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When Usefulness Outweighs Norms: Predictors of Generative Artificial Intelligence Use in a Mobile-First Teacher Education Context

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Abstract

Background. Generative artificial intelligence (GenAI) tools are increasingly integrated into higher education, yet the factors driving their adoption among pre-service teachers remain underexplored in Southeast Asian contexts.

Objectives. This study investigated predictors of generative AI use among 118 pre-service science teachers at a state college in Masbate, Philippines. Drawing on the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, and the Theory of Planned Behavior, five constructs were examined: Perceived Usefulness, Attitude Toward AI, Effort Expectancy, Facilitating Conditions, and Subjective Norms.

Materials and Method. A quantitative descriptive-predictive design with stratified random sampling was used. Data were collected using a validated 32-item instrument and analyzed using four multiple linear regression models.

Results. Generative AI use was rated high ($M = 3.67$, $SD = 0.72$). Perceived Usefulness ($M = 3.79$), Attitude Toward AI ($M = 3.71$), and Effort Expectancy ($M = 3.75$) were rated high, while Facilitating Conditions ($M = 3.44$) and Subjective Norms ($M = 3.35$) were rated moderate. Across all four models ($F = 50.47$ to 67.14, $p < .001$), Perceived Usefulness was the sole predictor consistently significant at $p < .001$ ($\beta = 0.443$ to 0.479), explaining 63.9 to 64.6% of the variance ($R^2 = 0.639$ to 0.646). Attitude Toward AI and Effort Expectancy reached significance in selected model configurations. Multicollinearity was within acceptable limits ($VIF = 1.40$ to 4.76).

Conclusion. These correlational findings, drawn from a single institutional sample, point to the primacy of perceived usefulness in technology adoption. As a hypothesis for future confirmation, teacher education programs may benefit from demonstrating the practical value of generative AI in science instruction.

Keywords: generative artificial intelligence, perceived usefulness, pre-service science teachers, science education, technology acceptance.

Introduction

Artificial intelligence has begun reshaping educational systems at a rate that few observers anticipated even a decade ago. Recent bibliometric and narrative reviews confirm the accelerating pace of this integration across educational levels and disciplines (Limna et al., 2022; Zhang & Aslan, 2021). The emergence of generative AI tools, defined broadly as systems capable of producing original text, images, code and other content in response to user prompts, has introduced a new category of cognitive technology into the learning environment (Crompton & Burke, 2023; UNESCO, 2023). Unlike earlier AI applications that functioned primarily as passive recommenders or adaptive content distributors, generative AI enables learners and instructors to engage in open-ended, conversational interactions that can support writing, reasoning, research synthesis and problem-solving at scale (Su & Yang, 2023; Zhao et al., 2026). Empirical evidence for these instructional benefits has begun to accumulate: AI-enabled personalized recommendations have improved learner engagement and performance in flipped-classroom settings (Huang et al., 2023), and adaptive natural-language-processing tools have improved the quality of student argumentative writing (Wambsganss et al., 2020). The rapid adoption of platforms such as ChatGPT has placed a central question at the forefront of educational research, specifically what determines whether a learner chooses to use these tools, and how consistently.

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Pre-service teachers occupy a particularly consequential position in this context. As individuals who are simultaneously learners in higher education and future professionals who will shape how the next generation relates to technology, their dispositions toward AI carry implications that extend well beyond their own academic performance. A pre-service teacher who understands and actively uses generative AI is far more likely to integrate it meaningfully into classroom practice after graduation than one who merely encounters it as a peripheral option (Mishra & Koehler, 2006; Sun et al., 2025; Wang et al., 2025). This upstream influence extends to ethical and literacy dimensions as well: interventions that build ethics-aware AI literacy during teacher preparation may shape how future K-12 students themselves come to use these tools responsibly (Zhang et al., 2023). This upstream influence on educational technology integration makes pre-service teacher populations a high-value subject group for adoption research.

Within the science education context, generative AI presents both distinctive opportunities and genuine tensions. Science inquiry depends on evidence evaluation, claim-warrant reasoning, and iterative model revision, competencies that can in principle be scaffolded by conversational AI, yet also potentially short-circuited by it if students accept AI-generated explanations uncritically (Holmes et al., 2019; Luan et al., 2020; Ouyang & Jiao, 2021). Realizing the benefits of generative AI without inviting this risk depends on students and instructors developing the digital competencies needed to use these tools critically and effectively (Kohnke et al., 2023). Understanding what drives science pre-service teachers to use or avoid these tools is therefore not simply a question of technology access or preference; it is a curricular and professional development concern with long-term consequences for science teaching quality.

Despite growing interest in AI adoption among university students broadly, empirical studies focused specifically on pre-service science teachers in the Philippines remain scarce. The country presents a context of particular interest because it combines high rates of smartphone penetration and social media engagement with persistent infrastructure disparities in internet reliability, especially in rural and island provinces (Ittefaq et al., 2025; Maheshwari, 2024; He & Ren, 2025). Pre-service teachers trained in state universities in these regions may encounter generative AI through mobile-first access patterns that differ substantially from those observed in studies conducted in urban or high-income settings. Theories developed and tested primarily in North American, East Asian, or Western European contexts may not transfer directly to this population without empirical verification.

The present study is grounded in three established frameworks for understanding technology adoption. The Technology Acceptance Model, first articulated by Davis (1989), identifies Perceived Usefulness and perceived ease of use as the two primary determinants of individual technology acceptance. Perceived Usefulness captures the degree to which a person believes that using a particular system will enhance their performance, and it has consistently emerged as the stronger of the two predictors across prior empirical tests (Haq et al., 2025; Venkatesh et al., 2003). The Unified Theory of Acceptance and Use of Technology, proposed by Venkatesh et al. (2003), extended this framework by incorporating social and organizational variables, including Subjective Norms, Facilitating Conditions, and Effort Expectancy, the latter conceptually aligned with perceived ease of use. The Theory of Planned Behavior (Ajzen, 1991; Fishbein & Ajzen, 1975) complements both models: it holds that behavioral intentions are jointly shaped by attitudes, subjective social norms, and perceived behavioral control. This tripartite structure aligns well with the multi-construct approach adopted in the present study.

