. H. (2023). Quality communication can improve patient-centred health outcomes among older patients: A rapid review. *BMC Health Services Research*, 23, 886. <https://doi.org/10.1186/s12913-023-09869-8>
- White Ribbon Alliance. (2011). *Respectful maternity care: The universal rights of childbearing women*. https://whiteribbonalliance.org/wp-content/uploads/2022/05/WRA_RMC_Charter_FINAL.pdf
- World Health Organization. (2018). *WHO recommendations: Intrapartum care for a positive childbirth experience*. <https://iris.who.int/handle/10665/260178>
- World Health Organization. (2019, October 9). *New evidence shows significant mistreatment of women during childbirth*. <https://www.who.int/news/item/09-10-2019-new-evidence-shows-significant-mistreatment-of-women-during-childbirth>