International Journal of Advances in Applied Sciences (IJAAS)
Vol. 15, No. 3, September 2026, pp. 998~1005
ISSN: 2252-8814, DOI: 10.11591/ijaas.v15.i3.pp998-1005 ❒ 998

Correlates and predictors of generative artificial intelligence adoption among Filipino college teachers

Almer B. Gamboa[1], John Paul P. Miranda[2]
[1]College of Education, Pampanga State University, Mexico, Philippines
[2]College of Computing Studies, Pampanga State University, Mexico, Philippines

Article Info

Article history:

Received Dec 15, 2025
Revised May 24, 2026
Accepted Jun 17, 2026

Keywords:

Instructional productivity
Philippine education
Social influence
Technology adoption
UTAUT

ABSTRACT

Filipino college teachers in public higher education institutions (HEIs) are increasingly expected to integrate generative artificial intelligence (GenAI) tools into their practice. Evidence on what drives this adoption in Philippine public universities, however, remains scarce. This study used a quantitative, cross-sectional correlational design to examine the levels, relationships, and predictors of GenAI adoption among 301 teachers from two public HEIs in Pampanga, Philippines, guided by the unified theory of acceptance and use of technology (UTAUT). Teachers reported strong agreement across all UTAUT constructs, with effort expectancy receiving the highest rating and facilitating conditions the lowest. Performance expectancy ($\beta = 0.406$, $p < 0.001$) was the strongest predictor of behavioral intention, followed by social influence ($\beta = 0.295$, $p < 0.001$) and effort expectancy ($\beta = 0.257$, $p < 0.001$), which together explained 65% of the variance in intention. Facilitating conditions did not significantly predict behavioral intention but, together with behavioral intention ($\beta = 0.629$, $p < 0.001$), predicted actual use ($\beta = 0.266$, $p < 0.001$). Teachers are more likely to adopt GenAI when they see clear instructional benefits and when peers and administrators encourage its use; sustained practice depends on whether institutions can provide the necessary infrastructure and training to support it. Public HEIs are urged to invest in AI literacy programs, strengthen peer and administrative endorsement, and address gaps in information and communication technology (ICT) infrastructure to support responsible and lasting GenAI integration.

Corresponding Author:

Almer B. Gamboa
College of Education, Pampanga State University
San Juan, Mexico, Pampanga, Philippines
Email: abgamboa@pampangastateu.edu.ph

1. INTRODUCTION

Generative artificial intelligence (GenAI) tools have gained significant traction in higher education globally, with institutions across different countries exploring their potential to improve teaching, streamline administrative work, and support more responsive learning environments [1]–[8]. Systems like chat generative pre-trained transformer (ChatGPT) and similar large language model-based tools have shifted rapidly from experimental instruments to practical tools, and educators are increasingly expected to engage with them as part of their professional work [6]–[8]. In higher education specifically, GenAI has been reported to assist teachers in lesson preparation, assessment design, feedback generation, and routine academic tasks, which can reduce workload and improve instructional efficiency [9]–[11]. This rapid uptake has prompted institutions worldwide to explore artificial intelligence (AI) integration as part of broader digital transformation agendas, though the success of these efforts depends heavily on whether teachers actually accept and use these tools in practice [12], [13].

Research on GenAI adoption in the Philippines has not adequately addressed teachers in public higher education institutions (HEIs). Most existing studies have focused on students or have been conducted in private or well-resourced institutions in other countries. Faculty in Philippine public HEIs face a distinct set of conditions that shape how they engage with new technologies: heavy teaching loads, large class sizes, multiple administrative responsibilities, limited digital infrastructure, and uneven internet connectivity across campuses [14], [15]. These conditions make the question of GenAI adoption among Filipino college teachers particularly relevant and underexplored in the literature.