The Diffusion of Innovations framework (Rogers, 2003) adds a further theoretical lens: it positions technology adoption as a social process in which the perceived relative advantage of an innovation, an analog of Perceived Usefulness, is among the strongest predictors of adoption speed and breadth. From a pedagogical standpoint, the Technological Pedagogical Content Knowledge framework (Mishra & Koehler, 2006) draws attention to the integrative competency teachers must develop to use technology not merely as a convenience but as a purposeful instructional resource. Together, these frameworks motivate the five-predictor model tested in this study. Acceptance constructs such as Perceived Usefulness capture a learner's subjective judgment about a tool, not a direct measure of instructional benefit. This study therefore also draws on Cognitive Load Theory (Sweller, 1988) and self-regulated learning frameworks (Zimmerman, 2002) to interpret what a high usefulness rating plausibly reflects about how generative AI is used in practice, for example as a means of offloading extraneous cognitive demand or supporting planning and self-monitoring during science coursework. This learning-theoretic lens is intended to complement rather than substitute for the acceptance-theoretic model that anchors the present analysis; its implications are established further in the Discussion.

Despite the theoretical richness of this literature, several empirical gaps remain. This pattern echoes a broader gap identified across the AIEd literature, where technological application has often outpaced integration with educational theory (Chen et al., 2020). First, most studies examining AI adoption among pre-service teachers have treated technology acceptance as a unidimensional or bivariate outcome, rarely comparing the relative predictive strength of multiple constructs across competing regression models (Suson, 2025; Wu et al., 2025). Second, the specific role of social influence through Subjective Norms in collectivist educational cultures such as the Philippines has received limited attention in the generative AI literature. Third, infrastructure constraints such as internet reliability and device type, which may moderate the relationship between facilitating conditions and actual use, have seldom been reported alongside behavioral outcome data (Haq et al., 2025; He & Ren, 2025).

A further complication in the Philippine context is the uneven distribution of digital literacy competencies across teacher education programs. Students entering pre-service programs from diverse socioeconomic backgrounds may have encountered technology-mediated instruction at dramatically different rates in secondary school, producing cohorts with varying degrees of prior exposure to digital tools. Prior exposure has been shown to moderate technology acceptance in prior studies by shaping baseline Perceived Usefulness and ease-of-use expectations before formal instruction begins (Bandura, 1977; Rogers, 2003). Understanding whether and how this heterogeneous prior exposure interacts with in-program AI experiences is a question that cannot be answered without first establishing the baseline predictors of current use behavior.

The present study also responds to a methodological gap in the existing literature. Most single-study examinations of AI adoption predictors test one or two constructs rather than systematically comparing multiple predictor combinations within the same sample. This study instead estimates four competing multiple regression models that vary in their inclusion of the five predictor variables. This model-comparison approach identifies which predictors are significant in isolation and whether that significance holds when competing variables are partialled out. The within-sample comparison reduces the risk of over-attributing predictive power to any single construct and provides a more conservative test of theoretical claims.

This study addresses these gaps by examining five predictor variables across four competing multiple regression models in a sample of 118 pre-service science teachers drawn from a rural Philippine state university. The research questions guiding this inquiry are as follows. First, what is the technology profile of pre-service science teachers in terms of internet reliability, devices used, and generative AI tools used? Second, how do pre-service science teachers rate the five predictor variables and their generative AI use? Third, which predictors significantly explain variance in generative AI use behavior?

The contribution of this study is best understood as a boundary-condition test rather than the introduction of a new predictor construct or theoretical model. TAM, UTAUT and TPB relationships have been established predominantly in North American, East Asian and urban high-income settings. This study examines whether those relationships hold, weaken or fail in a population and infrastructure context where they have rarely been tested jointly: mobile-first, connectivity-constrained pre-service science teachers in a rural Philippine state college. Culture and infrastructure have previously been identified as boundary conditions that can alter which UTAUT constructs retain predictive power (Bayaga & du Plessis, 2024; Venkatesh & Zhang, 2010), and the present multi-model comparative design extends this boundary-condition logic to generative AI specifically. As detailed in the Discussion, Facilitating Conditions and Subjective Norms failed to predict use in any of the four models, despite the Philippines' collectivist social structure and the theoretical importance ordinarily attributed to these constructs. This null result is itself a substantive empirical contribution: it suggests that in mobile-first, infrastructure-constrained contexts, individual utility judgments may outweigh social and institutional influences to a degree not anticipated by UTAUT's original specification. The finding qualifies established technology acceptance theory rather than simply confirming it.

Materials and Methods

Research Design

This study employed a quantitative descriptive-predictive design. The descriptive component characterized the technology profile and mean scores of study variables, while the predictive component used multiple linear regression to identify the constructs that significantly explained variance in generative AI use. This design is consistent with recent technology adoption research in higher education settings (Haq et al., 2025; Suson, 2025; Wu et al., 2025) and was selected because it enables systematic comparison of competing predictor models without requiring experimental manipulation.

Participants and Sampling

The population consisted of all pre-service science teachers enrolled at a state college in the Philippines during the academic year 2024 to 2025. A total of n = 118 participants were recruited using stratified random sampling, with year level serving as the stratification variable. This approach ensured proportional representation across all four undergraduate year levels. Inclusion criteria required that participants (a) were officially enrolled in the Bachelor of Secondary Education major in Science program, (b) had prior experience using at least one digital device for academic purposes, and (c) provided informed consent. Participation was voluntary and no incentives were offered.

