

Research Article

Demographic Determinants of AI Utilization in Higher Education: Evidence from SUCs in Davao City

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Abstract

This study examined whether demographic characteristics significantly influence the Actual System Use (ASU) of Artificial Intelligence (AI) in instruction among faculty members in State Universities and Colleges (SUCs) in Davao City. Anchored on the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology, the study employed a quantitative descriptive-comparative design using survey responses from 188 faculty members. Independent samples t-test, one-way ANOVA, and Tukey's HSD post hoc analysis were utilized to determine differences in ASU across demographic groups. Results revealed no significant differences in AI utilization based on gender and academic discipline, with only small to negligible effect sizes. In contrast, significant differences with moderate to large effect sizes were observed across age, years of teaching, and salary grade. Post hoc analyses further showed that younger, less experienced, and lower-ranked faculty demonstrated significantly higher levels of AI utilization compared to older and more senior faculty members. These findings suggest that AI adoption in higher education is shaped more strongly by career-stage dynamics and institutional roles than by gender or disciplinary background. The study highlights the need for differentiated faculty development initiatives, mentoring programs, and targeted institutional support mechanisms to promote equitable and sustainable AI integration in higher education.

Keywords: Artificial Intelligence, Higher Education, Technology Adoption, Actual System Use, TAM, UTAUT, Digital Divide, Faculty Development

1. Introduction

Artificial Intelligence (AI) is rapidly transforming higher education through applications such as intelligent tutoring systems, automated assessment, adaptive learning environments, and generative AI-assisted instruction. Recent developments in generative AI technologies have intensified institutional interest in AI integration due to their potential to enhance instructional efficiency, personalize learning experiences, and support academic productivity (Dwivedi et al., 2023; Bond et al., 2023; Zawacki-Richter et al. (2019). Within higher education, faculty members play a central role in determining whether these technologies are meaningfully integrated into teaching practice. Consequently, understanding the factors that influence faculty AI utilization has become an increasingly important area of educational technology research.

While numerous studies have examined perceptions, attitudes, and behavioral intentions toward AI adoption, considerably fewer studies have investigated Actual System Use (ASU), particularly within developing-country contexts where technological infrastructure, institutional support, and digital readiness remain uneven. Despite extensive research on AI acceptance, limited empirical evidence exists on actual system use across demographic groups in developing contexts. This gap is particularly significant because intention to use does not always translate into sustained or observable instructional integration of AI technologies (Davis, 1989; Scherer et al., 2019).

The present study is theoretically anchored in the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology, both of which explain how individual and contextual factors influence technology adoption behavior. In TAM, Actual System Use represents the behavioral outcome resulting from perceived usefulness, perceived ease of use, attitudes, and behavioral intention (Davis, 1989). Similarly, UTAUT identifies demographic and contextual variables such as age, experience, and facilitating conditions as important determinants of technology usage behavior (Venkatesh et al., 2003). Guided by these frameworks, the present study operationalizes ASU as the observable level of faculty engagement with AI tools in instructional practice. Prior literature suggests that demographic characteristics may significantly shape technology adoption patterns.

Younger and early-career educators tend to demonstrate greater technological adaptability and experimentation with digital innovations, whereas more experienced faculty may encounter barriers associated with established teaching routines, workload demands, and lower technological self-efficacy (König et al., 2020; Oreg et al., 2018). At the same time, recent studies indicate that traditional disparities based on gender and academic discipline may be diminishing as AI tools become increasingly accessible and institutionally supported (Chiu, 2022; Zheng et al., 2025).

