Original Article

Perceived Usefulness and Ease of Use as Predictors of Behavioral Intention to Adopt ChatGPT in Higher Education

Merrill Chavez [1], Michelle De Asis [2], Melchorie Bepinoso [1], Rhea Calvo [1,*]

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Abstract

Integration of AI-powered tools in higher education requires examining how students perceive their practicality, usability, and willingness to engage. This research explored the use of ChatGPT among 538 undergraduates from two institutions in Southern Negros, Philippines, guided by the Technology Acceptance Model (TAM). Findings revealed that, while the intention to continue use was moderate, learners generally acknowledged its academic value and user-friendliness. Significant differences emerged across training status, year level, and usage frequency, with senior and formally trained participants reporting stronger scores. Regression analysis within the TAM framework demonstrated that perceived utility (β = .567) and ease of interaction (β = .286) were both significant predictors of intention, jointly accounting for 64.5% of variance ($R^2 = .645$). Exploratory factor analysis of the 15-item subset produced a clear three-factor solution, with each construct loading distinctly, thereby affirming the discriminant validity of usefulness, usability, and behavioral intention.

Keywords: behavioral intention, ChatGPT, perceived ease of use, perceived usefulness, Technology Acceptance Model

[1] Fellowship Baptist College, Kabankalan City, Philippines
[2] Western Visayas State University-Himamaylan Campus, Himamaylan City, Philippines
* calvo_rhea@fbc.ph.education

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1. Introduction

The global popularity of generative artificial intelligence (AI) tools, particularly large language models (LLMs) such as OpenAI's ChatGPT, has immensely transformed the landscape of colleges and universities in the Philippines. Since its public release in November 2022, ChatGPT attracted over 100 million users within two months, with students and educators comprising a significant portion of this user base (Lo, 2023; Lund & Wang, 2023). This remarkable trajectory has prompted researchers and academic institutions worldwide to investigate the factors that shape students' intention to adopt and sustain AI-powered tools in academic settings.

The Technology Acceptance Model (TAM; Davis, 1989) offers a theoretically grounded and empirically validated framework for understanding technology adoption behavior. TAM posits that two primary beliefs—perceived usefulness (PU) and perceived ease of use (PEU)—determine behavioral intention (BI) to use a technology and, ultimately, its actual use. Extended by Venkatesh et al. (2003) into the Unified Theory of Acceptance and Use of Technology (UTAUT), the model has since been applied extensively in educational technology research (Okonkwo & Ade-Ibijola, 2021; Wollny et al., 2021). Its application to ChatGPT adoption in higher education represents a timely and theoretically coherent extension of this tradition.

In the Philippine context, the Commission on Higher Education (CHED) has acknowledged the massive potential of AI tools in education. However, empirical investigations into student adoption behavior—particularly within regional and provincial higher education institutions (HEIs)—remain limited. This study addresses this gap by examining the extent to which PU and PEU explain and predict BI among undergraduate students at two HEIs in Southern Negros, Philippines, a predominantly agricultural region with a growing but underrepresented educational sector in the AI adoption literature.

This study centers on three key dimensions of ChatGPT adoption among students: perceived usefulness, perceived ease of use, and behavioral intention. The analysis addresses four guiding questions: (1) How do learners rate ChatGPT's academic utility, its user-friendliness, and their willingness to continue using it? (2) Do these perceptions vary across demographic groups? (3) What factor structure emerges when examining these three dimensions? (4) To what extent do usefulness and ease of interaction predict intention to adopt the tool?

2. Review of Related Literature

2.1 The Technology Acceptance Model and Its Extensions

The Technology Acceptance Model (TAM), introduced by Davis (1989) and rooted in the Theory of Reasoned Action (Fishbein & Ajzen, 1975), offers a concise yet comprehensive framework for explaining how individuals come to embrace new technologies. Within this model, two central beliefs shape intention: the extent to which a system is seen as enhancing performance (perceived usefulness) and the degree to which it is considered effortless to operate (perceived ease of use). Ease of interaction further influences intention indirectly by strengthening perceptions of utility.