Research on technology adoption in educational settings has consistently relied on the unified theory of acceptance and use of technology (UTAUT) as an analytical framework [16]. UTAUT explains adoption behavior through four constructs: effort expectancy, performance expectancy, social influence, and facilitating conditions, which together shape behavioral intention and actual use. The framework has been applied across a range of higher education contexts, including studies of AI and ChatGPT adoption in Indonesia [17], Somalia [18], Spain [19], and Saudi Arabia [20], and has demonstrated strong explanatory power in both developed and developing country settings [21], [22].

Most UTAUT-based studies, however, have examined student populations or faculty in private institutions with comparatively stronger resources. Studies that focus specifically on teachers in resource-constrained public universities in Southeast Asia, and the Philippines in particular, are scarce. This gap matters because teachers in public HEIs operate under conditions that are structurally different from those in private institutions, and adoption decisions in these contexts are likely shaped by factors that studies not distinguishing institution type or focusing exclusively on students cannot fully capture.

This study addresses that gap by examining GenAI adoption among faculty members from two public HEIs in Pampanga, Philippines. It identifies the levels of UTAUT constructs among these teachers, examines how these constructs relate to behavioral intention and actual use, and determines which constructs most strongly predict adoption. Guided by the UTAUT, the research objectives are to: i) describe the levels of effort expectancy, performance expectancy, social influence, facilitating conditions, behavioral intention, and actual use of GenAI tools among Filipino public higher education teachers; ii) examine the relationships between UTAUT constructs and teachers' behavioral intention and actual use of GenAI tools; and iii) identify which UTAUT constructs predict teachers' intention to adopt and actual use of GenAI tools in Philippine public HEIs. The findings provide empirical evidence grounded in the Philippine public HEI context that can inform professional development programs, institutional AI governance, and Commission on Higher Education (CHED) policy directions for responsible and sustained GenAI integration in Philippine public universities.

2. METHOD

The study employed a quantitative, cross-sectional correlational design [23] to examine the relationships among the constructs of the UTAUT and to identify predictors of GenAI adoption among public higher education teachers in the Philippines. Data were collected through a structured, UTAUT-based questionnaire consisting of two parts. The first part gathered demographic information, including sex assigned at birth, years of teaching experience, highest educational attainment, academic rank, employment status, and professional licensure. The second part measured six UTAUT constructs using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree): effort expectancy, performance expectancy, social influence, facilitating conditions, behavioral intention, and actual use. The questionnaire underwent pilot testing prior to full administration to confirm item clarity and internal consistency.

The respondents comprised 301 public higher education teachers from two public HEIs in Pampanga. The sample included 164 males (54.5%) and 137 females (45.5%). Teaching experience ranged from 1 to 30 years (mean (M) = 6.63, standard deviation (SD) = 5.70). In terms of educational attainment, 51.8% of the respondents held a bachelor's degree, 34.9% held a master's degree, and 13.3% had completed a doctoral degree. Most respondents were instructors (80.1%), followed by assistant professors (11%), associate professors (6%), and professors (3%). Regarding employment status, 54.8% were permanently employed, while 45.2% held non-permanent appointments. Teachers with at least one year of teaching experience were included. Proportional stratified random sampling was used within each institution, with strata defined by academic rank, educational attainment, and employment status. The two institutions were selected based on access and institutional willingness to participate, which introduces a convenience element into the design. The demographic profile of the sample is summarized in Table 1.

Content validity was established through review by a panel of three experts in educational technology and survey methodology, who assessed the relevance and clarity of each item before pilot testing. To assess construct validity, confirmatory factor analysis (CFA) was conducted. All factor loadings were statistically significant and ranged from 0.72 to 0.91 across constructs. Composite reliability (CR) exceeded 0.70, and average variance extracted (AVE) exceeded 0.50 for all constructs, supporting convergent validity. Internal consistency was also strong across all constructs, as shown in Table 2.