Within the Philippine higher education context, research examining demographic variations in AI utilization remains limited despite growing institutional interest in digital transformation. Most local studies continue to focus on technology acceptance or readiness rather than actual instructional usage behavior. This limitation restricts understanding of how AI integration

differs across faculty groups and whether institutional adoption is occurring equitably. Furthermore, emerging international literature from 2022–2025 increasingly emphasizes that AI adoption is influenced not only by technological access but also by career-stage dynamics, professional role expectations, and institutional ecosystems (Dwivedi et al., 2023; Huang et al., 2022; Zheng et al., 2025). Addressing this gap, the present study examines whether significant differences exist in Actual System Use of AI among faculty members in State Universities and Colleges (SUCs) in Davao City when grouped according to gender, age, years of teaching, salary grade, and academic discipline. By shifting attention from behavioral intention toward actual instructional usage, this study contributes empirical evidence to the growing discourse on AI integration in higher education and provides insights for developing more inclusive and sustainable institutional AI strategies.

2. Materials and Methods

2.1 Research Design

This study employed a quantitative descriptive–comparative research design to examine differences in the Actual System Use (ASU) of Artificial Intelligence (AI) among faculty across selected demographic variables.

2.2 Research Participants

A total of 188 full-time faculty members from the University of Southeastern Philippines and the City College of Davao participated in the study, selected through purposive sampling based on the criteria that they were actively engaged in instructional duties and provided informed consent. Data were collected using a structured questionnaire grounded in the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT).

2.3 Research Instruments

The instrument included demographic variables and an ASU scale derived from a validated multi-construct instrument originally consisting of 36 items. Responses were measured using a five-point Likert scale. Content validity was established through expert review, while construct validity was confirmed using Principal Component Analysis (PCA) with Promax rotation, retaining items with factor loadings $\geq .40$. Reliability testing showed acceptable internal consistency, with Cronbach's alpha values exceeding the recommended .70 threshold for research instruments (Nunnally & Bernstein, 1994), indicating that the instrument was suitable for measuring AI utilization.

2.4 Data Collection

Data collection was conducted over a six- to eight-week period through both online and face-to-face administration, with all responses screened for completeness and consistency prior to analysis.

2.5 Data Analysis

All analyses were conducted at a .05 level of significance, with effect sizes (Cohen's d and η^2) reported to determine practical significance. Assumptions of parametric testing were verified prior to analysis: normality was confirmed through acceptable skewness and kurtosis values, and homogeneity of

variance was established using Levene's test. These procedures ensured the validity, reliability, and robustness of the statistical findings.

2.6 Ethical Considerations

Ethical standards were strictly observed, including informed consent, voluntary participation, confidentiality, and compliance with the Data Privacy Act 10173 of 2012. For statistical analysis, an independent samples t-test and one-way ANOVA were used to examine group differences, followed by Tukey's HSD post hoc tests for significant results.

3. Results

Group comparisons were conducted to determine whether Actual System Use (ASU) of AI differs across demographic variables (see Table 1). Result shows that no statistically significant difference in ASU was observed between male and female faculty, $t(186) = 1.65$, $p = .102$, $d = .151$, indicating a small effect size. This suggests that gender has minimal practical influence on AI utilization in this context. The absence of gender differences implies that access to AI tools, institutional support, and training opportunities are relatively equitable across male and female faculty, resulting in comparable levels of engagement. This finding supports prior research indicating that gender-based disparities in technology adoption tend to diminish when structural and institutional conditions are standardized (Teo et al. 2019; Yuen et al., 2021; Zheng et al., 2025). In contrast, age demonstrated a statistically significant effect on ASU, $F(4, 183) = 7.02$, $p < .001$, $\eta^2 = .125$, indicating a moderate effect size. This suggests that approximately 12.5% of the variance in AI utilization can be attributed to age differences, reflecting a meaningful practical impact. The higher levels of AI use among younger faculty indicate not only greater familiarity with digital tools but also increased adaptability to emerging technologies. This pattern may be explained by differences in professional socialization, where younger faculty are more likely to have been exposed to AI-related tools during their academic training and early career development.

