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Determinants of GenAI-Supported Experiential Learning Behavior in Undergraduate Nursing Education

Nualyai Pitsachart[1], Vitsanu Nittayathammakul[2], Tepin Craivanich[3], Pongthep Poungthong[4], Supitsara Arunrat[4], Thakorn Yuvijit[5], Sukit Chiranorawanit[6]

[1]School of Nursing, Shinawatra University, Pathum Thani, Thailand

[2]Ratchasuda Institute, Faculty of Medicine Ramathibodi Hospital, Mahidol University, Thailand

[3]National Broadcasting Services of Thailand (NBT), Bangkok, Thailand

[4]Department of Industrial Engineering, King Mongkut's Institute of Technology Ladkrabang, Bangkok, Thailand

[5]Division of Digital Technology, Faculty of Science and Technology, Rajamangala University of Technology Suvarnabhumi, Phra Nakhon Si Ayutthaya, Thailand

[6]Division of Technical Education, Faculty of Technical Education, Rajamangala University of Technology Krungthep, Bangkok, Thailand

Correspondence: Sukit Chiranorawanit, Division of Technical Education, Faculty of Technical Education, Rajamangala University of Technology Krungthep, Bangkok, Thailand.

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Abstract

Generative artificial intelligence (GenAI) is increasingly explored as a cognitive tool with the potential to reshape learning practices in higher education. In professional disciplines such as nursing education, where experiential learning is essential, GenAI has the potential to enhance knowledge creation, interaction, reflection, and active engagement. Guided by Kolb's experiential learning theory and organized by the Triple I Framework, we conceptualize individual factors with the Technology Acceptance Model (TAM) and Bandura's self-efficacy theory, interpersonal factors with social support theory and Vygotsky's social constructivism, and institutional factors with Rogers' diffusion of innovations. While adopting a digital communication lens that treats GenAI as a communicative medium, this study examined multi-level factors influencing GenAI-supported experiential learning behavior. A cross-sectional survey was conducted with 300 undergraduate nursing students using the developed questionnaire. The data were analyzed using descriptive statistics, Pearson's correlations, and multiple regression analysis. Results indicated that perceived usefulness, AI usage confidence, peer support, and institutional readiness significantly predicted this learning behavior, which together explained 67.1% of the variance. In contrast, perceived ease of use, family support, instructor support, and curriculum integration were not significant predictors. Theoretically, this study extends Kolb's experiential learning theory by positioning GenAI technologies as cognitive tools in the experiential learning cycle. Practically, the findings highlight the importance of building AI confidence, fostering peer collaboration, and strengthening institutional readiness for the effective integration of GenAI into nursing education. Together, these insights advance educational communication scholarship by illustrating how emerging AI technologies are reshaping the communicative ecology of experiential learning.

Keywords: ChatGPT, computer-mediated communication, higher education, nursing education, technology adoption

1. Introduction

Generative Artificial Intelligence (GenAI) has rapidly reshaped the landscape of higher education by enabling dialogic interaction, adaptive feedback, and rapid knowledge generation—though outputs require critical evaluation for accuracy. Unlike earlier digital learning tools, GenAI functions not only as a technological support system but also as a communicative medium that facilitates interaction, reflection, and experiential engagement in more flexible ways (Kasneci et al., 2023; Crompton & Burke, 2023). In professional programs such as nursing, where experiential learning is vital for developing clinical judgment, reflective practice, and communicative competence, the integration of GenAI into simulation-based activities has been shown to enhance student engagement and emotional connection to learning tasks (Reed & Dodson, 2024).

Although research on AI in education is expanding, empirical gaps remain in understanding which factors influence GenAI-supported experiential learning behavior. Prior studies drawing on the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) have emphasized perceived usefulness and ease of use, but such perspectives often neglect multi-level influences. In nursing education, clinical simulation-based learning has been widely studied, yet it typically depends on scheduled sessions and resource-intensive facilities. By contrast, GenAI provides 24/7 accessibility, extending beyond traditional simulations by functioning both as cognitive tools and communicative media that continuously support students' experiential learning behaviors.

This study is guided by Kolb's (1984) Experiential Learning Theory (ELT), which frames learning as a cyclical process of concrete experience, reflective observation, abstract conceptualization, and active experimentation. GenAI can enhance each of these stages by generating scenarios, prompting reflection, scaffolding conceptual understanding, and supporting experimentation. At the individual level, TAM and UTAUT explain perceptions of usefulness and ease of use, while self-confidence in AI usage has been increasingly recognized as an essential competency. At the interpersonal level, support from family, peers, and instructors shapes motivation and sustained engagement (Teo, 2019; Cant & Cooper, 2017). At the institutional level, readiness and curriculum integration are critical for meaningful technology adoption, as emphasized by recent studies in higher education policy and practice (Martín-Gutiérrez et al., 2017; Zawacki-Richter et al., 2019).

Accordingly, the aim of this study is to examine the influence of individual-, interpersonal-, and institutional-level factors on GenAI-supported experiential learning behavior among undergraduate nursing students. In doing so, the study seeks to test hypotheses, identify significant predictors, and establish a predictive model of learning behavior.

This research contributes to both theory and practice. Theoretically, it extends experiential learning and technology adoption frameworks by positioning GenAI as a mediating communicative technology in higher education. Practically, it provides actionable insights for nursing educators, curriculum designers, and institutional leaders on how to integrate GenAI responsibly into teaching and learning. More broadly, it contributes to media and communication scholarship by illustrating how emerging AI technologies are reshaping the communicative ecology of learning in the digital era.

2. Research Objectives

1. To examine the relationships between individual-level factors (i.e., perceived usefulness, perceived ease of use, and AI usage confidence), interpersonal-level factors (i.e., family support, peer support, and instructor support), and institutional-level factors (i.e., institutional readiness and curriculum integration) and GenAI-supported experiential learning behavior among undergraduate nursing students.

