

Review

Appropriating AI Tools in the Academic Workplace: Evaluation, Adaptation, and Incorporation among College Teachers

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Abstract: This study examined the appropriation of artificial intelligence tools among college teachers using the Model of Technology Appropriation as a framework and viewing the process through a human resource management lens. A total of 165 college teachers from the Philippines, selected through purposive sampling, completed an online questionnaire measuring six constructs across three levels of appropriation: evaluation, adaptation, and incorporation. The results showed that all six constructs fell within the strongly agree range, with the evaluation level scoring highest and the adaptation level scoring lowest; institutional support, in particular, showed the widest variation among teachers. All three levels were strongly and significantly correlated with one another, and among the two adaptation constructs, social shaping showed a stronger relationship with incorporation than institutional support. When grouped by teacher profile, licensure status showed no significant difference in incorporation, with licensed and non-licensed teachers reporting identical median scores. Academic rank showed a significant difference, with associate professors scoring higher than both assistant professors and instructors. Years of teaching experience and age both showed small but statistically significant negative correlations with incorporation. The results indicate that teachers reported favorable evaluation of the usability and value of AI tools, together with lower and more variable ratings of institutional support. Institutional support, social shaping, and differences across academic ranks are therefore areas that merit closer attention. The study offers practical implications for how academic institutions might design more targeted, rather than uniform, support for AI tool integration across their teaching workforces.

Keywords: technology appropriation; artificial intelligence; human resource management; higher education; faculty development; institutional support

1. Introduction

Human resource (HR) offices in academic institutions are usually associated with faculty recruitment, performance evaluation, and professional development (Zolak Poljašević et al., 2025). Artificial intelligence (AI) tools have recently entered this picture in a different way, through how teachers pick them up and use them in daily work rather than through any deliberate rollout (Hasan, 2025; Ukwandu et al., 2025). Many teachers already use AI for lesson preparation, grading, research, and administrative tasks, and most learned these tools on their own rather than through formal training (Traga Philippakos & Rocconi, 2025; van den Berg, 2025). Studies

in western institutions reported that faculty use AI platforms for course planning and grading, and that many want clearer policies and structured training (Iatrellis et al., 2025; Lyu et al., 2025). Miranda and Chamorro-Mera (2025) found that teachers' attitudes carried more weight than peer pressure in shaping the intention to adopt. Earlier studies have also shown that professors generally see the teaching value of generative AI but still set firm limits before allowing students to use it (Almisad & Aleidan, 2025; Lee et al., 2024; Mah et al., 2025; McDonald et al., 2025). These studies point to a gap between how quickly faculty adopt AI tools and how quickly institutions are able to support that adoption. How far institutional HR practice can close this gap has not been examined directly.

This pattern of trying a tool, adjusting how it is used, and either keeping it or letting it go is what the Model of Technology Appropriation (MTA) describes. Carroll et al. (2002) proposed a model as an alternative to TAM and UTAUT, both of which treat adoption as an intention formed before someone starts using a tool, based mainly on perceived usefulness and ease of use. The MTA describes what happens as users encounter a technology and work with it over time, moving through evaluation, adaptation, and either incorporation or abandonment. The present study measures the first three of these levels and does not measure abandonment. Fidock and Carroll (2006) applied this idea to a defense organization and argued that users, through their day-to-day use of a technology, end up completing its design. Alex et al. (2025) used the same model with faculty adjusting to hybrid teaching across several university campuses and found stages of exploration, partial integration, and incorporation that stalled wherever training or policy fell short. Xue et al. (2024) reviewed more than a hundred studies on UTAUT in higher education and found the model has mostly been tested on students. Faculty, they noted, face different pressures around institutional norms and how voluntary their use of a tool really is, a gap that a process model like the MTA may be better suited to capture.