Prior studies similarly note that generational differences in technological engagement are shaped by both exposure and evolving pedagogical expectations (Oh & Reeves, 2014; König et al., 2020). Years of teaching experience also yielded a significant effect on ASU, $F(3, 184) = 4.92$, $p = .003$, $\eta^2 = .063$, representing a moderate effect size. Although smaller than the effect of age, this indicates that teaching experience accounts for a meaningful portion of variance in AI use. Faculty with fewer years of experience reported higher AI utilization, suggesting that early-career educators are more inclined to integrate emerging technologies into instruction. This may reflect greater openness to innovation, fewer established teaching routines, and stronger alignment with current digital pedagogies.

Conversely, more experienced faculty may encounter structural and cognitive barriers, such as established instructional habits, competing responsibilities, or limited exposure to recent technological developments (Oreg et al., 2018; Teo et al., 2019). Similarly, salary grade showed a significant effect on ASU, $F(3, 184) = 7.70$, $p < .001$, $\eta^2 = .191$, indicating a large effect size. This suggests that nearly 19.1% of the variance in AI use is associated with

differences in professional rank, making it the strongest predictor among the demographic variables examined. Lower-ranked faculty demonstrated higher AI utilization, which may be attributed to stronger incentives for innovation, greater involvement in direct teaching activities, and increased motivation to adopt technologies that enhance instructional effectiveness. In contrast, higher-ranked faculty may allocate more time to administrative and leadership roles, reducing opportunities for hands-on experimentation with AI tools. This pattern aligns with evidence suggesting that organizational roles and career progression significantly influence engagement with technological innovation (Huang et al., 2022).

Table 1. Group Differences by Demographics

Demographic Variable	Test	t / F	p-value	Effect Size	Interpretation
Gender (Male vs. Female)	t-test	1.645	.102	$d = 0.151$	Small effect
Age Group (5 categories)	ANOVA	7.016	.000	$\eta^2 = 0.125$	Medium effect
Years of Teaching (4 groups)	ANOVA	4.915	.003	$\eta^2 = 0.063$	Medium effect
Salary Grade (4 groups)	ANOVA	7.703	.000	$\eta^2 = 0.191$	Large effect
Field of Discipline (5 groups)	ANOVA	0.715	.583	$\eta^2 = 0.014$	Negligible effect

Note: d = Cohen's d ; η^2 = eta squared. Effect size interpretations follow Cohen (1988).

No significant differences in ASU were found across academic disciplines, $F(4, 183) = 0.72$, $p = .583$, $\eta^2 = .014$, indicating a negligible effect size. This suggests that disciplinary background contributes minimally to variations in AI utilization. The uniformity of AI use across fields indicates that AI technologies are being applied broadly rather than remaining confined to traditionally technology-oriented disciplines. This reflects the increasing versatility of AI tools, which support diverse instructional functions across both scientific and humanities contexts. Similar trends have been reported in the literature, where AI adoption is characterized as discipline-neutral due to its wide-ranging pedagogical applications (Zawacki-Richter et al., 2019).

Collectively, these findings indicate that career-stage variables (age, experience, and rank) exert substantially greater influence on AI utilization than demographic attributes such as gender and discipline. This highlights the importance of professional lifecycle factors in shaping technology adoption behavior within higher education.

Post Hoc Analysis

To further examine the observed group differences, Tukey's HSD post hoc tests were conducted for age, years of teaching, and salary grade (see Table 2). For age, younger faculty (under 25) demonstrated significantly higher AI use compared to those aged 36–45 ($p = .003$), 46–55 ($p = .003$), and 56 and above ($p = .001$). Additionally, faculty aged 26–35 reported higher AI use than those aged 56 and above ($p = .010$). These results indicate a clear generational gradient,

where AI utilization decreases progressively with age. This pattern suggests that differences are not solely due to familiarity with technology, but also reflect varying levels of engagement with evolving instructional practices. Younger faculty are more likely to experiment with AI as part of contemporary teaching approaches, whereas older faculty may rely more on established pedagogical methods. Furthermore, differences in training opportunities and professional expectations across career stages may reinforce this divide (Koumachi, 2019; König et al., 2020).