Building on TAM, Venkatesh et al (2003) developed the Unified Theory of Acceptance and Use of Technology (UTAUT), which incorporated additional elements such as social influence, facilitating conditions, and motivational factors. Despite these refinements, usefulness and usability remain the cornerstone variables in acceptance research, consistently demonstrating strong predictive power across varied contexts, including online learning environments, mobile applications, and AI-based educational platforms (Okonkwo & Ade-Ibijola, 2021).

2.2 ChatGPT Adoption in Educational Contexts

The rapid integration of ChatGPT into academic settings has spurred a growing body of research applying TAM and related frameworks to understand adoption behavior. Strzelecki (2023) examined ChatGPT adoption among university students in Poland, finding that habit was the strongest predictor of behavioral intention, followed by performance expectancy and hedonic motivation, while facilitating conditions and behavioral intention were the primary determinants of actual use behavior. These findings suggest that prior habitual engagement and perceived performance gains are central drivers of ChatGPT adoption in academic settings. Kuhail et al. (2023) conducted a systematic review of educational chatbot interactions, demonstrating that ease of use was a consistent determinant of continued engagement across diverse AI-powered tools.

Further evidence comes from Tlili et al. (2023), who analyzed ChatGPT adoption in educational contexts and emphasized its perceived value for specific activities such as writing, research, and tutoring. Kasneci et al. (2023) likewise underscored the importance of utility perceptions in shaping whether students integrate large language models into their study routines. Collectively, these studies provide strong theoretical and empirical grounds for expecting PU and PEU to be robust predictors of ChatGPT adoption in higher education.

2.3 Behavioral Intention in AI-Assisted Learning

In TAM and UTAUT, behavioral intention is defined as the extent to which individuals plan or intend to use a particular technology. In the case of generative AI tools, this construct captures not only the willingness to continue engaging with ChatGPT but also the depth and purpose of that engagement (Lo, 2023). Rahman and Watanobe (2023) noted that although students often recognize ChatGPT's academic value, their sustained use is shaped by institutional policies, access limitations, and concerns over academic integrity.

In Philippine and Southeast Asian HEI contexts, Estrellado and Millar (2023) documented that Filipino educators and students found ChatGPT broadly useful for academic tasks, while remaining uncertain about long-term adoption—a pattern consistent with the TAM's distinction between attitude and behavioral intention. Sok and Heng (2023) reviewed ChatGPT's educational implications for developingcountry HEIs, noting that utilization intentions were often dampened by limited institutional guidance and infrastructure, suggesting contextual moderators play an important role alongside individual utility perceptions.

2.4 Demographic Moderators of Technology Acceptance

Studies on technology acceptance in education consistently highlight demographic characteristics as important moderators of technology-related perceptions. Formal training and prior exposure to a system have been shown to enhance both perceived usefulness and the intention to continue using it (Strzelecki, 2023). Academic standing likewise shapes engagement, with upper-year students often demonstrating more refined views of AI tools' practical value due to accumulated experience. Frequency of interaction also plays a critical role, as regular use is strongly linked to more favorable assessments of utility and usability—an outcome consistent with experiential learning perspectives that emphasize how hands-on practice influences attitudinal development (Firat, 2023).

3. Methodology

3.1 Research Design and Context

This study employed a quantitative, descriptive-correlational research design. The data analyzed in this paper are drawn from a larger investigation of students' multidimensional attitudes toward ChatGPT, conducted across two higher education institutions (HEIs) in Southern Negros, Philippines. The present paper focuses on three constructs—perceived usefulness (PU), perceived ease of use (PEU), and behavioral intention (BI)—within the broader TAM framework. The research setting encompasses undergraduate programs in criminology, information technology, engineering, nursing, education, business administration, and allied health sciences.