Instrument

The survey instrument contained 32 items distributed across six constructs, namely Generative AI Use (dependent variable), Perceived Usefulness, Attitude Toward AI, Subjective Norms, Facilitating Conditions, and Effort Expectancy. Items were rated on a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The instrument was adapted from validated scales used in prior technology acceptance research (Cabero-Almenara et al., 2024; Venkatesh et al., 2003) and underwent content validation by a panel of five experts with backgrounds in educational technology and science education. Internal consistency for the full instrument was Cronbach alpha = 0.797, which falls within the acceptable range for social science research.

Mean scores were interpreted using a five-level rubric in which 4.21 to 5.00 was classified as Very High, 3.51 to 4.20 as High, 2.51 to 3.50 as Moderate, 1.81 to 2.50 as Low, and 1.00 to 1.80 as Very Low. This descriptive scale, commonly applied in Philippine higher education research, provided a standardized and interpretively consistent basis for comparing mean scores across constructs and relating them to prior work that used similar scales.

Data Collection

Data were collected through a self-administered Google Form distributed to participants during scheduled class sessions in February to March 2025. Section one gathered technology profile information including internet reliability, primary device type, and generative AI tools used. Section two contained the 32 Likert-scale items. Completion required approximately 15 to 20 minutes. All responses were anonymized before analysis.

Data Analysis

Descriptive statistics including means, standard deviations, and frequency distributions were computed for all variables. Four multiple linear regression models were estimated to examine different predictor combinations and assess the robustness of each variable's contribution. Model 1 included PU, ATT, FC and EE. Model 2 included PU, ATT, SN and FC. Model 3 included PU, ATT, SN and EE. Model 4 included PU, ATT and EE. This model comparison approach allowed the identification of which predictors retained significance when competing variables were held constant.

Regression assumptions were tested prior to interpretation. Normality of residuals was assessed using the Shapiro-Wilk test ($W = 0.980$, $p = .076$), and homoscedasticity was confirmed via the Breusch-Pagan test ($BP = 1.910$, $df = 2$, $p = .385$). Multicollinearity was evaluated using Variance Inflation Factor values and tolerance statistics. All analyses were conducted using R 4.3 and SPSS 26. Statistical significance was set at alpha = .05.

Results

Technology Profile of Respondents

In terms of internet reliability, approximately half of the respondents (51.7%) rated their connection as moderate, while 40.7% reported good reliability. Very poor and very good ratings were minimal (0.0% and 1.7%, respectively), and only 5.9% reported poor connectivity. These data suggest that most respondents operate within a connectivity environment that is functional but not uniformly robust.

With respect to primary devices, the overwhelming majority of respondents (88.1%) used smartphones as their main access point for digital academic activities, compared to only 11.9% who relied on laptops or desktop computers. This mobile-first profile is consistent with patterns observed in other low-to-middle income country settings and has implications for how generative AI tools must function to be practically usable by this population. Table 1 details the technology profile of the respondents.

Regarding generative AI tool use, ChatGPT was by far the most frequently used platform (86.4%), followed by Gemini (38.1%), Meta AI (32.2%), QuillBot (28.0%) and Grammarly (26.3%). The dominance of ChatGPT mirrors findings in broader Southeast Asian student populations and reflects the platform's early market saturation and interface familiarity (Maheshwari, 2024).

Descriptive statistics of study variables

Table 2 presents the mean scores and standard deviations for all six study variables. Perceived Usefulness obtained the highest mean score ($M = 3.788$, $SD = 0.702$), followed by Effort Expectancy ($M = 3.746$, $SD = 0.636$), Attitude Toward AI ($M = 3.710$, $SD = 0.654$), and Generative AI Use itself ($M = 3.669$, $SD = 0.717$). All four of these variables fell within the High interpretation range (3.51 to 4.20). Facilitating Conditions ($M = 3.444$, $SD = 0.635$) and Subjective Norms ($M = 3.347$, $SD = 0.492$) were rated in the Moderate range, indicating that peer and institutional influences were perceived less strongly than internal utility and ease evaluations. Figure 1 illustrates the mean scores and variability across all six constructs.

Table 1. Technology Profile of Pre-Service Science Teachers (n = 118)

Variable	Category	n	%
Internet Reliability	Very Poor	0	0.0
	Poor	7	5.9
	Moderate	61	51.7
	Good	48	40.7
	Very Good	2	1.7
Primary Device Used	Smartphone	104	88.1
	Laptop/Desktop	14	11.9
Generative AI Tools Used (Multiple Response)	ChatGPT	102	86.4
	Gemini	45	38.1
	Meta AI	38	32.2
	QuillBot	33	28.0
	Grammarly	31	26.3

Table 2. Descriptive Statistics of Study Variables (n = 118)

Variable	Mean	SD	Interpretation
Generative AI Use	3.669	0.717	High
Perceived Usefulness (PU)	3.788	0.702	High
Attitude Toward AI (ATT)	3.710	0.654	High
Subjective Norms (SN)	3.347	0.492	Moderate
Facilitating Conditions (FC)	3.444	0.635	Moderate
Effort Expectancy (EE)	3.746	0.636	High

Multiple linear regression results

Table 3 presents the standardized regression coefficients across four models. Perceived Usefulness consistently emerged as the only predictor significant at $p < .001$ in every model, with beta coefficients ranging from 0.443 in