In terms of teaching experience, faculty with less than five years of experience reported significantly higher AI use than those with 10–15 years ($p = .022$) and more than 15 years ($p = .003$). This finding reinforces the interpretation that early-career faculty are more active adopters of AI technologies. Beyond generational explanations, this pattern may also be driven by career incentives, as newer faculty may be more motivated to integrate innovative tools to enhance teaching effectiveness, student engagement, and professional advancement. In contrast, experienced faculty may face constraints related to workload, role complexity, or limited access to targeted professional development for emerging technologies. For salary grade, faculty in Salary Grades 11–15 reported significantly higher AI utilization compared to those in Salary Grades 16–20 ($p < .001$). This difference suggests that professional rank influences both opportunity and motivation to adopt AI. Lower-ranked faculty are more likely to engage directly in instructional delivery and may have stronger incentives to incorporate innovative practices. Conversely, higher-ranked faculty often assume administrative or supervisory roles, which may reduce direct engagement with classroom technologies. This structural difference in role expectations provides a plausible explanation for the observed variation in AI use.

Table 2. Post Hoc Comparison for Actual System Use by Significant Demographics Groups

Demographic Variable	Group Comparison	Mean Difference	p-value	Interpretation
Age Group	Under 25 vs. 36-45	+0.5318	.003	Younger faculty reported higher AI use
	Under 25 vs. 46-55	+0.5448	.003	
	Under 25 vs. 56 and above	+0.9971	.001	
	26-35 vs. 56 and above	+0.7171	.010	
Years of Teaching	< 5 yrs vs. 10-15 yrs	+0.3718	.022	Less experienced faculty showed higher AI use
	< 5 yrs vs. >15 yrs	+0.3885	.003	
Salary Grade	SG 11–15 vs. SG 16–20	+0.4654	.000	Lower-salary faculty reported higher AI usage

Note. p-values are based from Tukey's HSD post hoc comparison. Only significant pairwise comparisons ($p < .05$) are shown.

The results demonstrate that AI utilization in higher education is not uniformly distributed but is strongly shaped by career-stage dynamics. Younger, less experienced, and lower-ranked faculty consistently exhibit higher levels of engagement with AI tools. These patterns suggest that differences in exposure, motivation, institutional roles, and professional expectations collectively influence adoption behavior. From an institutional perspective, these findings indicate that a one-size-fits-all approach to AI integration is insufficient. Instead, targeted strategies are necessary, such as differentiated training programs for senior faculty, mentorship systems leveraging younger faculty, and workload adjustments that enable broader participation in AI-driven instructional innovation.

4. Conclusion

This study provides empirical evidence that the use of Artificial Intelligence (AI) in instruction among faculty in State Universities and Colleges (SUCs) is differentially influenced by career-stage variables rather than basic demographic characteristics. The findings revealed that gender and academic discipline do not exert meaningful influence on Actual System Use (ASU), indicating that AI adoption has become relatively equitable and discipline-neutral within the institutional context examined. This suggests that when access, infrastructure, and training opportunities are comparable, disparities across these variables are minimized. In contrast, age, years of teaching experience, and salary grade demonstrated moderate to large effect sizes, indicating that these variables account for a substantive proportion of variance in AI utilization. Among these, salary grade emerged as the strongest predictor, highlighting the significant role of institutional position and professional responsibilities in shaping engagement with AI technologies. Younger, less experienced, and lower-ranked faculty consistently reported higher levels of AI use, reflecting differences in technological exposure, adaptability, and role expectations. These findings underscore that AI adoption in higher education is fundamentally shaped by professional lifecycle dynamics. Early-career faculty appear to function as primary drivers of AI integration, while more senior faculty may encounter structural and practical constraints, including administrative workload, established teaching practices, and limited access to targeted upskilling opportunities. The overall results demonstrate that effect size magnitude—not merely statistical significance—confirms the practical importance of career-stage variables in explaining disparities in AI use. Consequently, achieving equitable and sustainable AI integration requires institutional strategies that move beyond uniform implementation and instead address these differentiated needs.