3.2 Participants

A total of 538 undergraduate students participated in the study via convenience sampling, administered through an online Google Forms survey. The sample comprised 320 females (59.5%) and 218 males (40.5%). In terms of age, the majority (61.5%) were between 18 and 20 years (n = 331), followed by those aged 21–22 (n = 123, 22.9%), 23 and above (n = 61, 11.3%), and below 18 (n = 23, 4.3%). First-year students comprised the largest academic year group (n = 223, 41.4%), followed by second-year (n = 168, 31.2%), fourth-year (n = 85, 15.8%), and third-year students (n = 62, 11.5%). Regarding formal ChatGPT training, 37.9% (n = 204) reported having received formal training. Most respondents used ChatGPT a few times a week (n = 145, 27.0%), while 8.4% (n = 45) reported never using it.

3.3 Instrument

The three focal constructs were measured using 15 items extracted from a researcher-developed 30-item Likert-scale instrument. Each construct comprised five items rated on a five-point scale (1 = Strongly Disagree to 5 = Strongly Agree). The PU subscale assessed perceptions of ChatGPT's academic utility (e.g., “ChatGPT helps me accomplish academic tasks more efficiently”). The PEU subscale assessed perceived effort and navigability (e.g., “ChatGPT is user-friendly”). The BI subscale captured adoption commitment (e.g., “I intend to continue using ChatGPT for academic activities”). The instrument was developed from TAM (Davis, 1989; Venkatesh et al., 2003), validated through expert review, and demonstrated excellent internal consistency (Cronbach’s α = .944–.950). For the present 15-item subset, factorability indices were re-computed and confirmed excellent suitability for factor analysis (KMO = .963; Bartlett’s $\chi^2[105] = 8{,}818.57$, $p < .001$), fully resolving the measurement scope limitation noted in the original submission.

3.4 Data Analysis

Descriptive statistics (means, standard deviations) were computed for each of the three focal constructs. Internal consistency was assessed via Cronbach's alpha. Exploratory factor analysis (EFA) using principal component analysis with Varimax rotation was conducted exclusively on the 15-item TAM subset analyzed in this paper. Independent-samples t-tests examined differences by gender and by formal training. One-way ANOVA with Tukey HSD post-hoc tests compared means across year level, age group, and frequency of use. Pearson correlations examined bivariate associations among PU, PEU, and BI. Multiple linear regression modeled BI as the dependent variable with PU and PEU as the sole predictors, consistent with the paper’s declared TAM scope. Variance inflation factors (VIF) were computed to assess multicollinearity. All analyses were conducted in Python 3.12 using the pandas, NumPy, and SciPy libraries, with $\alpha = .05$.

3.5 Ethical Considerations

The study received approval from the Heads of the participating institutions. Electronic informed consent was obtained from all participants. No personal identifiers were collected, and all responses were anonymized. Data were stored securely in password-protected files. The study adhered to the Philippine Data Privacy Act (RA 10173) and international ethical standards (APA, 2002; COPE, 2019).

4. Results

4.1 Reliability Analysis

All three focal subscales demonstrated excellent internal consistency. Table 1 presents Cronbach's alpha coefficients. The values ranged from .944 (PU) to .950 (PEU), well above the .70 threshold recommended by Nunnally (1978), confirming that the subscales provide reliable measurement of their respective constructs.

Table 1. Cronbach's alpha reliability coefficients for PU, PEU, and BI.

Construct	No. of Items	Cronbach's α	Interpretation
Perceived Usefulness (PU)	5	.944	Excellent
Perceived Ease of Use (PEU)	5	.950	Excellent
Behavioral Intention (BI)	5	.947	Excellent

4.2 Descriptive Statistics

Table 2 presents descriptive statistics for the three focal constructs. Students agreed that ChatGPT was useful in their academic activities (PU: M = 3.48, SD = 0.96) and easy to use (PEU: M = 3.43, SD = 0.97). Behavioral intention fell within the neutral range (M = 3.19, SD = 0.96), indicating that while students held favorable perceptions of ChatGPT, their commitment to continued academic adoption remained moderate rather than firm.

Table 2. Descriptive statistics for PU, PEU, and BI.

Construct	M	SD	Interpretation
Perceived Usefulness (PU)	3.48	0.96	Agree
Perceived Ease of Use (PEU)	3.43	0.97	Agree
Behavioral Intention (BI)	3.19	0.96	Neutral

Note. Scale interpretation: 2.61–3.40 = Neutral; 3.41–4.20 = Agree.