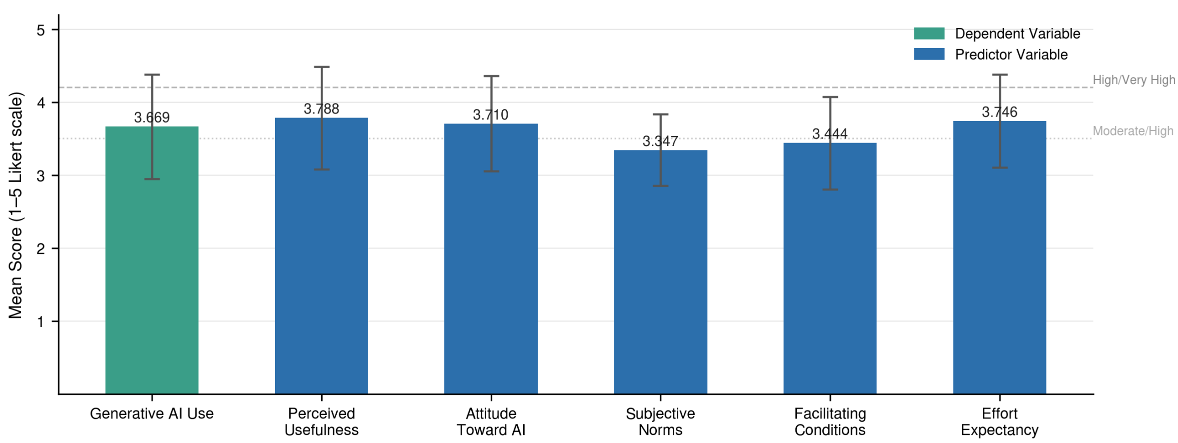

Fig. 1. Mean scores and standard deviations of study variables.

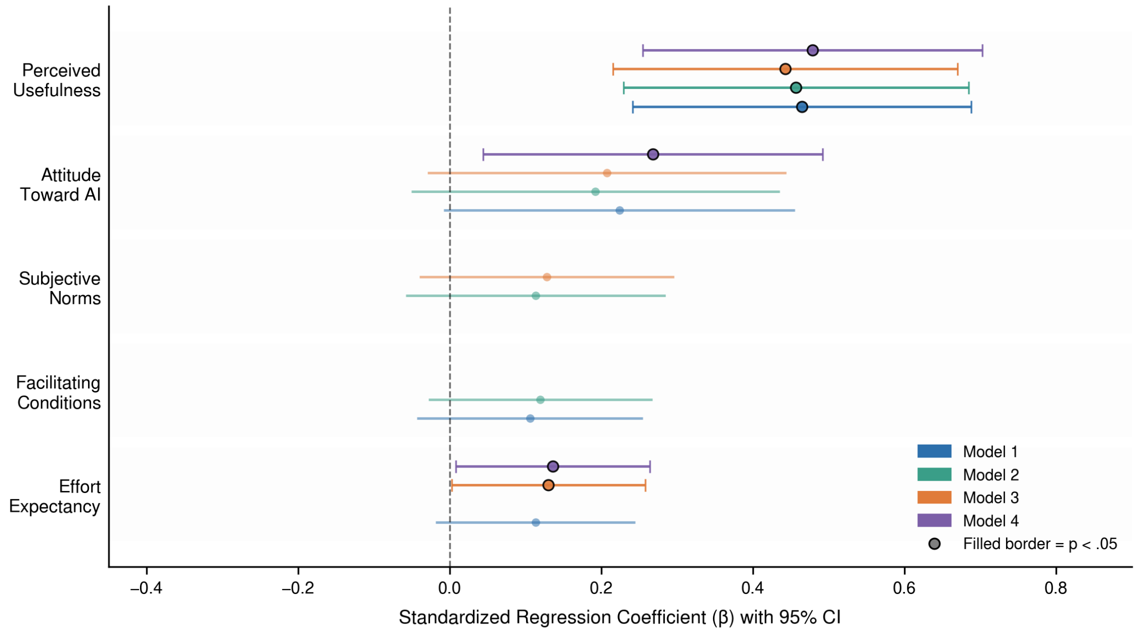

Fig. 2. Forest plot of standardized regression coefficients (β).

Table 3. Standardized Regression Coefficients Across Four Models (n = 118)

Predictor	Model 1		Model 2		Model 3		Model 4	
	β	p	β	p	β	p	β	p
PU	0.4650	<.001	0.4571	<.001	0.4431	<.001	0.4789	<.001
ATT	0.2240	.058	0.1925	.119	0.2075	.085	0.2684	.019
SN	—	—	0.1137	.192	0.1285	.133	—	—
FC	0.1061	.161	0.1199	.111	—	—	—	—
EE	0.1134	.090	—	—	0.1304	.045	0.1361	.037
R2	0.645		0.641		0.646		0.639	
Adjusted R2	0.632		0.628		0.633		0.629	
F	51.29	<.001	50.47	<.001	51.50	<.001	67.14	<.001

Note: Dashes indicate that the predictor was not included in that model. PU = Perceived Usefulness; ATT = Attitude Toward AI; SN = Subjective Norms; FC = Facilitating Conditions; EE = Effort Expectancy.

Model 3 to 0.479 in Model 4. The total variance explained by the models was similar, with R-squared values of 0.645, 0.641, 0.646, and 0.639 for Models 1 through 4, respectively, indicating that each model accounted for approximately 64 percent of variance in generative AI use.

Attitude Toward AI produced positive beta coefficients across all models, ranging from 0.193 to 0.268, reaching statistical significance in Model 4 ($\beta = 0.268$, $p = .019$). Effort Expectancy achieved statistical significance in Model 3 ($\beta = 0.130$, $p = .045$) and Model 4 ($\beta = 0.136$, $p = .037$), while its coefficients in Models 1 and 2 fell short of the significance threshold. Subjective Norms (Models 2 and 3) and Facilitating Conditions (Models 1 and 2) were non-significant in all configurations in which they were included.

Figure 2 presents a forest plot of the standardized regression coefficients with 95% confidence intervals for each predictor, plotted separately for all four models. The dashed vertical reference line at zero represents the null hypothesis of no effect. Filled-border markers denote statistically significant estimates ($p < .05$). The confidence intervals for Perceived Usefulness do not cross zero in any model, confirming the reliability and precision of its effect. By contrast, the intervals for Attitude Toward AI, Subjective Norms, Facilitating Conditions, and Effort Expectancy all straddle zero or rest near it, indicating that their apparent positive effects carry substantial uncertainty. The forest plot makes the contrast in estimation precision visually explicit and reinforces the conclusion that the PU effect is qualitatively different in nature from the effects of the other four predictors.