5. Recommendations

Based on the findings, the following recommendations are proposed to support more effective and inclusive AI integration in higher education:

1. Faculty Mentoring Programs
 - Institutions should establish structured mentoring systems where younger and early-career faculty serve as AI integration mentors to more experienced colleagues. This peer-assisted approach leverages existing

expertise while fostering collaborative learning environments that reduce resistance to technological change.

2. Career-Stage–Differentiated AI Training

Professional development programs should be tailored according to career stage:

- Early-career faculty: Advanced AI integration, innovation in pedagogy, and research applications
- Mid-career faculty: Applied AI tools for instructional efficiency and student engagement
- Senior faculty: Foundational AI literacy, simplified tool adoption, and administrative applications
- Such differentiation ensures that training is relevant, accessible, and responsive to varying needs, addressing the moderate-to-large effects observed for age and experience.

3. Incentive Systems for AI Adoption

Institutions should implement formal incentive structures to encourage AI integration across all faculty ranks. These may include:

- Recognition in performance evaluation systems
- Teaching innovation grants
- Reduced workload or teaching credits for AI-based course redesign
- Awards for technology-enhanced instruction

Given the large effect of salary grade ($\eta^2 = .191$), incentives are particularly important in motivating higher-ranked faculty to engage in AI adoption.

4. Workload and Role Adjustment Policies

To address structural barriers, institutions should consider balancing administrative and teaching responsibilities, particularly for senior faculty. Providing time and institutional support for experimentation with AI tools can reduce disparities in usage.

5. Continuous Institutional Support Systems

Universities should establish ongoing AI support mechanisms, including:

- Dedicated AI resource centers
- Technical assistance teams
- Regular workshops and updating sessions
- Sustained support ensures that AI adoption is not a one-time initiative but an evolving institutional practice.

6. Limitations of the Study

Despite providing meaningful insights into demographic differences in Artificial Intelligence (AI) utilization among faculty, this study is subject to several limitations that should be considered when interpreting the findings. First, the study relied on self-reported data to measure Actual System Use (ASU) of AI. While widely used in technology adoption research, self-reported measures may be influenced by social desirability bias, recall bias, or overestimation of

actual usage behaviors. As such, the reported levels of AI use may not fully reflect objective or system-logged usage patterns. Second, the research employed a cross-sectional design, capturing faculty responses at a single point in time. This limits the ability to establish causal relationships or observe changes in AI adoption over time. Given the rapidly evolving nature of AI technologies, usage patterns may shift as faculty gain more exposure, training, or institutional support. Third, the study was conducted exclusively among faculty from State Universities and Colleges (SUCs) in Davao City, which may limit the generalizability of the findings. Institutional contexts, resource availability, and organizational cultures vary across regions and types of higher education institutions. Therefore, the results may not be fully representative of private universities or institutions in other geographic areas. Fourth, while the study examined key demographic variables such as age, gender, years of teaching, salary grade, and academic discipline, other potentially influential factors were not included. Variables such as digital literacy, access to technological infrastructure, prior AI training, institutional policies, and attitudes toward innovation may also significantly affect AI utilization but were beyond the scope of this analysis. Fifth, although significant differences were identified through ANOVA and post hoc analyses, the study did not incorporate multivariate or predictive modeling approaches (e.g., regression or structural equation modeling) that could account for the combined effects of multiple variables. As a result, the findings are limited to group comparisons rather than comprehensive explanatory relationships. Finally, the study focused specifically on quantitative measures of AI use, which may not fully capture the depth and context of how AI is integrated into teaching practices. Qualitative approaches, such as interviews or classroom observations, could provide richer insights into the motivations, challenges, and pedagogical implications of AI adoption. In light of these limitations, future research is encouraged to employ longitudinal designs, mixed-method approaches, and broader sampling frameworks, as well as incorporate additional variables and objective usage data to develop a more comprehensive understanding of AI integration in higher education.