4.3 Differences by Demographic Variables

Gender. Independent samples t-tests revealed no statistically significant differences between male and female students in PU (t[536] = −1.54, p = .125), PEU (t[536] = −1.69, p = .092), or BI (t[536] = −1.60, p = .110), though female students consistently reported slightly higher means across all three constructs (Table 3).

Formal Training. Students who received formal ChatGPT training scored significantly higher in perceived usefulness (t[536] = 2.97, p = .003) and behavioral intention (t[536] = 3.39, p < .001), though not in perceived ease of use (t[536] = 1.51, p = .132; see Table 4). Trained students reported a PU mean of 3.63 (SD = 0.90) versus

3.38 (SD = 0.98) for untrained students, and a BI mean of 3.37 (SD = 0.93) versus 3.09 (SD = 0.97).

Table 3. Independent samples t-test results for PU, PEU, and BI by gender.

Construct	Male M (SD)	Female M (SD)	t(536)	p
Perceived Usefulness	3.40 (1.01)	3.53 (0.93)	−1.54	.125
Perceived Ease of Use	3.34 (1.01)	3.48 (0.95)	−1.69	.092
Behavioral Intention	3.11 (0.98)	3.25 (0.94)	−1.60	.110

*Note. *p < .05.*

Table 4. Independent samples t-test results for PU, PEU, and BI by formal training.

Construct	Trained M (SD)	Untrained M (SD)	t(536)	p
Perceived Usefulness	3.63 (0.90)	3.38 (0.98)	2.97	.003*
Perceived Ease of Use	3.51 (0.95)	3.38 (0.99)	1.51	.132
Behavioral Intention	3.37 (0.93)	3.09 (0.97)	3.39	<.001**

*Note. *p < .05. **p < .001.*

Year Level. One-way ANOVA revealed significant differences across year levels for all three constructs (Table 5). Tukey HSD post hoc tests indicated that fourth-year students scored significantly higher than first-year students on PU ($p < .001$), PEU ($p < .001$), and BI ($p = .001$). For PEU, second-year students also scored significantly higher than first-year students ($p = .026$). For BI, fourth-year students also differed from second-year students ($p = .043$).

Table 5. One-Way ANOVA results for PU, PEU, and BI by year level.

Construct	1st M (SD)	2nd M (SD)	3rd M (SD)	4th M (SD)	F(3,534)	p
PU	3.32 (1.00)	3.49 (0.92)	3.50 (0.94)	3.83 (0.82)	6.07	<.001***
PEU	3.16 (1.00)	3.54 (0.90)	3.54 (1.00)	3.82 (0.83)	12.02	<.001***
BI	3.02 (0.98)	3.19 (0.88)	3.20 (1.00)	3.65 (0.85)	9.50	<.001***

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

Frequency of Use. One-way ANOVA results showed highly significant differences across frequency-of-use groups for all three constructs (all $p < .001$; Table 6). Tukey HSD post hoc tests consistently revealed that students who had never used ChatGPT scored significantly lower than all more frequent user groups on PU (Never M = 2.43), PEU (Never M = 2.28), and BI (Never M = 2.16). Students who used

ChatGPT also rarely scored lower than those who used it a few times per week on both PU (p = .037) and PEU (p = .037), indicating a dose-response relationship between usage frequency and technology acceptance perceptions.

Table 6. One-Way ANOVA results for PU, PEU, and BI by frequency of use.

Construct	**Never M**	**Rarely M**	**Few/mo M**	**Few/wk M**	**F(5,532)**	**p**
PU	2.43	3.32	3.41	3.77	18.74	<.001***
PEU	2.28	3.26	3.55	3.75	20.00	<.001***
BI	2.16	3.09	3.09	3.43	17.17	<.001***

*Note. ***p < .001. Never group differed significantly from all other groups on all three constructs.*

4.4 Correlational Analysis

Table 7 presents the Pearson correlation matrix for PU, PEU, and BI. All pairwise correlations were positive and statistically significant (p < .001). The strongest correlation was between PU and BI (r = .780), consistent with TAM's prediction that perceived usefulness is the primary driver of behavioral intention. PEU also correlated strongly with both PU (r = .747) and BI (r = .709), reflecting the well-established TAM pathway in which ease of use reinforces both utility perceptions and adoption intentions.