2. To identify significant predictors of GenAI-supported experiential learning behavior and construct a predictive model.

3. To validate hypotheses on multi-level factors influencing GenAI-supported experiential learning behavior, with implications for theory and practice in higher education communication.

3. Literature Review

The integration of generative artificial intelligence (GenAI) into nursing education—particularly in experiential learning contexts—necessitates a nuanced understanding of the key factors shaping students' engagement with such technologies. As tools like ChatGPT become increasingly embedded in academic and clinical environments (Kasneci et al., 2023), it is critical to explore what enables or impedes their effective use in learning.

To frame this analysis, the present study adopts the Triple I Framework (Chiranorawanit & Nittayathammakul, 2024), which classifies influencing factors into three interrelated levels: individual, interpersonal, and institutional. This framework offers a holistic perspective for examining the complex nature of student learning behavior in higher education. The individual level focuses on students' beliefs, perceptions, and self-efficacy; the interpersonal level emphasizes social influences such as peer, instructor, and family support; and the institutional level considers broader organizational conditions, including infrastructure, policy, and curriculum design. By applying this framework, the study seeks to generate deeper insights into GenAI-supported experiential learning behavior among undergraduate nursing students.

3.1 Individual-Level Factors

Individual-level factors refer to students' internal perceptions, attitudes, and self-beliefs regarding the use of generative AI (GenAI) for learning. These constructs are primarily grounded in the Technology Acceptance Model (TAM) by Davis (1989) and Bandura's self-efficacy theory (Bandura, 1997).

3.1.1 Perceived Usefulness

Perceived usefulness refers to the extent to which students believe that GenAI can enhance their academic performance. According to TAM, perceived usefulness is a key determinant of technology adoption. Recent studies have shown that nursing students actively use GenAI tools like ChatGPT for clinical reasoning, academic writing, and health-related tasks

(Han et al., 2025). Nursing students are more likely to adopt GenAI when they perceive it as directly improving clinical reasoning, academic tasks, and evidence-based decision-making. Accordingly, the following hypotheses are proposed:

H1 a: Perceived usefulness of GenAI has a significant positive influence on GenAI-supported experiential learning behavior.

3.1.2 Perceived Ease of Use

This refers to students' belief that GenAI is easy to use and does not require substantial effort. TAM suggests that perceived ease of use reduces cognitive barriers and facilitates adoption. Nursing students frequently describe GenAI platforms as intuitive, accessible, and capable of simplifying complex medical or clinical concepts (Han et al., 2025). Because nursing students face intensive schedules, tools that are intuitive and require minimal effort are more readily accepted. Accordingly, the following hypotheses are proposed:

H1b: Perceived ease of use of GenAI has a significant positive influence on GenAI-supported experiential learning behavior.

3.1.3 AI Usage Confidence

AI usage confidence reflects students' self-efficacy in applying GenAI for academic purposes. Bandura's theory posits that individuals who believe in their ability to perform tasks are more likely to engage and persist in those tasks. In the context of GenAI, literacy and familiarity with the technology are emerging as essential digital competencies in nursing education (El-Sayed et al., 2025; Simms, 2025; Shahzad et al., 2025; Kwon, 2024). Confidence in applying GenAI reduces anxiety and strengthens persistence, enabling students to integrate it effectively in both simulations and reflective practice. Accordingly, the following hypotheses are proposed:

H1c: AI usage confidence has a significant positive influence on GenAI-supported experiential learning behavior.

3.2 Interpersonal-Level Factors

Interpersonal-level factors emphasize the role of social interactions and support systems in promoting GenAI adoption. This dimension is informed by social support theory (Cohen & Wills, 1985) and Vygotsky's social constructivist theory (Vygotsky, 1978).

3.2.1 Family Support

Family support, including emotional encouragement and financial assistance, plays a crucial role in sustaining students' academic engagement. In relation to GenAI, some students have pointed to financial constraints in accessing premium AI tools (Han et al., 2025). In nursing education, where students often balance demanding clinical rotations, long study hours, and emotional stress, family support provides psychological stability and practical resources. Emotional encouragement helps students manage stress from clinical practice, while financial support enables access to digital tools such as GenAI, which may otherwise be unaffordable. Thus, family involvement can directly facilitate the continuity and quality of GenAI-supported learning. Accordingly, the following hypotheses are proposed:

H2a: Family support has a significant positive influence on GenAI-supported experiential learning behavior.

3.2.2 Peer Support

Vygotsky emphasized that cognitive development is driven by social interaction. Students often report learning how to use GenAI tools more effectively through peer collaboration and shared experimentation (Topaz et al., 2025). Peer collaboration promotes shared strategies and digital exploration, reinforcing students' confidence in using GenAI within group learning contexts. Accordingly, the following hypotheses are proposed:

H2b: Peer support has a significant positive influence on GenAI-supported experiential learning behavior.

3.2.3 Instructor Support

Instructor modeling, encouragement, and structured guidance are pivotal in legitimizing and reinforcing GenAI usage. Studies suggest that students gain greater confidence and trust in using GenAI when instructors clearly communicate policies and demonstrate responsible use (Topaz et al., 2025; Simms, 2025). Instructor endorsement legitimizes GenAI as a learning tool, fostering student trust and aligning use with professional and ethical standards. Accordingly, the following hypotheses are proposed:

H2c: Instructor support has a significant positive influence on GenAI-supported experiential learning behavior.

3.3 Institutional-Level Factors

Institutional-level factors relate to structural readiness and curricular integration, both of which influence the effective adoption of GenAI. These factors are informed by Rogers' diffusion of innovations theory (Rogers, 2003) and educational technology integration frameworks.