Regression assumption diagnostics

Table 4 presents multicollinearity diagnostics. Tolerance values ranged from 0.210 (Attitude Toward AI) to 0.713 (Effort Expectancy), and VIF values ranged from 1.40 to 4.76, all well below the conventional cutoffs of 0.10 and 10.0 respectively. The highest VIF was observed for Attitude Toward AI (4.76), reflecting its strong theoretical and empirical overlap with Perceived Usefulness ($r = 0.864$). Perceived Usefulness itself had a VIF of 4.21. Nevertheless, all values remained within acceptable bounds and do not indicate problematic multicollinearity.

Table 4. Multicollinearity Diagnostics Across Predictor Variables

Predictor	Tolerance	VIF	Min VIF	Max VIF
Perceived Usefulness (PU)	0.237	4.21		
Attitude Toward AI (ATT)	0.210	4.76		
Subjective Norms (SN)	0.423	2.36		
Facilitating Conditions (FC)	0.539	1.85		
Effort Expectancy (EE)	0.713	1.40		
Range across models			1.40	4.76

Note: VIF = Variance Inflation Factor. All VIF values are below the conventional threshold of 10.0, and all tolerance values are above 0.10.

Residual normality was confirmed by the Shapiro-Wilk test ($W = 0.980$, $p = .076$), and homoscedasticity was supported by the Breusch-Pagan test ($BP = 1.910$, $df = 2$, $p = .385$). These diagnostics collectively indicate that the regression models meet standard assumptions and that the coefficient estimates are reliable.

Discussion

Technology Access and Tool Preferences

The finding that nearly nine in ten respondents relied primarily on smartphones to access digital tools reflects the broader mobile-first orientation of students in provincial Philippine higher education. While smartphone ownership is widespread in this context, the moderate internet reliability ratings reported by more than half of the respondents introduce practical constraints on tool use. Generative AI applications, particularly text-based interfaces like ChatGPT, are lightweight in bandwidth requirements compared with video- or image-heavy platforms. This may explain why these students were still able to adopt and use such tools regularly despite connectivity limitations. This observation is consistent with Maheshwari (2024), who noted that Southeast Asian students adapt their technology use pragmatically to available infrastructure conditions.

The dominance of ChatGPT (86.4%) over other platforms points to the role of early adoption network effects and platform visibility. Students who begin using a tool because peers or instructors mention it are likely to recommend it in turn, creating a cascade that concentrates use around one or two dominant platforms even when alternatives exist. Grammarly (26.3%) and QuillBot (28.0%) saw lower uptake. Both function primarily as writing-assistance tools rather than conversational AI systems, which suggests that respondents prioritized interactive reasoning support over grammar correction when choosing among generative AI platforms.

Perceived Usefulness and Favorable Attitudes

The high mean scores for Perceived Usefulness ($M = 3.788$) and Attitude Toward AI ($M = 3.710$) suggest that the respondents entered the study with broadly positive dispositions toward generative AI. These findings extend a pattern observed in comparable studies. Haq et al. (2025) found that university students in higher education settings across multiple countries similarly rated AI usefulness positively, while Cabero-Almenara et al. (2024) reported favorable AI acceptance scores among Spanish-speaking university students using the AI4U scale. Maheshwari (2024) identified positive attitudes as a significant antecedent to ChatGPT behavioral intention among Vietnamese students, reinforcing the cross-contextual generalizability of this finding within Southeast Asia.

The alignment between high usefulness perceptions and high use behavior in the present sample supports the core prediction of the Technology Acceptance Model (Davis, 1989), that individuals adopt technologies they perceive as useful for their work or learning. For pre-service science teachers specifically, usefulness is likely tied to concrete applications such as simplifying complex scientific concepts for lesson planning, generating practice problems, drafting explanatory texts for diverse learners, and supporting research writing. These are all high-frequency tasks in teacher education programs that generative AI can plausibly reduce the cognitive load of completing. Recognizing this, teacher educators who explicitly frame AI tools around these discipline-specific applications may find that usefulness perceptions, and with them adoption rates, respond favorably.

What the present data cannot resolve is whether the high PU scores in this sample reflect well-calibrated perceptions grounded in actual productive use, or optimistic anticipatory beliefs that have not yet been tested against the real limitations of generative AI in science educational contexts. Distinguishing calibrated from aspirational usefulness perceptions would require a longitudinal design that tracks PU scores alongside objective indicators of AI-assisted task quality over an academic term. This distinction matters because interventions designed to sustain rather than merely initiate adoption would differ, and would need to ensure that early enthusiasm is supported by structured experiences in which AI tools demonstrably deliver on the usefulness they are perceived to offer. An unmet usefulness expectation, if it accumulates, could depress PU scores and adoption rates in later cohorts, creating a trough in the adoption curve following the initial enthusiasm wave characteristic of emerging technology diffusion (Rogers, 2003).

Moderate Social Influence and Institutional Support

The moderate ratings for Facilitating Conditions ($M = 3.444$) and Subjective Norms ($M = 3.347$) deserve careful interpretation. In collectivist societies such as the Philippines, group conformity and social referents typically exert strong behavioral influence (Ajzen, 1991). Here, however, peer and institutional normative pressure yielded only moderate scores. This suggests that the social milieu around generative AI at this institution has not yet crystallized into a clear descriptive norm. Peer use of AI tools may not yet be visible enough, or sufficiently encouraged by faculty, to register as a potent social force. This interpretation is consistent with He and Ren (2025), who found that social influence on AI tool adoption among university students was weaker in samples characterized by lower institutional AI policy clarity.