Table 7. Pearson correlation matrix for PU, PEU, and BI.

Construct	**PU**	**PEU**	**BI**
PU	—		
PEU	.747***	—	
BI	.780***	.709***	—

*Note. ***p < .001 (two-tailed).*

4.5 Exploratory Factor Analysis: Relevant Factor Structure

EFA was conducted exclusively on the 15-item TAM subset (KMO = .963; Bartlett's $\chi^2[105] = 8{,}818.57$, p < .001), and three factors were extracted, accounting for 82.98% of the total variance. The solution yielded a clean, theoretically congruent factor structure in which each TAM construct loaded exclusively on its own dedicated factor. Factor 1 (Behavioral Intention) was defined entirely by BI items (loadings ranged from .701 to .823), accounting for 27.84% of the variance (eigenvalue = 4.18). Factor 2 (Perceived Ease of Use) was defined entirely by PEU items (loadings .750–.828), accounting for 28.67% of variance (eigenvalue = 4.30). Factor 3 (Perceived Usefulness) was defined entirely by PU items (loadings .714–.780), accounting for 26.47% of variance (eigenvalue = 3.97). This clean three-factor structure directly resolves the earlier concern regarding PU–BI co-loading: when the EFA is appropriately restricted to the 15 focal items, PU and BI emerge as empirically distinct factors, fully supporting their treatment as predictor and criterion in the regression analysis.

4.6 Multiple Regression Analysis

Multiple linear regression with BI as the dependent variable was conducted using PU and PEU as the sole predictors, consistent with the paper's TAM-focused scope. The model (Table 8) was statistically significant, $F(2, 535) = 486.21$, $p < .001$, $R^2 = .645$, Adjusted $R^2 = .644$. Perceived usefulness emerged as the strongest significant predictor ($\beta = .567$, $t = 14.621$, $p < .001$), followed by perceived ease of use ($\beta = .286$, $t = 7.370$, $p < .001$). Together, PU and PEU explained 64.5% of the variance in BI, confirming their centrality in the ChatGPT adoption process. Multicollinearity diagnostics indicated acceptable levels (VIF = 2.27 for both PU and PEU), well below the threshold of 5 (Hair et al., 2010), confirming that the predictors are sufficiently distinguishable in the regression model.

Table 8. Multiple regression analysis on the predictors of behavioral intention.

Predictor	B	SE	β	t	P
(Constant)	0.078	0.103	—	0.756	.450
Perceived Usefulness	0.566	0.040	.567	14.621	<.001***
Perceived Ease of Use	0.280	0.044	.286	7.370	<.001***

Note. $R^2 = .645$, *Adjusted* $R^2 = .644$, $F(2, 535) = 486.21$, $p < .001$. *VIF = 2.27 for both predictors.* ***$p < .001$.

5. Discussion

The finding that students agreed on ChatGPT's usefulness and ease of use while expressing only neutral behavioral intention reflects a theoretically important gap between positive technology perceptions and committed adoption. This pattern aligns with TAM's recognition that utility beliefs are necessary but not always sufficient for solidifying behavioral intention, particularly in contexts marked by institutional policy ambiguity, digital infrastructure constraints, or social normative pressures (Davis, 1989; Venkatesh et al., 2003). In regional Philippine HEIs, where institutional AI policies are nascent and faculty guidance on ChatGPT use remains inconsistent, such ambivalence is both understandable and predictable.

The strong predictive power of PU ($\beta = .567$) is consistent with the broader TAM and ChatGPT adoption literature (Strzelecki, 2023; Lo, 2023) and reinforces the centrality of functional utility as the primary driver of AI tool adoption in educational settings. Students who perceive ChatGPT as genuinely enhancing their academic performance are substantially more likely to continue using it. The significant contribution of PEU ($\beta = .286$) confirms the established indirect pathway in TAM, wherein ease of use reinforces adoption both directly and through its effect on perceived usefulness.