3.3.1 Institutional Readiness

Institutional readiness encompasses infrastructure, faculty preparedness, and supportive governance. A recent scoping review highlights that successful implementation depends heavily on leadership, ethical guidelines, and alignment with standards (Simms, 2025). In nursing programs, institutional readiness is especially critical because GenAI must align with clinical competencies, accreditation requirements, and patient safety standards. Reliable infrastructure and trained faculty ensure that GenAI is not just available, but meaningfully integrated into clinical simulations, case-based learning, and practicum support. Institutional readiness, therefore, signals to students that GenAI use is legitimate, sustainable, and aligned with professional nursing education standards. Accordingly, the following hypotheses are proposed:

H3a: Institutional readiness has a significant positive influence on GenAI-supported experiential learning behavior.

3.3.2 Curriculum Integration

Curriculum integration refers to the systematic inclusion of GenAI tools in course design, learning activities, and assessments. Evidence suggests that ChatGPT can support alignment between course content and national competencies, streamline instructional design, and reduce faculty workload (Sraboyants & Winer, 2024). Embedding GenAI systematically into curricula ensures consistent use, reinforcing adoption and aligning with nursing competencies and clinical standards. Accordingly, the following hypotheses are proposed:

H3b: Curriculum integration has a significant positive influence on GenAI-supported experiential learning behavior.

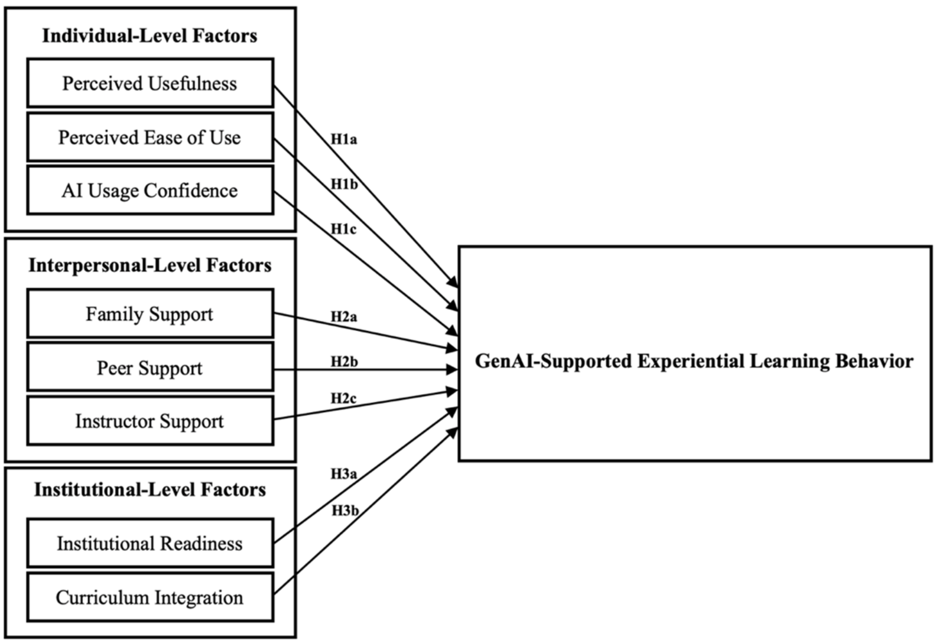

Figure 1. Conceptual Framework

4. Methodology

4.1 Research Design

This study employed a cross-sectional survey to examine factors influencing generative AI-supported experiential learning behavior among undergraduate nursing students. This design was deemed appropriate for identifying significant predictors and constructing a statistical model through multiple regression analysis. Cross-sectional surveys are commonly applied in nursing education to explore behavioral patterns and technology use because of their efficiency and cost-effectiveness (Wu et al., 2021).

4.2 Population and Sample

The study population consisted of 526 undergraduate nursing students enrolled in the Bachelor of Nursing Science (BNS) program at the Faculty of Nursing, Shinawatra University, during the second semester of the 2024 academic year. This group comprised 202 freshmen, 117 sophomores, 115 juniors, and 92 seniors.

The required sample size was estimated using two approaches. First, a power analysis conducted with G*Power 3.1 (Faul et al., 2009) indicated a minimum of 109 participants, based on a medium effect size ($f^2 = 0.15$), a significance level of $\alpha = 0.05$, a statistical power of 0.80, and eight predictor variables. Second, the rule of thumb by Tabachnick and Fidell

(2013), which recommends 10–20 participants per predictor variable, suggested a minimum of 160 participants. To ensure stronger statistical power and greater reliability of findings, the final target sample size was expanded to 300 participants.

Proportionate stratified random sampling was applied to maintain representation across academic years, resulting in 115 freshmen, 67 sophomores, 66 juniors, and 52 seniors. The inclusion criteria were: (1) enrollment in the BNS program during the study semester, (2) voluntary consent to participate, and (3) prior experience with generative AI tools. The exclusion criteria were: (1) lack of consent and (2) no prior exposure to generative AI tools.

4.3 Instrumentation

Data were collected using a structured questionnaire developed specifically for this study, entitled Factors Influencing Generative AI-Supported Experiential Learning Behavior Among Nursing Students. The instrument was constructed based on the study's proposed conceptual framework. The questionnaire comprised three sections. The first section captured demographic information, including gender, age, academic year, and prior experience with generative AI tools. The second section measured the independent variables, organized across three levels of analysis: at the individual level (Perceived Usefulness of GenAI, Perceived Ease of Use of GenAI, and AI Usage Confidence), at the interpersonal level (Family Support, Peer Support, and Instructor Support), and at the institutional level (Institutional Readiness and Curriculum Integration). The third section assessed the dependent variable, GenAI-Supported Experiential Learning Behavior, based on Kolb's (1984) experiential learning cycle, which includes four dimensions: concrete experience, reflective observation, abstract conceptualization, and active experimentation. Kolb's model has been widely applied in nursing education and validated as a robust model for evaluating experiential learning outcomes (Wu et al., 2021). All items in the instrument were rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

4.4 Validity and Reliability

Content validity was evaluated by five experts in nursing education and AI technology. Item-level content validity indices (I-CVI) and the scale-level content validity index (S-CVI/Ave) were calculated. The S-CVI/Ave values for individual constructs ranged from 0.92 to 1.00, with an overall index of 0.95, exceeding the recommended threshold of 0.90 and indicating excellent content validity (Polit & Beck, 2006).