The literature also suggests indirectly that HR-related factors play a role in this process. Khatoon et al. (2025) found that organizations whose HR practices were closely tied to technology rollout saw stronger adoption and less resistance than organizations where HR stayed on the sidelines. Feng et al. (2025), in a systematic review, identified institutional support and social influence as recurring predictors of technology adoption in higher education, and noted that inadequate infrastructure and support structures remain persistent challenges. Najjar et al. (2026) found that a lack of structured faculty development and clear policy effectively separated faculty who kept using AI from those who only tried it once, leaving many stuck in ad hoc experimentation. Other studies point to different conclusions. Some studies have stated that peers can shape adoption decisions more than any formal channel (Eckhardt et al., 2009; Gill & Nair, 2025). Several studies report a similar pattern, where institutional support mainly works by making a tool feel easier to use, while social influence has a more direct effect on intention (Gârdan et al., 2025; Gill & Nair, 2025; Liang & Suwanragasa, 2025; Liu & Li, 2025).

How readiness differs across the teaching workforce is equally unsettled. Mahmoud (2025) found assistant and associate professors used AI more than both lecturers and full professors. Jraiban et al. (2026) found a similar but smaller rank effect in a different country. Other findings contradict this. Nevárez Montes and Elizondo-Garcia (2025) found no real difference in acceptance by age or years of teaching at all. A recent study reported that senior faculty used AI at rates only slightly behind younger colleagues and pointed to weak training access and unclear

policy as the actual problem, not seniority itself (DEC, 2026). Gao and Yang (2026) offered one possible reason for these mixed results. In their study, senior faculty adopted AI mostly because their institution expected it of them, not because they wanted to, a pattern that MTA would describe as compliance rather than appropriation in the broader sense. Jiang et al. (2025) found something similar, that discipline and teaching context predicted AI use better than rank did, even though faculty at every rank said they wanted clearer guidance from their institution.

Recent studies applying the MTA to faculty have primarily examined how teachers evaluate, adapt to, and incorporate digital technologies into their work. However, they have given limited attention to how human resource management (HRM) functions, such as faculty development, training design, academic rank, and institutional policy, may be associated with movement from initial adoption to continued incorporation. Most recent applications of MTA in educational settings treat institutional support and social shaping as contextual influences on appropriation rather than as organizational mechanisms that HR departments may strengthen through faculty development, mentoring, institutional policy, and workplace culture. The present study addresses this gap by examining AI tool appropriation from an HRM perspective. It conceptualizes institutional support and social shaping as HR-related conditions rather than as background context, and considers how they may relate to movement from adaptation to continued incorporation. Specifically, this study sought to answer the following questions:

1. What is the level of AI tool appropriation among college teachers in terms of evaluation, adaptation, and incorporation?
2. Is there a significant relationship among the three levels of AI tool appropriation, evaluation, adaptation, and incorporation?
3. Is there a significant difference in the level of incorporation of AI tools among college teachers when grouped according to licensure status, academic rank, years of teaching experience, and age?

2. Materials and methods

2.1. Research design

This study used a quantitative, cross-sectional survey design to describe how college teachers evaluate, adapt to, and incorporate AI tools in their work. The analyses were descriptive and correlational, and included between-group comparisons based on licensure status and academic rank. The MTA served as the theoretical lens, treating appropriation as a sequence of three levels: evaluation, adaptation, and incorporation. Because the adaptation constructs capture perceptions of institutional support, training, policy, and workplace social influence, this study adopts an HRM perspective by interpreting these organizational conditions as areas that human resource practices can influence.

Figure 1 illustrates this framework. Level 1 evaluation covers how teachers judge the usability and value of AI tools before regular use. Level 2, adaptation, covers how social influence and institutional support shape teachers' adjustment of AI tools to their own teaching context. Level 3, incorporation, covers how far AI tools have become part of daily routines, in both intention and actual practice. The arrows represent the hypothesized sequence, where evaluation precedes adaptation, which, in turn, precedes incorporation.