The significant training effects on PU and BI, but not on PEU, offer important practical insights. Formal ChatGPT training appeared to sharpen students' appreciation of the tool's academic utility and strengthen their commitment to adoption, perhaps by providing structured exposure to specific use cases and capabilities. The absence of a training effect on PEU suggests that students generally find ChatGPT intuitive to navigate regardless of training status, consistent with the tool's conversational interface design. These findings suggest that AI literacy programs aimed at accelerating ChatGPT adoption should prioritize demonstrating concrete academic utility rather than focusing solely on technical navigation.

The consistent advantage of fourth-year students across PU, PEU, and BI supports an experiential learning interpretation: prolonged academic engagement deepens both functional competence with AI tools and the motivational orientation toward continued use (Firat, 2023; Kuhail et al., 2023). Similarly, the dose-response relationship between usage frequency and technology acceptance perceptions—where non-users scored dramatically lower than all other groups—underscores the importance of initial adoption in shaping positive utility beliefs. Institutional initiatives encouraging structured first-use experiences may therefore have outsized effects on long-term adoption trajectories.

The recomputed EFA on the 15-item subset yielded a clean three-factor structure, with each TAM construct loading exclusively on its dedicated factor: BI items on Factor 1, PEU items on Factor 2, and PU items on Factor 3, accounting for 82.98% of the total variance. This outcome directly resolves the construct validity concern raised in the review: when the factor analysis is appropriately restricted to the 15 focal TAM items, PU and BI emerge as empirically distinct factors, fully supporting their treatment as predictors and criterion in the regression model. VIF diagnostics (VIF = 2.27 for both PU and PEU) further confirm that multicollinearity is well within acceptable bounds (Hair et al., 2010). The clean factor separation also reinforces PEU's role as a distinct usability-oriented construct, separate from both the utility beliefs captured by PU and the motivational-behavioral disposition captured by BI. This distinction has practical implications for AI literacy curricula: PU-oriented content demonstrating specific academic use cases may drive adoption more powerfully than instruction focused narrowly on navigation and interface skills.

6. Conclusion

This study provides empirical evidence for the applicability of the Technology Acceptance Model to ChatGPT adoption in Philippine higher education. Drawing on data from 538 students across two regional HEIs, findings confirm that perceived usefulness is the dominant predictor of behavioral intention to adopt ChatGPT, followed by perceived ease of use, which together account for 64.5% of the variance in BI ($R^2 = .645$) in a TAM-focused two-predictor model. While students held positive perceptions of ChatGPT's utility and usability, behavioral intention remained neutral, highlighting a gap between favorable attitudes and committed adoption in this context.

Practically, these findings call for AI literacy programs that move beyond technical skill-building to explicitly demonstrate ChatGPT's academic utility through structured, discipline-specific use cases. Institutions in regional Philippine HEIs should develop formal AI integration policies and provide training that bridges the gap between positive perceptions and committed, purposeful adoption. Fourth-year and formally trained students' higher scores suggest that accumulated experience and deliberate instruction are both effective levers for accelerating adoption.

Limitations include the cross-sectional design, convenience sampling via an online Google Form, and the regional specificity of the sample, which constrain causal inference and limit generalizability. The online administration method warrants particular attention: students without consistent internet access, those who do not regularly engage with digital platforms, or those less familiar with AI tools were likely underrepresented. The high reported frequency of ChatGPT use in this sample may therefore reflect the characteristics of a digitally engaged subpopulation rather than the broader undergraduate student body. This limits the extent to which findings can be generalized to students from more under-resourced contexts. Accordingly, the broad recommendations for regional Philippine HEIs should be interpreted cautiously and understood as indicative rather than representative. Future research should employ longitudinal designs to trace the development of adoption intentions over time, structural equation modeling to formally test the mediated TAM pathways, and probability-based sampling strategies to improve representativeness. Replication across diverse Philippine HEIs and internationally would further strengthen the external validity of these findings.

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Conflict of Interest Statement

The authors declare no relevant financial or non-financial interests to disclose.

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