Reliability was examined through a pilot test with 30 undergraduate nursing students. Cronbach's alpha coefficients ranged from 0.767 to 0.938, with an overall reliability coefficient of 0.932. All constructs exceeded the recommended minimum of 0.70 (Nunnally & Bernstein, 1994), demonstrating satisfactory internal consistency. These results are consistent with prior studies in nursing education, which reported Cronbach's alpha values between 0.78 and 0.94 for multi-construct instruments assessing technology adoption and learning behaviors (Hebeshy et al., 2021; Wu et al., 2021).

The detailed outcomes of the validity and reliability analyses are presented in Table 1. All constructs—at the individual, interpersonal, and institutional levels, as well as the dependent variable of GenAI-supported experiential learning behavior—achieved both strong content validity and robust reliability, confirming the adequacy of the instrument for use in the main study.

Table 1. Validity and Reliability of Questionnaire Constructs

Construct	Items	S-CVI/Ave	Cronbach's α
Individual-Level Factors			
Perceived Usefulness	5	0.92	0.833
Perceived Ease of Use	5	0.92	0.767
AI Usage Confidence	5	0.96	0.827
Interpersonal-Level Factors			
Family Support	5	0.92	0.909
Peer Support	5	0.96	0.857
Instructor Support	5	0.96	0.938
Institutional-Level Factors			
Institutional Readiness	5	0.96	0.872
Curriculum Integration	5	0.92	0.866
Dependent Variable			
GenAI-Supported Experiential Learning Behavior	5	1.00	0.896
Overview	45	0.95	0.932

4.5 Data Collection

The online questionnaire was administered in January 2025 via institutional email and social media platforms. Two reminder notices were distributed at one-week intervals to improve the response rate. Prior to participation, students were informed about the study objectives, procedures, and their rights, and electronic informed consent was obtained before accessing the survey. Anonymity and confidentiality were assured, with all data stored on password-protected devices accessible only to the research team. To ensure data quality, responses were continuously monitored and screened. The number of valid responses was tracked against the planned sample size for each academic year. Once the required quota for a given year level was achieved, data collection for that group was closed. Online surveys have become increasingly common in nursing education research due to their accessibility, ease of administration, and effectiveness in engaging digital-native students (Zhang et al., 2019).

4.6 Data Analysis

Data analysis was conducted using Jamovi (Version 2.3). Descriptive statistics, including frequencies, percentages, means, and standard deviations, were employed to summarize demographic characteristics and construct scores. Pearson's correlation coefficients were then calculated to examine the bivariate relationships among the independent and dependent variables. Before performing multiple regression analysis, assumption testing was carried out to ensure the validity of the model. The assumptions of linearity, normality, homoscedasticity, and multicollinearity were assessed through residual plots, skewness and kurtosis statistics, normal probability (P–P) plots, the Breusch–Pagan test, and multicollinearity diagnostics (VIF and tolerance). After confirming the assumptions, multiple regression analysis was conducted using the Enter method with a significance level of 0.05. The analysis reported regression coefficients (β), significance levels (p), and model fit indices (R^2 and adjusted R^2). Jamovi was selected as it is a widely adopted open-source statistical software in the social sciences and health education, offering robust functionality with transparency and accessibility (The Jamovi Project, 2023).

4.7 Ethical Considerations

This study complied with the ethical guidelines issued by the Office of the Permanent Secretary, Ministry of Higher Education, Science, Research, and Innovation, Thailand (MESI Circular No. 7017, April 11, 2023) and the Office of the National Higher Education, Science, Research, and Innovation Policy Council (MESI Circular No. 6309.FB 6.1/1/2564, March 22, 2021). According to these guidelines, research involving teaching processes or the assessment of learning and teaching in the behavioral, social, and human sciences is exempt from review by Human Research Ethics Committee.

5. Results

5.1 Descriptive Statistics

Table 2 presents the demographic characteristics of the participants (N = 300). The majority of respondents were female (90.3%), followed by LGBTQ+ students (6.3%) and male students (3.3%). In terms of academic year, the largest group were first-year students (38.3%), followed by second-year (22.3%), third-year (22.0%), and fourth-year students (17.3%). With respect to GenAI experience, most students reported occasional use (68.0%), defined as using Generative AI approximately 1–2 times per week or only when needed. Frequent use was reported by 22.3%, indicating use on a daily or regular basis, while 9.7% of participants reported regular use, defined as multiple times per day or continuous use in daily tasks. In terms of platform usage, ChatGPT was the most frequently used platform (89.7%). Bard/Gemini was used by 24.3% of participants, Microsoft Copilot by 4.3%, Claude by 2.7%, and other platforms by 10.0%.

Table 2. Demographic Characteristics of Participants (N = 300)

Demographic Characteristics	Category	Frequency	Percentage (%)
Gender	Male	10	3.3
	Female	271	90.3
	LGBTQ+	19	6.3
Academic Year	1st year	115	38.3
	2nd year	67	22.3
	3rd year	66	22.0
	4th year	52	17.3
GenAI Experience	Occasionally used (e.g., used approximately 1–2 times per week or only when needed)	204	68.0
	Frequently used (e.g., used approximately once a day or on a regular basis in daily activities)	67	22.3
	Regularly used (e.g., used multiple times per day or continuously in daily tasks)	29	9.7
Usage of GenAI Platforms (multiple responses allowed)	ChatGPT	269	89.7
	Bard/ Gemini	73	24.3
	Microsoft Copilot	13	4.3
	Claude	8	2.7
	Other	30	10

Table 3 summarizes descriptive statistics for the study constructs. Among the independent variables, perceived usefulness obtained the highest mean score (M = 4.00, SD = 0.71), followed closely by perceived ease of use (M = 3.94, SD = 0.65). Institutional readiness was rated lowest (M = 3.66, SD = 0.81). The dependent variable, GenAI-supported experiential learning behavior, had a moderately high mean (M = 3.80, SD = 0.70).