Table 1. Demographic details

Variable	Category	Frequency	Percentage (%)
Sex assigned at birth	Male	164	54.5
	Female	137	45.5
Educational attainment	Bachelor's degree	156	51.8
	Master's degree	105	34.9
	Doctoral degree	40	13.3
Academic rank	Instructor	241	80.1
	Assistant professor	33	11
	Associate professor	18	6
	Professor	9	3
Employment status	Permanent	165	54.8
	Non-permanent	136	45.2
Years of teaching (Mean ± SD)		6.63 ± 5.70	

Table 2. Reliability and validity indices of the UTAUT constructs

Construct	No. of items	Cronbach's α	CR	AVE	Factor loadings range
Effort expectancy	4	0.864	0.881	0.651	0.74-0.86
Performance expectancy	4	0.850	0.872	0.632	0.76-0.84
Social influence	4	0.904	0.917	0.735	0.82-0.90
Facilitating conditions	6	0.932	0.940	0.722	0.79-0.91
Behavioral intention	3	0.804	0.821	0.606	0.72-0.83
Actual use	3	0.844	0.860	0.671	0.78-0.87

Prior to data collection, the study received approval from the ethics review committee. Approval from the heads of the respondents' respective institutions was also sought. The questionnaire was administered through both online and printed formats to accommodate differences in access across campuses. Participation was voluntary, informed consent was obtained from all respondents, and confidentiality of responses was ensured. Data collection spanned from November to December 2024. Statistical analyses were conducted using IBM SPSS version 25. Descriptive statistics summarized respondent characteristics and construct levels. Pearson correlation analysis examined relationships among variables, and multiple linear regression identified predictors of behavioral intention and actual use. Assumptions of normality, linearity, and multicollinearity were assessed prior to analysis, and no serious violations were detected.

3. RESULTS AND DISCUSSION

3.1. Descriptive patterns of GenAI adoption

Descriptive statistics indicate high levels of agreement across all UTAUT constructs as shown in Table 3. Effort expectancy recorded the highest mean score (M = 4.50, SD = 0.57), suggesting that teachers generally perceive GenAI tools as easy to learn and use. Performance expectancy also showed a high mean (M = 4.44, SD = 0.59), indicating strong beliefs in the usefulness of AI for improving teaching effectiveness and administrative productivity. Behavioral intention registered a similarly high mean (M = 4.43, SD = 0.63), reflecting strong willingness among teachers to adopt GenAI tools. Actual use showed a high level as well (M = 4.34, SD = 0.74). Social influence (M = 4.18, SD = 0.77) and facilitating conditions (M = 4.00, SD = 0.90) showed slightly lower but still positive mean scores. The higher variability observed in facilitating conditions indicates differences in perceived institutional support, access to infrastructure, and availability of training, which may influence sustained AI use.

Table 3. Descriptive statistics of the UTAUT constructs

Construct	Mean	SD
Effort expectancy	4.50	0.57
Performance expectancy	4.44	0.59
Social influence	4.18	0.77
Facilitating conditions	4.00	0.90
Behavioral intention	4.43	0.63
Actual use	4.34	0.74

3.2. Interrelationships among UTAUT constructs

Pearson correlation analysis revealed statistically significant positive relationships among all UTAUT constructs (all $p < 0.001$; Table 4), consistent with the structure proposed by the UTAUT framework. Similar interrelationships among UTAUT constructs have been reported in prior technology adoption studies across educational contexts, including systematic evidence from university settings grounded in UTAUT and UTAUT2 models [21], [22]. Behavioral intention exhibited the strongest correlation with actual use ($r = 0.768$), confirming it as the most immediate determinant of AI adoption behavior. This pattern aligns with empirical findings on AI and ChatGPT use in higher education that consistently identify intention as a robust predictor of use behavior [17], [18], [22]. Among the antecedents of behavioral intention, performance expectancy showed the strongest association ($r = 0.737$), followed by effort expectancy ($r = 0.650$) and social influence ($r = 0.603$).