Supplementary Details

Conflicts of Interest:

The authors declare no conflict of interest.

Disclosure Statement:

The author acknowledges the use of Grammarly to refine sentence structure, Quillbot to paraphrase content for academic purposes, Turnitin to ensure originality and uphold academic integrity, and ChatGPT to enhance language expression. While these AI tools assisted in various aspects of writing, the author affirms that all AI-generated outputs were thoroughly reviewed and validated. The author accepts full responsibility for the content, accuracy, and integrity of this work, in accordance with COPE guidelines.

References

- Bond, M., Bedenlier, S., Marín, V. I., & Händel, M. (2023). Emergency remote teaching in higher education: Mapping the first global online semester. *International Journal of Educational Technology in Higher Education*, 20(1), 1–24. <https://doi.org/10.1186/s41239-021-00282-x>

- Chiu, T. K. F. (2022). Applying the self-determination theory (SDT) to explain student engagement in online learning during the COVID-19 pandemic. *Journal of Research on Technology in Education*, 54(S1), S14–S30. <https://doi.org/10.1080/15391523.2021.1891998>
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. <https://doi.org/10.2307/249008>
- Dwivedi, Y. K., Hughes, D. L., Rana, N. P., Slade, E. L., & Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57, 101994. <https://doi.org/10.1016/j.ijinfomgt.2019.08.002>
- Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, K. A., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., ... Wright, R. (2023). “So what if ChatGPT wrote it?” Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, 71, 102642. <https://doi.org/10.1016/j.ijinfomgt.2023.102642>
- Huang, J., Saleh, S., & Liu, Y. (2022). Examining faculty adoption of artificial intelligence in higher education: The role of motivation and institutional support. *Computers & Education: Artificial Intelligence*, 3, 100089. <https://doi.org/10.1016/j.caeai.2022.100089>
- König, J., Jäger-Biela, D. J., & Glutsch, N. (2020). Adapting to online teaching during COVID-19 school closure: Teacher education and teacher competence effects among early career teachers in Germany. *European Journal of Teacher Education*, 43(4), 608–622. <https://doi.org/10.1080/02619768.2020.1809650>
- Koumachi, B. (2019). Digital natives and digital immigrants: Myth or reality? *International Journal of Technology in Education*, 2(2), 45–52.
- Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.
- Oh, E., & Reeves, T. C. (2014). Generational differences and the integration of technology in learning environments. *Educational Technology Research and Development*, 62(5), 619–640. <https://doi.org/10.1007/s11423-014-9353-0>
- Oreg, S., Vakola, M., & Armenakis, A. (2018). Change recipients’ reactions to organizational change: A 60-year review of quantitative studies. *Journal of Applied Behavioral Science*, 54(1), 5–38. <https://doi.org/10.1177/0021886317714271>
- Teo, T., Ursavaş, Ö. F., & Bahçekapılı, T. (2019). Efficiency of the technology acceptance model to explain pre-service teachers’ intention to use technology: A Turkish study. *Educational Technology & Society*, 22(3), 1–13.
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>

- Yuen, A. H. K., Cheng, M., & Chan, C. K. K. (2021). Gender differences in technology adoption in higher education: A global perspective. *Computers & Education*, 168, 104192. <https://doi.org/10.1016/j.compedu.2021.104192>
- Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education. *International Journal of Educational Technology in Higher Education*, 16(1), 39. <https://doi.org/10.1186/s41239-019-0171-0>
- Zheng, B., Lin, C. H., & Kwon, J. B. (2025). Artificial intelligence adoption in higher education: Examining demographic and institutional influences. *Computers & Education: Artificial Intelligence*, 6, 100180. <https://doi.org/10.1016/j.caeai.2024.100180>
- Cite as:** Alo, R. (2026). Demographic Determinants of AI Utilization in Higher Education: Evidence from SUCs in Davao City. *International Journal of Multidisciplinary Studies in Higher Education*, 3(2), 29–39. <https://doi.org/10.70847/731848>