The moderate Facilitating Conditions score likewise points to infrastructural and institutional gaps. The respondents could access generative AI tools on their smartphones, but the absence of formal training programs, institutional guidelines on academic integrity in AI use, guidelines that would ideally be grounded in established ethical frameworks for AIED (Nguyen et al., 2023), and faculty-modeled integration of AI into science pedagogy likely constrained their sense that conditions were fully in place to support that use. Selwyn (2022) cautioned that access alone does not generate productive use and that students need scaffolded environments that show how AI tools connect to learning goals. The present data suggest that the institution, like many regional state universities, has yet to fully provide that scaffolding at the institutional level.

Perceived Usefulness as the Dominant Predictor

The most important finding of this study is the consistent significance of Perceived Usefulness across all four regression models at $p < .001$. With beta coefficients ranging from 0.443 to 0.479 and significance sustained regardless of which competing variables were included, PU demonstrated a degree of predictive robustness that was not matched by any other variable. Attitude Toward AI and Effort Expectancy achieved significance in select model configurations, suggesting secondary roles that are condition-dependent rather than universal. This pattern is theoretically coherent and carries direct practical implications.

Theoretically, the finding replicates and extends the central prediction of Davis (1989) into a generative AI context. Earlier TAM applications in education already established that usefulness perceptions predict adoption more reliably than ease of use, social norms, or individual attitudes in isolation (Venkatesh et al., 2003). The present study extends this evidence to a new technology category, generative AI, and to a population that has not been extensively studied: Filipino pre-service science teachers. The present findings also converge with recent work. Haq et al. (2025) identified PU as the strongest TAM predictor in a multi-country generative AI adoption study, and Wu et al. (2025) found PU dominant over social norms and facilitating conditions in a pre-service teacher sample in China. Together, these findings suggest that the primacy of usefulness is a cross-cultural and cross-technology phenomenon. The secondary significance of Attitude Toward AI in Model 4 ($\beta = 0.268$, $p = .019$) is consistent with TPB formulations that grant attitude an independent role in behavioral outcomes when social influence constructs are absent from the model.

This pattern is consistent with a straightforward reading of TAM: usefulness perceptions and use behavior covary closely, while favorable attitudes, peer support or easy access do not appear to compensate for low perceived usefulness in this sample. Because the design is cross-sectional and both PU and use were measured concurrently via self-report, this association should not be read as evidence that raising PU perceptions would causally increase use. It is equally consistent with reverse or reciprocal influence, in which repeated use of generative AI tools shapes how useful students subsequently judge them to be. With that caveat, the pattern suggests that interventions aiming to increase generative AI adoption might usefully prioritize demonstrating utility rather than focusing on access alone. Hands-on workshops that show pre-service science teachers how ChatGPT or Gemini can improve lesson plan quality, simplify abstract concepts or generate differentiated practice materials would be a reasonable hypothesis for future intervention research to test, rather than a validated recommendation at this stage.

The robustness of PU across four different model specifications further supports its theoretical standing. In each model, between two and four other theoretically grounded predictors were present and competing for predictive variance. None of them absorbed or substantially diminished the PU effect. This suggests that the relationship between usefulness perception and use behavior in this sample is not an artifact of model misspecification or omitted variable bias attributable to the specific predictors included. The PU-use relationship appears to be a genuine, direct relationship that persists regardless of the social and contextual variables alongside which it is estimated. From a theory-testing standpoint, this is notable because it suggests that TAM's core mechanism retains explanatory power even when embedded within more socially complex frameworks such as UTAUT and TPB.

The practical magnitude of the PU effect is also substantial. In Model 4, where EE and ATT appear alongside PU, the PU beta coefficient of 0.479 indicates that a one-standard-deviation increase in usefulness perception is associated with approximately 0.48 standard deviation increase in generative AI use. In the context of a behavioral use scale, this is a sizeable and practically meaningful effect. It signals that even modest shifts in how strongly students perceive these tools as useful could produce meaningful differences in adoption rates at the program or cohort level.

Wang et al. (2024) argued that the educational value of generative AI is most clearly perceived when students encounter it in discipline-specific rather than generic contexts. This suggestion is directly applicable to science teacher education. Rather than introducing AI tools in orientation programs that treat them as general productivity aids, teacher educators should embed them in subject methods courses where the connection between AI capability and science pedagogical need is explicit and immediately actionable. Su and Yang (2023) made a similar argument for framework-guided AI integration, noting that perceived value increases when students see tools applied to authentic professional tasks.

Pedagogical Mechanisms Underlying Perceived Usefulness

The statistical dominance of Perceived Usefulness raises the question of what a high usefulness rating might mechanistically represent in terms of learning theory rather than adoption theory alone. One plausible account draws on Cognitive Load Theory (Sweller, 1988), which holds that learning is constrained by the limited capacity of working memory. Instructional tools that reduce extraneous cognitive load, the effort spent on task features that are not intrinsic to the learning goal, free capacity for germane processing of the material itself. Generative AI tools that draft explanatory text, generate practice items or restructure complex scientific content may function for pre-service teachers as a means of offloading extraneous cognitive demand during lesson preparation, a mechanism directly documented in recent mobile-context studies of ChatGPT use (Patac & Patac, 2025; Sharma & Khadka, 2026). If this account holds, high PU scores in the present sample would reflect an implicit judgment that generative AI reduces the cognitive burden of specific academic tasks, not simply a favorable opinion of the technology.