Prior studies on GenAI adoption similarly report that perceived usefulness, ease of use, and social influence contribute significantly to users' intention to adopt AI tools, particularly in university contexts [19], [21], [24]. Facilitating conditions demonstrated a moderate correlation with behavioral intention ($r = 0.520$), indicating that institutional support plays a supportive rather than primary role at the intention stage, a pattern also noted in UTAUT-based syntheses of higher education technology adoption [21], [22]. For actual use, the strongest correlations occurred with behavioral intention ($r = 0.768$), performance expectancy ($r = 0.660$), and social influence ($r = 0.634$). Facilitating conditions also showed a substantial association with actual use ($r = 0.594$), reinforcing the role of institutional readiness in enabling teachers to operationalize AI adoption, as observed in prior studies conducted in higher education and developing country contexts [21], [25], [26].

Table 4. Pearson correlation matrix of UTAUT constructs

Variable	Effort expectancy	Performance expectancy	Social influence	Facilitating conditions	Behavioral intention	Actual use
Effort expectancy	1					
Performance expectancy	0.676**	1				
Social influence	0.598**	0.657**	1			
Facilitating conditions	0.566**	0.602**	0.668**	1		
Behavioral intention	0.650**	0.737**	0.603**	0.520**	1	
Actual use	0.573**	0.660**	0.634**	0.594**	0.768**	1

**$p < 0.001$

3.3. Predictors of behavioral intention

Multiple linear regression analysis was conducted to identify predictors of behavioral intention as shown in Table 5. The model was statistically significant ($F(4, 296) = 137.50$, $p < 0.001$) and explained 65% of the variance in behavioral intention ($R^2 = 0.650$). Performance expectancy emerged as the strongest predictor ($\beta = 0.406$, $p < 0.001$), indicating that teachers are more likely to intend to adopt GenAI when they perceive clear performance benefits. Similar findings have been reported in foundational UTAUT research and in recent studies on GenAI and ChatGPT adoption, where perceived usefulness consistently shows the strongest effect on behavioral intention [19], [22]. Social influence also showed a substantial effect ($\beta = 0.295$, $p < 0.001$), suggesting that encouragement from colleagues and administrators plays an important role in shaping adoption intentions. This result aligns with empirical evidence from higher education settings that highlights the influence of peer norms and institutional signals on technology adoption decisions [21], [27], [28].

Table 5. Multiple regression results for behavioral intention

Predictor	β	p	95% confidence interval	Cohen's f²
Effort expectancy	0.257	< .001	[0.16, 0.36]	0.082 (medium)
Performance expectancy	0.406	< .001	[0.30, 0.51]	0.198 (large)
Social influence	0.295	< .001	[0.20, 0.39]	0.107 (medium)
Facilitating conditions	0.011	.814	[-0.08, 0.10]	< 0.001

$R^2 = 0.650$, adjusted $R^2 = 0.645$, $F(4,296) = 137.50$, $p < 0.001$

Effort expectancy had a significant but comparatively smaller effect ($\beta = 0.257$, $p < 0.001$), indicating that ease of use supports adoption but does not dominate adoption decisions. Prior UTAUT-based studies similarly report that ease of use facilitates intention but becomes secondary once users recognize functional value in work-related technologies [29], [30]. Facilitating conditions did not significantly predict behavioral intention (β = 0.011, p = 0.814), consistent with earlier UTAUT findings showing that facilitating conditions exert stronger influence on actual use than on intention formation, particularly in organizational and educational contexts [30], [31]. Filipino college teachers are therefore more likely to intend to adopt GenAI when they perceive clear instructional and productivity benefits and when adoption is socially encouraged, while institutional support functions as an enabling rather than motivating factor at the intention stage [20], [21], [32].

3.4. Prediction of actual use

A second regression analysis examined predictors of actual use as shown in Table 6. Consistent with the UTAUT theoretical structure, which identifies behavioral intention and facilitating conditions as the primary direct predictors of use behavior, these two variables were entered first. The model was statistically significant ($F(2, 298) = 266.60$, $p < 0.001$) and explained 64.1% of the variance in actual use ($R^2 = 0.641$). Behavioral intention demonstrated a strong positive effect (β = 0.629, $p < 0.001$), confirming its role as the primary driver of actual AI use. Facilitating conditions also showed a significant effect (β = 0.266, $p < 0.001$), indicating that access to infrastructure, training, and technical support enables teachers to translate intention into practice. When effort expectancy, performance expectancy, and social influence were added to the model, the explained variance increased to 66.8% ($R^2 = 0.668$). In this expanded model, behavioral intention (β = 0.455, $p < 0.001$), social influence (β = 0.190, $p < 0.001$), and facilitating conditions (β = 0.164, $p < 0.001$) remained significant predictors, while effort expectancy and performance expectancy did not retain significance, indicating that their effects on actual use operate indirectly through behavioral intention rather than exerting direct influence.