5.2 Correlation Analysis

Pearson's product–moment correlations were computed to examine the relationships among the study variables (Table 4). All independent variables were positively and significantly correlated with GenAI-supported experiential learning behavior (r = .61–.74, $p < .001$). The strongest correlations with the dependent variable were found for AI usage confidence (r = .74) and peer support (r = .69). Additionally, several predictors were highly intercorrelated. In particular, institutional readiness and curriculum integration showed a very strong positive correlation (r = .89), indicating potential redundancy and warranting caution when interpreting regression results.

Table 3. Descriptive Statistics of Study Variables

Construct	Items	M	SD
Perceived Usefulness	5	4.00	0.71
Perceived Ease of Use	5	3.94	0.65
AI Usage Confidence	5	3.85	0.72
Family Support	5	3.74	0.71
Peer Support	5	3.92	0.68
Instructor Support	5	3.82	0.74
Institutional Readiness	5	3.66	0.81
Curriculum Integration	5	3.76	0.75
GenAI-supported experiential learning behavior	5	3.80	0.70

Table 4. Correlation Matrix of Study Variables (N = 300)

Variable	1	2	3	4	5	6	7	8	9
1. Perceived Usefulness (PU)	1.00	.81**	.78**	.64**	.66**	.55**	.33**	.43**	.65**
2. Perceived Ease of Use (PEOU)		1.00	.79**	.57**	.63**	.61**	.37**	.47**	.61**
3. AI Usage Confidence (AUC)			1.00	.74**	.77**	.70**	.52**	.59**	.74**
4. Family Support (FS)				1.00	.81**	.77**	.52**	.58**	.68**
5. Peer Support (PS)					1.00	.79**	.47**	.57**	.69**
6. Instructor Support (IS)						1.00	.60**	.67**	.66**
7. Institutional Readiness (IR)							1.00	.89**	.61**
8. Curriculum Integration (CI)								1.00	.66**
9. GenAI-supported experiential learning behavior									1.00

Note. ***p < .001 (two-tailed). All correlations were statistically significant at the .001 level.*

5.3 Assessment of Regression Assumptions

Prior to conducting multiple regression analysis, the assumptions of linearity, normality, homoscedasticity, and multicollinearity were assessed.

5.3.1 Linearity

The assumption of linearity was assessed by examining the scatterplot of standardized residuals against predicted values. As shown in Figure 2, the points were randomly dispersed around the zero line without evidence of curvilinear patterns, indicating that the linearity assumption was satisfied.

5.3.2 Normality

Normality of residuals was assessed using a Normal P–P plot and skewness–kurtosis statistics. The Normal P–P plot (Figure 3) revealed that the observed values closely followed the diagonal line, which supported the assumption of normality. Additionally, the skewness (−0.77) and kurtosis (2.19) of the regression residuals were within acceptable ranges (−2 to +2 for skewness; −7 to +7 for kurtosis). Although the kurtosis value suggested slight leptokurtosis, it was within the acceptable range and consistent with Kline's (2016) thresholds, confirming normality of residuals.