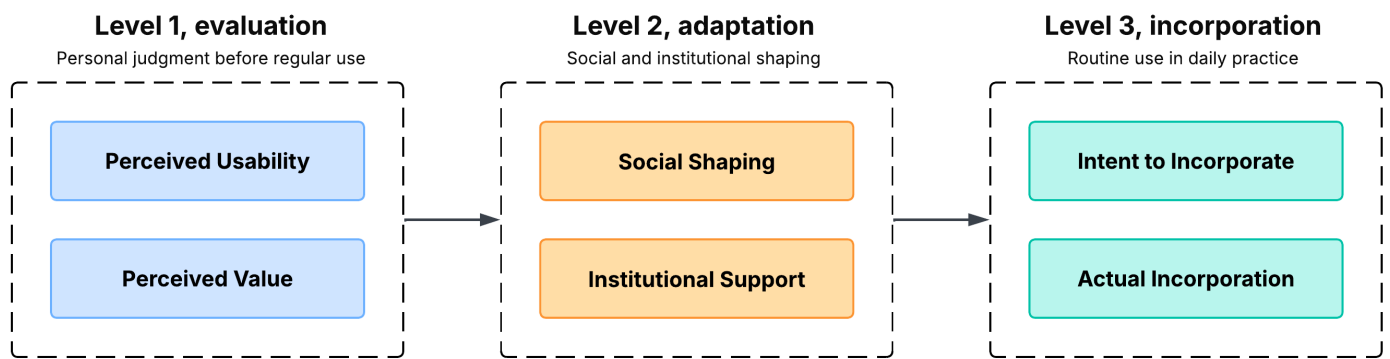


Figure 1. Conceptual model of this study.

2.2. Sample and research instrument

The respondents were 165 college teachers from the Philippines, selected through purposive sampling. The sample varied by age, years of teaching experience, sex, educational attainment, academic rank, and licensure status. Data were gathered using a researcher-made online questionnaire comprising two parts. The first part collected the demographic information listed above. The second part contained six constructs with 24 statements across the three levels of appropriation. Level 1 was measured through perceived usability (four items) and perceived value (four items). Level 2 was measured through social shaping (four items), covering peer and administrator encouragement, and institutional support (six items), covering training, technical resources, and policies. These two constructs capture different sources of influence within the same adaptation stage. Social shaping refers to informal influence from the people a teacher interacts with day to day, such as a colleague or an administrator. Institutional support refers to formal structures the institution puts in place on its own, such as training, tool access, and written policy. The two are treated as distinct constructs because one works through interpersonal example and the other through organizational provision. Level 3 was measured through the intent to incorporate (three items) and actual incorporation (three items). The instrument was validated by two professors with a background in educational management from a state university, who reviewed the items for content validity, and it passed the reliability test, with a Cronbach's alpha greater than .70, based on a pilot test of 30 respondents separate from the main sample.

As shown in **Table 1**, the sample had a mean age of 35.41 years and mean teaching experience of 8.73 years. Of the 165 respondents, 86 were male and 79 were female. Most held a master's degree, followed by a doctorate and bachelor's degrees. In terms of academic rank, the sample was composed mostly of instructors, with fewer assistant professors, associate professors, and professors. Academic rank in this study serves as a proxy for organizational seniority, since employment status data, permanent versus non-permanent, were not available for this sample. A total of 115 respondents held professional teaching licenses, while 50 did not.

Table 1. Demographic profiles of respondents.

Variable	Category	n	%
Sex	Male	86	52.1
	Female	79	47.9

Continuation Table:

Variable	Category	n	%
Highest educational attainment	Master's degree	89	53.9
	Doctorate degree	40	24.2
	Bachelor's degree	36	21.8
Academic rank	Instructor	106	64.2
	Assistant professor	32	19.4
	Associate professor	18	10.9
	Professor	9	5.5
Licensure status	Licensed	115	69.7
	Not licensed	50	30.3

2.3. Data collection and analysis

The questionnaire was administered online. Respondents were informed of the study's purpose and provided their consent before answering the questions. Responses were collected over the early quarter of 2026 and then cleaned and recoded for analysis. Likert responses were converted into numeric scores from 1 to 5 and averaged into the six construct scores and three level scores. Descriptive statistics, specifically the mean and standard deviation, were used to describe the scores and to answer the first research question. The Shapiro-Wilk test checked the normality of the three-level scores, and based on this result, Spearman's correlation was used to examine the relationship among the three levels and separately to compare social shaping and institutional support against Level 3, answering the second research question. For the third research question, the Mann-Whitney U test compared Level 3 scores by licensure status, and the Kruskal-Wallis H test compared Level 3 scores by academic rank, followed by Dunn's post hoc test with Bonferroni correction when the Kruskal-Wallis test was significant. Spearman's correlation was also used to examine the relationship between Level 3 scores and years of teaching experience, and between Level 3 scores and age. All tests were performed at a .05 level of significance.