A second, complementary account draws on self-regulated learning theory (Zimmerman, 2002), which frames effective learning as a cycle of forethought, performance monitoring and self-reflection that learners actively manage. Generative AI tools can support this cycle, for instance by helping learners plan a task or check their understanding. They can also short-circuit it if learners depend on AI output without engaging their own monitoring and evaluation processes, a risk documented in recent generative-AI and self-regulated-learning research (Xu et al., 2025). Science-specific evidence suggests generative AI tools can be designed to support rather than replace self-regulation. Ng et al. (2024) found that a generative AI chatbot improved science knowledge, behavioral engagement and self-regulated learning among secondary science students when the tool was structured to prompt planning and reflection rather than simply supply answers. Whether this sample's pre-service science teachers are using generative AI in ways that support or substitute for their own self-regulatory processes cannot be determined from the present cross-sectional, self-reported data; this is an important open question for future observational or experimental work that directly measures how AI-assisted tasks are completed, not merely how useful they are perceived to be.

The Secondary Role of Effort Expectancy

The significance of Effort Expectancy in Models 3 ($\beta = 0.130$, $p = .045$) and 4 ($\beta = 0.136$, $p = .037$) warrants attention, as it suggests that perceived ease of use contributes to adoption beyond usefulness perceptions in certain model configurations. EE captures the perceived ease of using a technology and corresponds conceptually to Davis's (1989) perceived ease of use construct. The fact that EE achieves significance only when specific combinations of other predictors are present, while remaining non-significant in Models 1 and 2, suggests that its contribution is modulated by the competing variance attributable to Subjective Norms and Facilitating Conditions. When social influence constructs are absent, ease perceptions explain a small but statistically detectable share of use variance. The high EE mean score ($M = 3.746$) suggests a relative ceiling, limiting its range and predictive power, which may explain why significance is marginal rather than strong.

The specific model configuration in which EE achieved significance is worth noting: Model 3 included PU, ATT, SN, and EE, but excluded FC. In that specification, the removal of Facilitating Conditions may have freed up variance that EE was then able to capture. FC and EE share some theoretical overlap, since both represent the resource conditions that support technology use. This confounding of FC and EE is a recognized issue in UTAUT research and suggests that these constructs should not be treated as fully independent in applied settings. Future studies using latent variable modeling through structural equation modeling, rather than observed-variable regression, would be better positioned to partition the shared and unique variance between these constructs and to provide a cleaner estimate of each construct's direct effect on use behavior.

Implications for Teacher Education and Practice

These findings point to several practical implications worth testing in future work, though the data alone cannot establish them. First, teacher education programs might consider designing explicit AI integration modules for science methods courses, with activities that illustrate how generative AI tools can support the planning and delivery of science instruction. The present correlational data cannot confirm that such modules would shift adoption behavior, but the consistent primacy of Perceived Usefulness across models makes this a reasonable hypothesis for future intervention studies to test.

Second, institutions may wish to consider developing clearer policies around AI use in academic work, since the moderate Facilitating Conditions scores suggest that respondents were uncertain about what institutional support is available and whether use is formally sanctioned. Facilitating Conditions was not itself a significant predictor of use in this sample, so this suggestion is grounded more directly in the descriptive data than in the regression results, and its practical value would need to be tested rather than assumed (Crompton & Burke, 2023; UNESCO, 2023).

Third, faculty who serve as social referents for pre-service teachers might benefit from support in developing their own AI literacy and modeled use of generative AI tools in instruction, since the moderate Subjective Norms scores suggest that peer and institutional influence toward AI use is not currently strong in this sample. As with Facilitating Conditions, Subjective Norms did not predict use in the regression models, so this suggestion should be treated as a plausible avenue for future intervention research rather than a direct implication of the predictive findings.

Fourth, the mobile-first access profile of this population should inform how AI tools are introduced and practiced. Instructors and workshop facilitators should assume smartphone use as the default access mode and demonstrate generative AI workflows that function effectively on small screens with moderate bandwidth. Desktop-centric demonstrations that assume stable high-speed connections will not reflect the reality of most students in this context.

Fifth, the study findings raise questions relevant to how pre-service science teachers are assessed during their teacher education program. If generative AI tools are perceived as useful for producing academic outputs, as the high PU scores in this sample suggest, then traditional assessment formats that rely on individual unaided writing may need to be reconsidered, though the present study did not directly examine assessment practices or outcomes. Rubrics that emphasize disciplinary reasoning, evidence evaluation and critical synthesis rather than production fluency alone are one option programs might consider piloting, consistent with calls from Rudolph et al. (2023) and Saunders and Ellison (2026) for assessment reform in the context of generative AI and with UNESCO's (2023) broader guidance on human-centered AI integration in education.

Finally, the pattern of findings across this study invites reflection on what teacher readiness for AI integration actually requires. If pre-service teachers are already using generative AI tools at moderately high rates and perceive them as useful, the more pressing competency gap may lie not in motivating initial adoption but in developing the critical evaluation skills needed to use AI-generated content responsibly. TPACK (Mishra & Koehler, 2006) predicts that meaningful technology integration requires not just tool access and motivation but a sophisticated integration of content knowledge, pedagogical repertoire, and technological understanding. Preparing science pre-service teachers to evaluate AI-generated explanations against disciplinary standards, identify errors or misconceptions in AI outputs, and design learning tasks where AI augments rather than replaces student reasoning are competencies that current teacher education curricula have only begun to address. The present findings suggest that the adoption threshold has largely been crossed; the more challenging work of quality integration remains. Framed this way, the contribution of this study extends beyond technology acceptance research. It suggests that pre-service science teacher education should treat AI evaluation literacy, rather than adoption promotion, as the primary learning-theoretic challenge going forward, a reframing consistent with TPACK (Mishra & Koehler, 2006) and with the cognitive-load and self-regulation mechanisms discussed above.