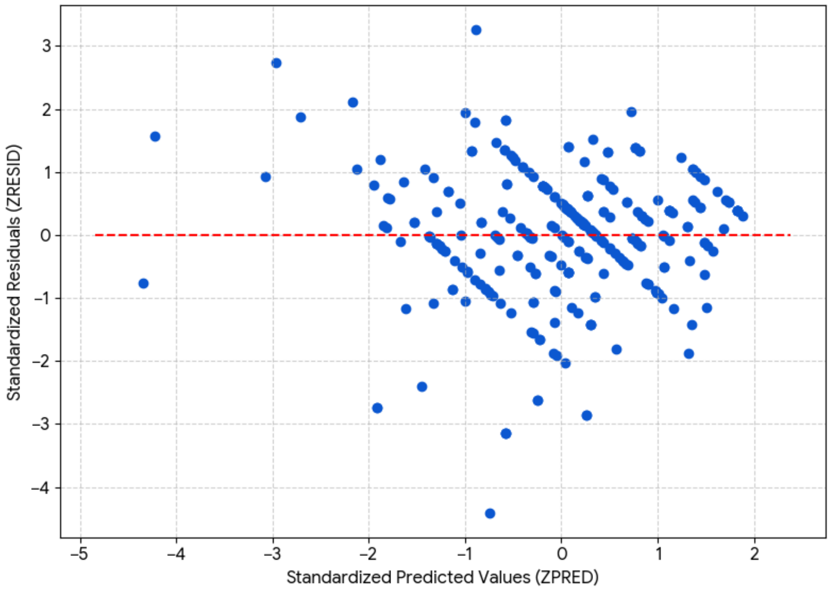

Figure 2. Scatterplot of Standardized Residuals Versus Predicted Values

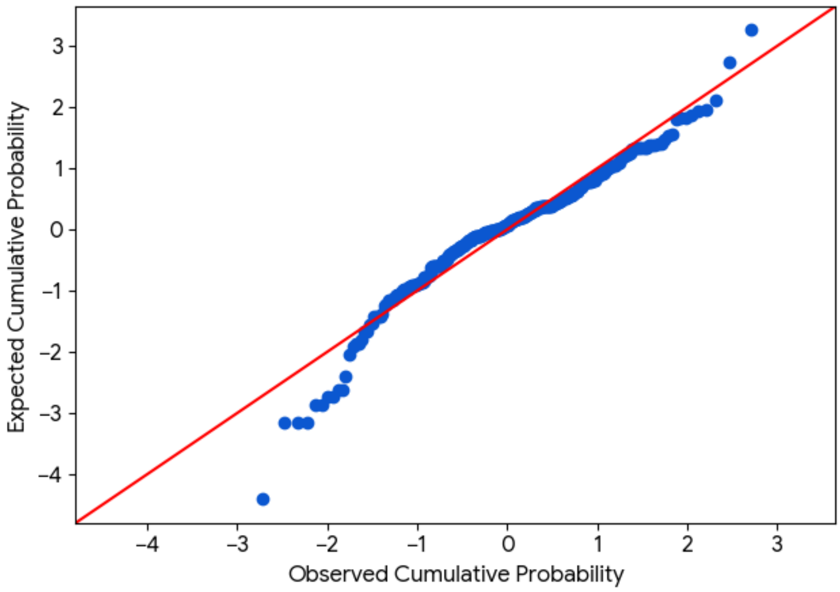

Figure 3. Normal P–P Plot of Regression Standardized Residuals

Table 5. Skewness and Kurtosis of Regression Residuals

Statistic	Value	Acceptable Range	Interpretation
Skewness	−0.77	Between −2 and +2	Within acceptable range → residuals approximately symmetric
Kurtosis	2.19	Between −7 and +7	Within acceptable range → residuals approximately normal

5.3.3 Homoscedasticity

The assumption of homoscedasticity was tested using the residuals-versus-predicted values plot. As presented in Figure 4, residuals were distributed evenly across predicted scores without funneling or clustering patterns, suggesting that the variance of residuals was constant and the assumption of homoscedasticity was met.

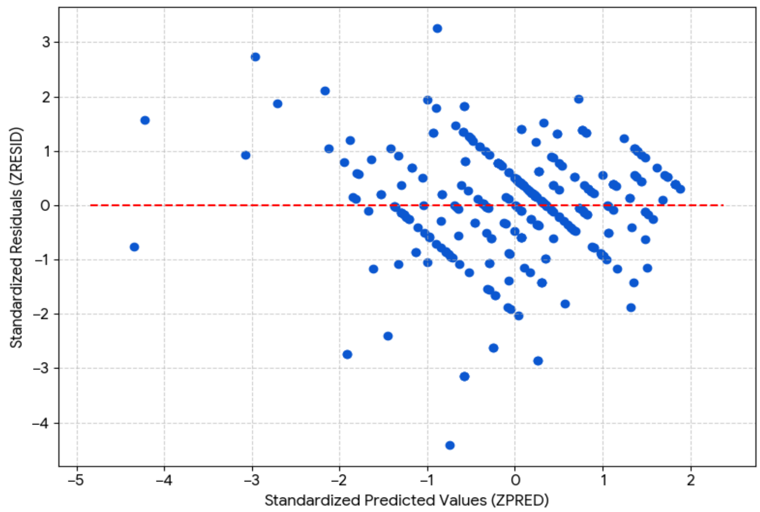

Figure 4. Scatterplot of Standardized Residuals Versus Predicted Values (Homoscedasticity Check)

5.3.4 Multicollinearity

Multicollinearity among independent variables was examined using tolerance and variance inflation factor (VIF) values. As shown in Table 6, tolerance values ranged from .17 to .27 (all > .10) and VIF values ranged from 3.70 to 5.87. While Institutional Readiness (VIF = 5.06) and Curriculum Integration (VIF = 5.87) exhibited relatively higher values due to their strong intercorrelation ($r = .89$), these values remained below the conventional cutoff of 10.

Table 6. Multicollinearity Diagnostics (Tolerance and VIF)

Predictive Variable	Tolerance	VIF
Perceived Usefulness (PU)	0.27	3.70
Perceived Ease of Use (PEOU)	0.26	3.82
AI Usage Confidence (AUC)	0.21	4.77
Family Support (FS)	0.26	3.89
Peer Support (PS)	0.23	4.27
Instructor Support (IS)	0.26	3.85
Institutional Readiness (IR)	0.20	5.06
Curriculum Integration (CI)	0.17	5.87

5.4 Multiple Regression Analysis

A standard multiple regression analysis was conducted to examine the extent to which the eight predictors explained variance in GenAI-supported experiential learning behavior. The overall regression model was statistically significant, $F(8, 291) = 74.24$, $p < .001$, accounting for 67.1% of the variance in the dependent variable ($R^2 = .671$, Adjusted $R^2 = .662$). This indicates that the set of predictors collectively explained a substantial proportion of the variance in students' experiential learning behavior with GenAI.

As presented in Table 7, perceived usefulness ($\beta = .231$, $p < .001$), AI usage confidence ($\beta = .272$, $p < .001$), peer support ($\beta = .158$, $p = .024$), and institutional readiness ($\beta = .220$, $p = .004$) emerged as significant positive predictors of GenAI-supported experiential learning behavior. In contrast, perceived ease of use ($\beta = -.063$, $p = .336$), family support ($\beta = .065$, $p = .325$), instructor support ($\beta = -.003$, $p = .970$), and curriculum integration ($\beta = .105$, $p = .199$) were not statistically significant.

Table 7. Multiple Regression Analysis Predicting GenAI-Supported Experiential Learning Behavior (N = 300)

Predictive Variable	B	SE	β	t	p
Constant	0.185	0.166	-	1.12	0.265
Perceived Usefulness (X_1)	0.229	0.064	0.231	3.58	< .001
Perceived Ease of Use (X_2)	-0.068	0.071	-0.063	-0.96	0.336
AI Usage Confidence (X_3)	0.265	0.072	0.272	3.71	< .001
Family Support (X_4)	0.064	0.065	0.065	0.99	0.325
Peer Support (X_5)	0.164	0.072	0.158	2.28	0.024
Instructor Support (X_6)	-0.002	0.063	-0.003	-0.04	0.97
Institutional Readiness (X_7)	0.192	0.066	0.22	2.91	0.004
Curriculum Integration (X_8)	0.098	0.076	0.105	1.29	0.199

Note. B = unstandardized regression coefficient; SE = standard error; β = standardized regression coefficient. $R^2 = .671$, Adjusted $R^2 = .662$, $F(8, 291) = 74.24$, $p < .001$.