2.4. Ethical considerations

Participation was voluntary, and responses were treated with confidentiality and used solely for academic purposes. Consent was provided by the respondents before they continued to the Google Form. No personally identifiable information was collected, in accordance with the Data Privacy Act of 2012 (Republic Act No. 10173).

3. Results

3.1. Level of AI tool appropriation among college teachers in terms of evaluation, adaptation, and incorporation

All six constructs fell within the strongly agree range (Table 2). Level 1 obtained the highest mean among the three levels ($M = 4.57$), whereas Level 2 obtained the lowest ($M = 4.27$). Among the six constructs, institutional support recorded the lowest mean ($M = 4.21$) and the largest standard deviation ($SD = 0.88$).

Table 2. Descriptive statistics for the six constructs and three levels of appropriation.

Construct	M	SD	Verbal interpretation
Perceived usability	4.59	0.48	Strongly agree
Perceived value	4.55	0.47	Strongly agree
Level 1, evaluation	4.57	0.45	Strongly agree
Social shaping	4.33	0.71	Strongly agree
Institutional support	4.21	0.88	Strongly agree
Level 2, adaptation	4.27	0.71	Strongly agree
Intent to incorporate	4.49	0.57	Strongly agree
Actual incorporation	4.45	0.69	Strongly agree
Level 3, incorporation	4.47	0.60	Strongly agree

3.2. Relationship among the three levels of AI tool appropriation, evaluation, adaptation, and incorporation

Shapiro-Wilk tests showed that all three level scores departed significantly from normality: Level 1 ($W = .81, p < .001$), Level 2 ($W = .85, p < .001$), and Level 3 ($W = .81, p < .001$). All three levels showed strong, positive, and statistically significant correlations with one another (**Table 3**). Between the two adaptation constructs, social shaping showed a higher correlation with Level 3 ($\rho = .797$) than institutional support ($\rho = .674$).

Table 3. Spearman correlations among the three levels of appropriation, and between adaptation constructs and incorporation.

Variable pair	ρ	p
Level 1 and Level 2	0.753	< .001
Level 1 and Level 3	0.753	< .001
Level 2 and Level 3	0.739	< .001
Social shaping and Level 3	0.797	< .001
Institutional support and Level 3	0.674	< .001

3.3. Difference in the level of incorporation of AI tools among college teachers when grouped according to licensure status, academic rank, years of teaching experience, and age

Licensure status showed no statistically significant difference in the Level 3 scores (Mann-Whitney $U = 2788, p = .756, r = .024$), indicating a negligible effect. **Table 4** presents the differences in Level 3 (Incorporation) scores by teacher profile. Licensed ($Mdn = 4.67$) and nonlicensed ($Mdn = 4.67$) teachers reported identical median scores. Academic rank showed a statistically significant difference with a large effect ($H(3) = 25.39, p < .001, \eta^2 = .139$). A Dunn post hoc test with Bonferroni correction showed that associate professors ($Mdn = 5.00$) scored significantly higher than assistant professors ($p = .001$) and instructors ($p < .001$). Professors did not differ significantly from any other rank groups. Years of teaching experience ($\rho =$

-.197, $p = .011$) and age ($\rho = -.244$, $p = .002$) each showed a small but statistically significant negative correlation with Level 3 scores.

Table 4. Differences in Level 3 (Incorporation) scores by teacher profile.