Limitations

Several limitations qualify how these findings should be interpreted. First, the cross-sectional design means that Perceived Usefulness, Attitude Toward AI and Generative AI Use were all measured at a single point in time using self-report instruments. The regression models therefore establish association, not causal direction. Reverse or reciprocal relationships, for example that habitual use shapes subsequent usefulness judgments rather than the other way around, remain equally plausible interpretations of the data. Longitudinal or experimental designs that manipulate exposure to generative AI tools and track usefulness perceptions and use behavior over time would be required to test causal claims directly. Second, all data were self-reported, which introduces the possibility of common method bias and social desirability effects, particularly given that generative AI use intersects with ongoing debates about academic integrity in this population. Third, the sample was drawn from a single rural state college in the Philippines using stratified random sampling within that institution; while this design supports internal validity for the sample studied, it does not support generalization to pre-service teachers in other regions, disciplines or institutional types without further replication. The practical implications and curriculum recommendations discussed above should accordingly be read as hypotheses derived from this single-institution sample rather than as validated, broadly generalizable prescriptions. Multi-institutional and longitudinal replication, of the kind called for in the Conclusion, is needed before these implications can be extended with confidence beyond the studied context.

Conclusions

This study examined the predictors of generative AI use among pre-service science teachers at a rural state college in the Philippines. Perceived Usefulness emerged as the dominant and most consistent statistical predictor across all four regression models, with Attitude Toward AI and Effort Expectancy reaching significance in more parsimonious specifications; Subjective Norms and Facilitating Conditions did not predict use under any model configuration. Rather than simply reaffirming the Technology Acceptance Model, this pattern functions as a boundary-condition test. In a mobile-first, infrastructure-limited, collectivist educational context where social and institutional constructs would ordinarily be expected to matter a great deal, individual utility judgments appear to outweigh them. This is a qualification of UTAUT's assumed universality, and it extends technology acceptance theory to a population and setting that remains underrepresented in the literature. Read alongside Cognitive Load Theory (Sweller, 1988) and self-regulated learning frameworks (Zimmerman, 2002), the dominance of Perceived Usefulness is also consistent with the possibility that generative AI is valued in this population chiefly for its capacity to reduce the cognitive burden of routine academic tasks. This study's cross-sectional, self-reported design cannot establish this mechanism directly. The single-institution, cross-sectional design and self-reported use data limit both causal interpretation and generalizability beyond the studied context; the curriculum and policy suggestions discussed above are accordingly offered as hypotheses for future confirmation rather than validated recommendations. Multi-institutional longitudinal studies across comparable regional universities in Southeast Asia that track actual AI use behavior and directly measure the cognitive and self-regulatory mechanisms proposed here would be the most productive next step.

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Not applicable.

Ethics Statement

This study involved voluntary participation of pre-service science teacher respondents. Prior to data collection, participants were informed of the purpose of the study, their right to withdraw at any point without penalty, and the confidentiality and anonymity of their responses, and informed consent was obtained from all participants. As the study posed minimal risk and involved only anonymous survey data, it did not require formal review by an institutional ethics review board.

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Data Availability Statement

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

AI Disclosure Statement

Generative artificial intelligence was used in the preparation of this manuscript to assist with language editing.

It was not used in the design of the study, data collection, statistical analysis, or interpretation of results. The authors reviewed, edited and take full responsibility for the content of this manuscript.

Conflict of Interest

The authors declare that they have no conflicts of interest related to this work.

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Коли корисність переважає норми: предиктори використання генеративного штучного інтелекту в контексті мобільно-орієнтованої педагогічної освіти

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Авторський вклад: A – дизайн дослідження; B – збір даних; C – статаналіз; D – підготовка рукопису; E – збір коштів

Реферат. Стаття: 12 с., 4 табл., 2 рис., 43 джерела.

Передумови. Інструменти генеративного штучного інтелекту (GenAI) дедалі ширше інтегруються у вищу освіту, проте чинники, що визначають їх прийняття майбутніми вчителями, залишаються недостатньо дослідженими в контексті країн Південно-Східної Азії.

Мета. У дослідженні вивчали предиктори використання генеративного штучного інтелекту серед 118 майбутніх учителів природничих наук державного коледжу в Масбате, Філіппіни. На основі моделі прийняття технологій (Technology Acceptance Model), уніфікованої теорії прийняття та використання технологій (Unified Theory of Acceptance and Use of Technology) і теорії запланованої поведінки (Theory of Planned Behavior) було досліджено п'ять конструктів: сприйнята корисність, ставлення до штучного інтелекту, очікувана легкість використання, сприятливі умови та суб'єктивні норми.

Матеріали та методи. Використано кількісний описово-прогностичний дизайн зі стратифікованою випадковою вибіркою. Дані збирали за допомогою валідованого інструменту з 32 пунктів та аналізували з використанням чотирьох моделей множинної лінійної регресії.

Результати. Рівень використання генеративного штучного інтелекту оцінено як високий (M = 3,67; SD = 0,72). Сприйнята корисність (M = 3,79), ставлення до штучного інтелекту (M = 3,71) та очікувана легкість використання (M = 3,75) мали високий рівень, тоді як сприятливі умови (M = 3,44) і суб'єктивні норми (M = 3,35) — помірний. У всіх чотирьох моделях (F = 50,47–67,14; p < 0,001) сприйнята корисність була єдиним предиктором, який стабільно залишався статистично значущим при p < 0,001 (β = 0,443–0,479), пояснюючи 63,9–64,6% дисперсії (R^2 = 0,639–0,646). Ставлення до штучного інтелекту та очікувана легкість використання досягали статистичної значущості в окремих конфігураціях моделей. Мультиколінеарність перебувала в допустимих межах (VIF = 1,40–4,76).

Висновки. Отримані кореляційні результати, що ґрунтуються на вибірці з одного закладу освіти, вказують на провідну роль сприйнятої корисності у прийнятті технологій. Як гіпотезу для подальшої перевірки можна припустити, що програми підготовки вчителів можуть бути ефективнішими за умови демонстрації практичної цінності генеративного штучного інтелекту у викладанні природничих наук.

Ключові слова: генеративний штучний інтелект, сприйнята корисність, майбутні вчителі природничих наук, природнича освіта, прийняття технологій.

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