5.5 Predictive Equation

Based on the unstandardized regression coefficients (B) from the multiple regression analysis, the predictive equation for GenAI-supported experiential learning behavior (Y) can be expressed as follows: $Y = 0.185 + 0.229X_1 - 0.068X_2 + 0.265X_3 + 0.064X_4 + 0.164X_5 - 0.002X_6 + 0.192X_7 + 0.098X_8$

where Y represents GenAI-supported experiential learning behavior, X_1 = Perceived Usefulness (PU), X_2 = Perceived Ease of Use (PEOU), X_3 = AI Usage Confidence (AUC), X_4 = Family Support (FS), X_5 = Peer Support (PS), X_6 = Instructor Support (IS), X_7 = Institutional Readiness (IR), and X_8 = Curriculum Integration (CI).

The model explained 67.1% of the variance in the dependent variable, $R^2 = .671$, adjusted $R^2 = .662$, $F(8, 291) = 74.24$, $p < .001$. Among the predictors, PU, AUC, PS, and IR demonstrated statistically significant positive effects, while PEOU, FS, IS, and CI were not significant predictors.

5.6 Hypothesis Testing

Table 8 summarizes the results of hypothesis testing. Four hypotheses (H1a, H1c, H2b, and H3a) were supported, indicating that perceived usefulness, AI usage confidence, peer support, and institutional readiness, significantly and positively influenced GenAI-supported experiential learning behavior. Conversely, four hypotheses (H1b, H2a, H2c, H3b) were not supported, as perceived ease of use, family support, instructor support, and curriculum integration did not demonstrate significant predictive effects when controlling for other factors.

Table 8. Summary of Hypothesis Testing Results (N = 300)

Hypothesis	**Statement**	**Result**
Individual-Level Factors		
H1a	Perceived Usefulness (PU) has a significant positive influence on GenAI-supported experiential learning behavior.	Supported ($\beta = .231$, $p < .001$)
H1b	Perceived Ease of Use (PEOU) has a significant positive influence on GenAI-supported experiential learning behavior.	Not Supported ($\beta = -.063$, $p = .336$)
H1c	AI Usage Confidence (AUC) has a significant positive influence on GenAI-supported experiential learning behavior.	Supported ($\beta = .272$, $p < .001$)
Interpersonal-Level Factors		
H2a	Family Support (FS) has a significant positive influence on GenAI-supported experiential learning behavior.	Not Supported ($\beta = .065$, $p = .325$)
H2b	Peer Support (PS) has a significant positive influence on GenAI-supported experiential learning behavior.	Supported ($\beta = .158$, $p = .024$)
H2c	Instructor Support (IS) has a significant positive influence on GenAI-supported experiential learning behavior.	Not Supported ($\beta = -.003$, $p = .970$)
Institutional-Level Factors		
H3a	Institutional Readiness (IR) has a significant positive influence on GenAI-supported experiential learning behavior.	Supported ($\beta = .220$, $p = .004$)
H3b	Curriculum Integration (CI) has a significant positive influence on GenAI-supported experiential learning behavior.	Not Supported ($\beta = .105$, $p = .199$)

6. Discussion

The findings of this study shed light on the multi-level determinants of GenAI-supported experiential learning behavior among undergraduate nursing students. At the individual level, perceived usefulness emerged as a significant predictor, consistent with the Technology Acceptance Model (Davis, 1989), which has repeatedly emphasized usefulness as the strongest factor driving technology adoption. Nursing students were more likely to engage with GenAI when they perceived it as enhancing their clinical reasoning, reflective practice, and academic tasks. By contrast, perceived ease of use did not significantly predict behavior. This suggests that GenAI platforms, particularly ChatGPT, are already widely regarded as intuitive and accessible, resulting in minimal variance in students' perceptions of usability. In such contexts, ease of use becomes a baseline expectation rather than a differentiating factor in adoption. AI usage confidence, grounded in Bandura's (1997) self-efficacy theory, was also a strong predictor of learning behavior. Students who felt capable of using GenAI tools were more willing to integrate them into experiential learning processes, highlighting the importance of digital self-efficacy as a determinant of educational outcomes in technology-rich environments.

At the interpersonal level, peer support significantly influenced students' experiential learning behavior with GenAI. This finding resonates with Vygotsky's (1978) social constructivist perspective, which underscores the role of social interaction in knowledge construction. Peers provided models for use, shared strategies, and reinforced confidence, thereby facilitating diffusion of innovation. In contrast, neither family support nor instructor support significantly shaped students' behavior. Family support may have been too indirect or general to affect technology-related practices, while instructor support may not yet have reached sufficient consistency or visibility to influence adoption. Faculty members themselves are in the early stages of GenAI adoption, and without clear institutional policies or pedagogical frameworks, their support may not translate into students' experiential practices.

At the institutional level, readiness played a crucial role, confirming that infrastructure, governance, and organizational signaling strongly influence student behavior. When institutions visibly endorse and legitimize GenAI use through ethical guidelines, training, and resource provision, students are more likely to adopt it. This finding reflects Rogers' (2003) diffusion of innovations theory, in which organizational readiness functions as a legitimizing force for new practices. Interestingly, curriculum integration did not significantly predict behavior. This result may be explained by the fact that GenAI integration in curricula remains largely symbolic, with references in course objectives but limited concrete use in tasks or assessments. Without embedded, hands-on applications, curriculum integration may fail to motivate adoption, leaving students to rely instead on institutional cues and peer networks.