Variable	Test	Statistic	p
Licensure status	Mann-Whitney U	2788	0.756
Academic rank	Kruskal-Wallis H(3)	25.39	< .001
Years teaching	Spearman rho	-0.197	0.011
Age	Spearman rho	-0.244	0.002

4. Discussion

All six constructs registered within the strongly agree range, with evaluation highest among the three levels ($M = 4.57$). Teachers in this sample therefore reported favorable perceptions of AI tools at every stage measured, though the design cannot establish when these perceptions were formed. This is broadly consistent with Najjar et al. (2026), who found that the majority of faculty across two Lebanese universities reported moderate to high familiarity with AI tools, and with Shata and Hartley (2025), who found that perceived usefulness strongly predicted faculty intention to adopt generative AI among American university professors. At the same time, Najjar et al. (2026) also found that actual classroom use among their respondents remained shallow, limited mostly to chatbots and translation tools, which is a useful caution against reading a high evaluation score as evidence of deep or sophisticated use of the tool. The Level 1 findings of the present study should be read in the same way, as a measure of favorable perception rather than a guarantee of how that perception translates into practice.

Level 2 scored lowest among the three levels ($M = 4.27$), and within it, institutional support had both the lowest mean ($M = 4.21$) and the widest spread ($SD = 0.88$) of any construct in the study. This finding aligns with Najjar et al. (2026), who identified training deficits and resource limitations as the two most commonly cited barriers among their Lebanese sample, and with Jackman et al. (2024), who found that both perceived benefits and institutional facilitating conditions were significant predictors of faculty readiness to adopt AI, whereas individual attitudes towards AI did not significantly influence readiness. The wide variation in institutional support in the present data suggests that this is not experienced uniformly across the sample; some teachers report feeling well resourced while others do not, which points to inconsistent rollout rather than a wholesale absence of support across the institution.

All three levels were strongly and significantly related to each other, which is consistent with the premise of the MTA that evaluation, adaptation, and incorporation are connected rather than independent. What the data show is that teachers who score higher on evaluation also tend to score higher on adaptation and incorporation at the same point in time. Because the design is cross-sectional, this pattern is consistent with the model but is not a test of its sequential mechanism.

The comparison between social shaping and institutional support produced results that need to be weighed against genuinely mixed evidence in the literature. Social shaping showed a higher correlation with Level 3 incorporation ($\rho = .797$) than institutional support ($\rho = .674$). Pereira-González et al. (2025), in their

initial validation of the IMPACT model, reported that social influence was not a significant predictor of ChatGPT appropriation among university faculty; instead, the explanatory weight is carried by functional appropriation, ethical concerns, and facilitating conditions. Given this disagreement across studies, the social shaping result in this study is better treated as a data point in an unsettled debate rather than as confirmation of a settled mechanism. One possible explanation is that social shaping and institutional support may operate through different paths, one through visible peer examples and the other through removing practical barriers to access and training (Mikolajczak-Degrauwe et al., 2023). Liang and Suwanragasa (2025) argued for stronger institutional backing after finding that facilitating conditions primarily influence adoption intentions indirectly. Both paths could lead to similar outcomes through different routes, although this study did not directly test this mechanism.

Licensure status produced no significant difference, with licensed and non-licensed teachers reporting identical median scores. This finding, limited to the present sample, suggests that holding a professional license is not associated with how much a teacher incorporates AI tools into daily work in this group of respondents. Academic rank showed a significant difference, with associate professors scoring higher than assistant professors and instructors. However, a higher score does not necessarily indicate deeper pedagogical integration of generative AI. Institutional pressures can shape faculty members' intentions to adopt institutionally supported technologies (Leow et al., 2021). Similarly, Lu and Wang (2023) found that coercive institutional pressure accelerated teachers' technology adoption even when readiness remained limited, suggesting that organizational expectations may encourage technology use before meaningful instructional integration occurs. Consistent with this interpretation, Cheah et al. (2025) reported that teachers primarily used generative AI for lesson preparation and administrative tasks rather than direct classroom instruction, while other studies found that educators remained cautious about pedagogical integration because of concerns regarding ethics, trust, and instructional quality (Fajardo-Ramos et al., 2025; Ofosu-Ampong, 2024; Xiang et al., 2025). In contrast, Alnasib (2023) found that academic rank was not associated with AI readiness, suggesting that the influence of rank may depend on institutional context and opportunities for professional development.