These results suggest that while teachers may form intentions based on perceived usefulness and social encouragement, sustained and regular use depends on both intention and institutional support. This pattern mirrors empirical findings from UTAUT-based studies on AI and ChatGPT adoption, which show facilitating conditions as a stronger determinant of use behavior than of intention [21], [22]. In the Philippine public higher education context, uneven access to infrastructure, training, and technical support may constrain the translation of intention into consistent practice [33], [34]. Inconsistent internet access, limited learning management system integration, and unequal device availability can prevent motivated teachers from using GenAI regularly without adequate institutional backing [33], [34]. The overall pattern of relationships among the UTAUT constructs and their respective outcomes is summarized in Figure 1.

Table 6. Multiple regression results for actual use

Predictor	β	p	95% confidence interval	Cohen's f^2
Behavioral intention	0.629	< .001	[0.53, 0.72]	0.437 (large)
Facilitating conditions	0.266	< .001	[0.19, 0.35]	0.126 (large)

$R^2 = 0.641$, adjusted $R^2 = 0.639$, $F(2,298) = 266.60$, $p < 0.001$

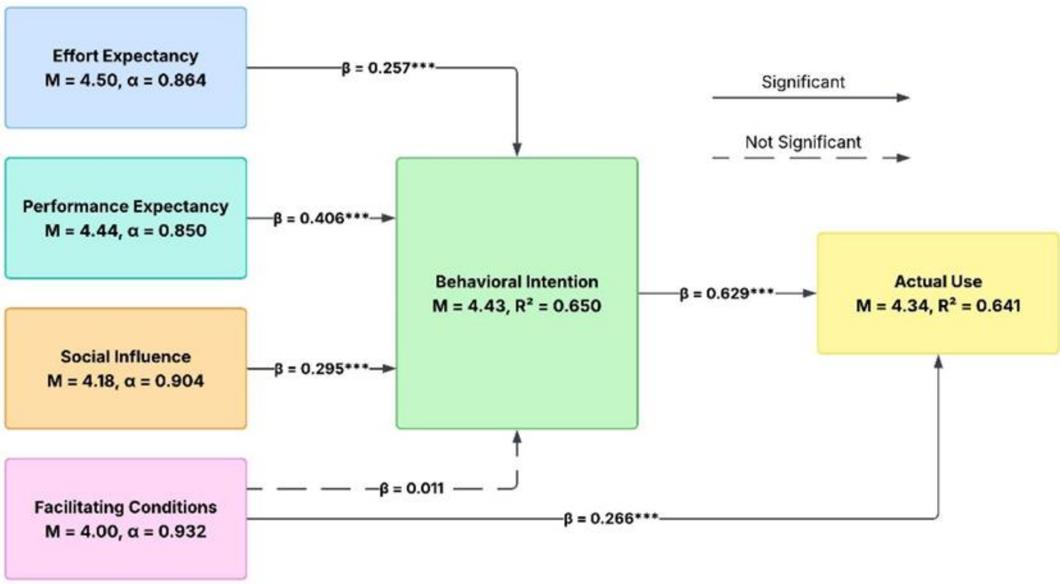

Figure 1. UTAUT path diagram of regression results

4. CONCLUSION

This study examined the levels, relationships, and predictors of GenAI adoption among Filipino public higher education teachers using the UTAUT. Teachers reported high levels across all UTAUT constructs, reflecting widespread acceptance and active use of GenAI tools among faculty in Philippine public HEIs. Correlation and regression analyses revealed that performance expectancy and social influence were the strongest predictors of behavioral intention, while behavioral intention and facilitating conditions primarily determined actual use. Filipino college teachers are more likely to adopt GenAI when they perceive clear instructional and productivity benefits and when adoption is reinforced by peer and administrative support within their institutions. Sustained use further depends on the availability of institutional resources, infrastructure, and technical support, which remain uneven across public HEIs in the Philippines. These findings should be read with the recognition that the study was conducted in only two public HEIs selected partly on the basis of access; the cross-sectional design cannot establish causal relationships, and actual use was measured through self-report rather than observed behavior, which may inflate use estimates. Since performance expectancy is the strongest driver of adoption intention, institutions should demonstrate the concrete instructional and productivity value of GenAI through faculty orientations, peer showcases, and discipline-specific training. Administrative and peer endorsement are equally important for building a culture where GenAI use is normalized in teaching practice, while sustained use requires that infrastructure and training are consistently available, not just formally prescribed. At the national level, CHED should integrate GenAI literacy into faculty development programs and connect AI adoption to workload reform initiatives, recognizing that tools reducing time spent on lesson preparation, assessment, and feedback can address one of the sector’s most persistent problems. AI governance frameworks for public universities should be grounded in the actual experiences and constraints of faculty, ensuring that innovation is pursued responsibly and that support structures accompany policy mandates.