The regression model demonstrated strong explanatory power for behavioral research contexts (R^2 = .671; Adjusted R^2 = .662; $F(8, 291) = 74.24$, $p < .001$), indicating that roughly two-thirds of the variance in GenAI-supported experiential learning behavior was accounted for by the proposed predictors. Assumption checks supported the model's validity (linearity, normality, and homoscedasticity), and diagnostics suggested acceptable—though non-trivial—multicollinearity (VIFs ≈ 3.7–5.9). The very high correlation between institutional readiness and curriculum integration (r = .89) likely attenuated the latter's coefficient in the full model, helping explain why curriculum integration was non-significant despite meaningful bivariate associations. Interpreting the standardized effects, AI usage confidence (β = .272) and perceived usefulness (β = .231) exerted the largest unique contributions, followed by institutional readiness (β = .220) and peer support (β = .158), aligning with the theorized salience of self-efficacy, instrumental value, and organizational signaling. At the same time, approximately one-third of the variance remains unexplained, suggesting the potential roles of unmeasured drivers (e.g., clinical placement culture, assessment design, or AI policy enforcement at course level).

Thus, these findings extend Kolb's (1984) experiential learning theory by positioning GenAI as both a cognitive tool and a communicative medium within the learning cycle. GenAI supported concrete experience through scenario generation, reflective observation through prompting, abstract conceptualization through scaffolding, and active experimentation through iterative feedback. The results also refine adoption frameworks by illustrating that self-efficacy and peer influence exert stronger effects on learning behavior than ease of use or formal curriculum directives. In doing so, this study highlights the need to reconsider traditional technology acceptance models when applied to rapidly diffused tools such as generative AI.

Given the intercorrelations among institutional variables, future work could use hierarchical regression aligned with the Triple I framework (entering individual, then interpersonal, then institutional blocks) to test incremental variance explained, or apply penalized regression (ridge/lasso) or structural equation modeling to parse shared versus unique variance and evaluate measurement error explicitly. Cross-validated R^2 (e.g., k-fold) would further guard against sample-specific inflation, and multi-group analyses could examine stability across academic years or experience strata.

7. Practical Implications

The findings of this study offer several implications for nursing education and higher education communication more broadly. First, the strong role of AI usage confidence underscores the importance of embedding GenAI literacy into curricula and training programs. Rather than assuming that digital-native students inherently possess the necessary skills, institutions should provide structured workshops and modules to enhance students' ability to use GenAI responsibly and effectively. Building confidence will not only reduce anxiety but also encourage students to experiment with AI tools as part of experiential learning cycles.

Second, the influence of peer support suggests that collaborative learning environments should be deliberately cultivated. Nursing educators could integrate group projects, peer mentoring, or communities of practice in which students jointly explore and apply GenAI. Such activities not only reinforce the social dimension of learning but also help establish norms of responsible use. These peer-driven practices align with the communicative ecology of higher education, where meaning-making increasingly occurs within digitally mediated peer networks.

Third, the significant effect of institutional readiness points to the need for universities and nursing faculties to provide visible, concrete signals of support for GenAI adoption. This includes establishing ethical guidelines, ensuring robust digital infrastructure, and offering faculty development programs that equip instructors to model responsible use. Even though instructor support was not a significant predictor in this study, its limited role may reflect a transitional stage in which institutions have not yet systematically prepared faculty members for AI integration. As readiness becomes institutionalized, faculty support is likely to exert stronger influence.

Finally, the non-significant role of curriculum integration highlights the need for more than symbolic inclusion of AI in course materials. Educators should move beyond mentioning GenAI in learning outcomes to embedding it into practical assignments, clinical simulations, and assessments that mirror professional nursing contexts. Without such embedded practices, curriculum integration risks remaining superficial, offering little influence on students' experiential behavior. Collectively, these implications emphasize that successful adoption of GenAI in nursing education requires a multi-level strategy that combines student training, peer-based collaboration, institutional investment, and curricular innovation.

8. Conclusion

This study contributes to the growing body of scholarship on generative artificial intelligence in higher education by examining the multi-level determinants of GenAI-supported experiential learning behavior among undergraduate nursing students. Using Kolb's experiential learning theory as a pedagogical lens and the Triple I Framework as an organizational structure, the study identified perceived usefulness, AI usage confidence, peer support, and institutional readiness as significant predictors, while perceived ease of use, family support, instructor support, and curriculum integration were not significant. Together, these findings underscore that GenAI adoption is shaped less by usability or formal curricular directives and more by students' confidence, peer dynamics, and organizational readiness.

Theoretically, the study extends experiential learning theory by demonstrating how GenAI functions as both a cognitive tool and a communicative medium that enriches each phase of the learning cycle. It also refines technology adoption frameworks by showing that ease of use is insufficient as a determinant when technologies are already widely regarded as intuitive. Practically, the results highlight the need for targeted strategies in nursing education that build AI self-efficacy, leverage peer collaboration, and institutionalize readiness measures.

As higher education continues to adapt to emerging technologies, the integration of GenAI offers both opportunities and challenges for communicative and experiential learning. By situating GenAI within the communicative ecology of nursing education, this study advances media and communication research while offering actionable insights for educators and policymakers. Overall, the findings suggest that the transformative potential of GenAI in nursing education will depend on how effectively institutions foster confidence, collaboration, and readiness for a future in which experiential learning is deeply mediated by artificial intelligence.

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Author contributions

Nualyai Pitsachart was responsible for conceptualization, investigation, and drafting the manuscript. Vitsanu Nittayathammakul was responsible for methodology, data curation, validation, and revising the manuscript. Tepin Craivanich was responsible for investigation and validation. Pongthep Poungthong was responsible for investigation, data curation, and project administration. Supitsara Arunrat was responsible for investigation. Thakorn Yuvijit was responsible for visualization. Sukit Chiranorawanit was responsible for software, resources, and funding acquisition. All authors read and approved the final manuscript.

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