In the present study, both variables were statistically significant but differed in magnitude. Academic rank was associated with a large difference in incorporation scores, while the correlations with years of teaching experience ($\rho = -.197$) and age ($\rho = -.244$) were small and should not be overstated. This may reflect the institutional context of the samples, or it may indicate that rank and years of experience, although related, are not interchangeable measures of seniority.

Beyond their practical implications, these findings support an interpretation of the MTA in which organizational conditions commonly associated with HR practice may help account for differences in reported incorporation. Where earlier studies have treated institutional support and social influence as contextual determinants of adoption (Feng et al., 2025; Shata & Hartley, 2025; Xue et al., 2024), the present findings suggest they can also be read as organizational conditions that HR departments are in a position to strengthen. This interpretation is proposed rather than tested, since the study measured teachers' perceptions of those conditions rather than the HR practices themselves.

The findings also provide direction for faculty development and organizational policy. Baran (2016) reported that faculty who took part in a structured technology

mentoring program increased their adoption and continued use of educational technologies, with individualized guidance and peer support as central features of the program. More recent evidence likewise suggests that AI competency develops most effectively through structured, continuous professional development rather than isolated training sessions. A six-month professional development intervention significantly improved teachers' AI technological and pedagogical competencies, demonstrating the value of sustained institutional investment in faculty development (Tan et al., 2025). UNESCO's AI Competency Framework for Teachers (Miao & Cukurova, 2024), together with emerging competency models for higher education faculty, provides an evidence-based foundation for designing competency standards, development pathways, and proficiency assessments that HR departments can integrate into faculty development systems (Cha et al., 2024). Because associate professors demonstrated higher levels of AI incorporation than assistant professors and instructors, HR departments may consider incorporating AI competency into faculty development plans and onboarding programs for new faculty, while also considering AI-related competencies during performance appraisal and professional development planning as institutional AI adoption continues to develop. HR offices may establish institutional AI governance policies that define acceptable use, ethical standards, competency expectations, and professional development pathways. Structured mentoring programs and communities of practice can further support sustained technology appropriation by enabling faculty to share effective practices and receive continuous guidance. Such strategies can strengthen faculty capability while promoting consistent and sustainable AI integration across the academic workforce (Hou et al., 2026).

5. Conclusion

This study examined AI tool appropriation among college teachers through the MTA from an HRM perspective. Teachers reported high levels of AI tool evaluation alongside high levels of AI incorporation, and the three levels of appropriation were strongly interrelated in this sample. Within adaptation, social shaping showed a higher correlation with incorporation than institutional support, suggesting that encouragement from peers and academic leaders may complement formal institutional support in promoting AI use. Incorporation also differed by academic rank, whereas licensure status showed no meaningful difference. These findings highlight the need for human resource strategies that integrate formal AI training, structured peer learning, and rank-sensitive professional development rather than adopting a uniform approach for all faculty members. The study also proposes an interpretation of the MTA in which institutional support and social shaping are treated as HR-related conditions rather than as background context.

6. Limitations and Future Research

The cross-sectional design measured evaluation, adaptation, and incorporation at a single point in time and could not examine how teachers progress through these stages over time. The significant relationships among the three levels are consistent with the MTA but do not confirm its proposed sequential process. The sample was from college teachers from Philippine institutions selected through purposive sampling, so the findings describe this group rather than college teachers in general, and generalizability to other national and institutional contexts is limited. Institutional support and social shaping were assessed through teachers' perceptions rather

than direct organizational measures of HR practices, such as faculty development, mentoring programs, AI governance policies, or institutional implementation strategies. The study also relied on a single self-reported questionnaire, which may have introduced common method bias and social desirability bias. Future research should use longitudinal designs to examine changes in AI appropriation over time, include organizational measures of HR practices, and combine self-reported data with classroom observations, institutional records, peer evaluations, or supervisor assessments to provide a more comprehensive understanding of AI appropriation in higher education.

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