ACKNOWLEDGEMENTS

This study was supported by Pampanga State University.

FUNDING INFORMATION

This study is funded by Pampanga State University.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Almer B. Gamboa	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓
John Paul P. Miranda	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

The author declares that there are no known conflicts of interest associated with this publication. There are no financial or personal relationships that could inappropriately influence or bias the content of this work.

INFORMED CONSENT

The authors obtained informed consent from all individuals included in this study. Participation was voluntary, and all participants were informed about the study procedures and their right to withdraw at any time. Their confidentiality and privacy were maintained throughout the study.

ETHICAL APPROVAL

The research complied with the tenets of the Belmont Report, Helsinki Declaration, and the Philippine Data Privacy Act of 2012.

DATA AVAILABILITY

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

REFERENCES

[1] M. Belkina *et al.*, "Implementing generative AI (GenAI) in higher education: a systematic review of case studies," *Computers and Education: Artificial Intelligence*, vol. 8, 2025, doi: 10.1016/j.caeai.2025.100407.

[2] D. M. Tbaishat and M. W. Elfadel, "Exploring students' perceptions of GenAI tools in higher education: a case study," *Cogent Education*, vol. 12, no. 1, Dec. 2025, doi: 10.1080/2331186X.2025.2560613.

[3] S. S. Lee and R. L. Moore, "Harnessing generative AI (GenAI) for automated feedback in higher education: a systematic review," *Online Learning Journal*, vol. 28, no. 3, pp. 82–104, Sep. 2024, doi: 10.24059/olj.v28i3.4593.

[4] M. Mariani and Y. K. Dwivedi, "Generative artificial intelligence in innovation management: a preview of future research developments," *Journal of Business Research*, vol. 175, 2024, doi: 10.1016/j.jbusres.2024.114542.

[5] M. Moundridou, N. Matzakos, and S. Doukakis, "Generative AI tools as educators' assistants: designing and implementing inquiry-based lesson plans," *Computers and Education: Artificial Intelligence*, vol. 7, 2024, doi: 10.1016/j.caeai.2024.100277.

[6] M. Giannakos *et al.*, "The promise and challenges of generative AI in education," *Behaviour and Information Technology*, vol. 44, no. 11, pp. 2518–2544, Jul. 2025, doi: 10.1080/0144929X.2024.2394886.

[7] A. Yusuf, N. Pervin, and M. R. -González, "Generative AI and the future of higher education: a threat to academic integrity or reformation? evidence from multicultural perspectives," *International Journal of Educational Technology in Higher Education*, vol. 21, no. 1, 2024, doi: 10.1186/s41239-024-00453-6.

[8] H. Wang, A. Dang, Z. Wu, and S. Mac, "Generative AI in higher education: seeing ChatGPT through universities' policies, resources, and guidelines," *Computers and Education: Artificial Intelligence*, vol. 7, 2024, doi: 10.1016/j.caeai.2024.100326.

[9] X. Tan, G. Cheng, and M. H. Ling, "Artificial intelligence in teaching and teacher professional development: a systematic review," *Computers and Education: Artificial Intelligence*, vol. 8, 2025, doi: 10.1016/j.caeai.2024.100355.

[10] W. N. Alwakid, N. A. Dahri, M. Humayun, and G. N. Alwakid, "Exploring the role of AI and teacher competencies on instructional planning and student performance in an outcome-based education system," *Systems*, vol. 13, no. 7, 2025, doi: 10.3390/systems13070517.

[11] D. K. Mah, N. Knoth, and M. Egloffstein, "Perspectives of academic staff on artificial intelligence in higher education: exploring areas of relevance," *Frontiers in Education*, vol. 10, 2025, doi: 10.3389/feduc.2025.1484904.

[12] D. T. K. Ng, E. K. C. Chan, and C. K. Lo, "Opportunities, challenges and school strategies for integrating generative AI in education," *Computers and Education: Artificial Intelligence*, vol. 8, 2025, doi: 10.1016/j.caeai.2025.100373.

[13] J. Xu, R. Shen, M. Tian, and D. Hu, "A multi-method study on influencing factors of teachers' willingness to use generative artificial intelligence," *Interactive Learning Environments*, vol. 34, no. 4, pp. 1–19, Jul. 2025, doi: 10.1080/10494820.2025.2535680.

[14] H. O. Tarraya, "Teachers' workload policy: its impact on Philippine public school teachers (public policy analysis and review)," *Puissant*, vol. 5, pp. 1614–1629, 2024.

[15] J. Chan and S. Walker, "Filipino teachers need workload reform," opinion.inquirer.net, Dec. 2024. Accessed: Dec. 14, 2025. [Online]. Available: https://opinion.inquirer.net/179491/filipino-teachers-need-workload-reform

[16] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: toward a unified view," *MIS Quarterly: Management Information Systems*, vol. 27, no. 3, pp. 425–478, Sep. 2003, doi: 10.2307/30036540.

[17] Helmiatin, A. Hidayat, and M. R. Kahar, "Investigating the adoption of AI in higher education: a study of public universities in Indonesia," *Cogent Education*, vol. 11, no. 1, Dec. 2024, doi: 10.1080/2331186X.2024.2380175.

[18] A. N. M. Abdi, A. M. Omar, M. H. Ahmed, and A. A. Ahmed, "The predictors of behavioral intention to use ChatGPT for academic purposes: evidence from higher education in Somalia," *Cogent Education*, vol. 12, no. 1, Dec. 2025, doi: 10.1080/2331186X.2025.2460250.

[19] F. J. Miranda and A. C. -Mera, "Exploring the adoption of generative artificial intelligence tools among university teachers," *Higher Education Research and Development*, vol. 45, no. 3, pp. 1–17, Oct. 2025, doi: 10.1080/07294360.2025.2559648.

[20] D. M. Bamasoud, R. Mohammad, and S. Bilal, "Adopting generative AI in higher education: a dual-perspective study of students and lecturers in Saudi Universities," *Big Data and Cognitive Computing*, vol. 9, no. 10. 2025, doi: 10.3390/bdcc9100264.

[21] B. G. A.-Enriquez *et al.*, "Acceptance of artificial intelligence in university contexts: a conceptual analysis based on UTAUT2 theory," *Heliyon*, vol. 10, no. 19, 2024, doi: 10.1016/j.heliyon.2024.e38315.

[22] D. Menon and K. Shilpa, "'Chatting with ChatGPT': analyzing the factors influencing users' intention to use OpenAI's ChatGPT using the UTAUT model," *Heliyon*, vol. 9, no. 11, Nov. 2023, doi: 10.1016/j.heliyon.2023.e20962.

[23] X. Wang and Z. Cheng, "Cross-sectional studies: strengths, weaknesses, and recommendations," *Chest*, vol. 158, no. 1, pp. 65–71, Jul. 2020, doi: 10.1016/j.chest.2020.03.012.

[24] H. Lu, L. He, H. Yu, T. Pan, and K. Fu, "A study on teachers' willingness to use generative AI technology and its influencing factors: based on an integrated model," *Sustainability*, vol. 16, no. 16. 2024, doi: 10.3390/su16167216.

[25] M. M. Rana, M. S. Siddiqee, M. N. Sakib, and M. R. Ahamed, "Assessing AI adoption in developing country academia: a trust and privacy-augmented UTAUT framework," *Heliyon*, vol. 10, no. 18, 2024, doi: 10.1016/j.heliyon.2024.e37569.

[26] U. J. Ofem *et al.*, "Teachers' preparedness for the utilization of artificial intelligence in classroom assessment: the contributory effects of attitude toward technology, technological readiness, and pedagogical beliefs with perceived ease of use and perceived usefulness as mediators," *Frontiers in Education*, vol. 10, 2025, doi: 10.3389/feduc.2025.1568306.

[27] J. J. S. -Alonso, V. M. H. Rivero, A. L. S. Mesa, and A. B. Aguilar, "Adoption of digital educational resources by early childhood education teachers: a fad or a conviction?," *Computers and Education*, vol. 238, 2025, doi: 10.1016/j.compedu.2025.105396.

[28] J. Zhao, S. Li, and J. Zhang, "Understanding teachers' adoption of AI technologies: an empirical study from Chinese middle schools," *Systems*, vol. 13, no. 4, 2025, doi: 10.3390/systems13040302.
[29] L. Xue, A. M. Rashid, and S. Ouyang, "The unified theory of acceptance and use of technology (UTAUT) in higher education: a systematic review," *SAGE Open*, vol. 14, no. 1, Jan. 2024, doi: 10.1177/21582440241229570.
[30] K. P. Gupta, "Understanding teachers' intentions and use of AI tools for research," *Journal of E-Learning and Knowledge Society*, vol. 20, no. 2, pp. 13–25, 2024, doi: 10.20368/1971-8829/1135969.
[31] H. Moradi, "Integrating AI in higher education: factors influencing ChatGPT acceptance among Chinese university EFL students," *International Journal of Educational Technology in Higher Education*, vol. 22, no. 1, pp. 1–25, Jun. 2025, doi: 10.1186/s41239-025-00530-4.
[32] M. B. Garcia, "Factors affecting adoption intention of productivity software applications among teachers: a structural equation modeling investigation," *International Journal of Human-Computer Interaction*, vol. 40, no. 10, pp. 2546–2559, May 2024, doi: 10.1080/10447318.2022.2163565.
[33] R. A. O. -D. Cruz and R. Z. D. Cruz, "AI integration in IT education: challenges, opportunities, and future directions," *Journal of Teaching and Learning*, vol. 19, no. 4, pp. 6–19, 2025, doi: 10.22329/jtl.v19i4.9362.
[34] A. S. Espartinez, "Between innovation and tradition: a narrative inquiry of students' and teachers' experiences with ChatGPT in Philippine higher education," *Social Sciences*, vol. 14, no. 6, 2025, doi: 10.3390/socsci14060359.

BIOGRAPHIES OF AUTHORS

Almer B. Gamboa is the student services coordinator for the Mexico campus at Pampanga State University, Philippines. He holds doctorate in education, major in educational management. His research interests are in professional education, AI in education, and educational technology. He can be contacted at email: abgamboa@pampangastateu.edu.ph.

John Paul P. Miranda is an associate professor at Pampanga State University, Philippines. His publications are indexed in Scopus, Web of Science, ACM, and IEEE databases. His research interests include data analytics, AI in education, educational technology, and digital transformation. He can be contacted at email: jppmiranda@pampangastateu.edu.ph.