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When knowledge is not enough: Faculty competencies, training challenges, and AI integration in higher ed-ucation aligned with SDG 4

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ABSTRACT

Faculty AI integration in higher education depends critically on educator competencies, yet studies examin-ing multiple predictors simultaneously remain scarce. This cross-sectional quantitative study surveyed 329 higher education faculty members to model AI integration as a function of five predictors: AI literacy, ped-agogical readiness, technical readiness, ethical awareness, and AI-related challenges, while also examining variation by academic rank and formal AI training experience using OLS regression, moderation analysis, ANOVA, and independent-samples t-tests implemented in a reproducible Python-based pipeline. Technical Readiness emerged as the strongest independent predictor of AI integration ($\beta = 0.43$, $p < .001$), followed by Pedagogical Readiness ($\beta = 0.35$, $p < .001$), together explaining 35% of outcome variance, while AI Literacy and Ethical Awareness showed no significant direct effects. Counterintuitively, formally trained faculty re-ported lower AI integration than untrained peers alongside heightened perceptions of AI-related challenges, suggesting a knowing–doing gap whereby professional development raises critical awareness without pro-portionally enabling classroom experimentation. Academic rank significantly influenced integration levels, with Lecturers and Professors reporting the highest scores. Sustainable AI adoption in higher education re-quires institutional strategies that build technical confidence and pedagogical adaptability concurrently, supplemented by structured experimentation opportunities and differentiated career-stage support rather than awareness-focused training alone.

KEYWORDS: artificial intelligence integration, faculty competencies, pedagogical readiness, technical readiness, training paradox, higher education, SDG 4

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1. Introduction

The rapid proliferation of artificial intelligence (AI) across institutional and professional domains has significantly reshaped the landscape of higher education, creating new opportunities for pedagogical innovation while simultaneously introducing complex challenges for educators and institutions (Chassignol et al., 2018; Holmes et al., 2019). AI-based technologies such as intelligent tutoring systems, adaptive learning environments, and more recently generative AI tools like ChatGPT have rapidly moved from experimental applications to widely discussed instructional resources in higher education (Kasneci et al., 2023; Ouyang & Jiao, 2021). Universities worldwide are increasingly investing in AI-supported infrastructures with the expectation that these technologies can enhance personalized learning, support automated assessment processes, and generate data-driven insights that inform educational decision-making (Chassignol et al., 2018; Holmes et al., 2019). However, the successful realization of these benefits depends largely on a critical factor: the readiness, competence, and willingness of faculty members to meaningfully integrate AI technologies into their teaching practices (Crompton & Burke, 2023).

Within this evolving technological environment, faculty members occupy a crucial mediating role, acting as the human bridge between advanced AI systems and the diverse learners these technologies are intended to support (Mishra & Koehler, 2006; Zawacki-Richter et al., 2019). Unlike students, who may encounter AI tools passively through institutional learning platforms, faculty members are required to actively evaluate, select, adapt, and implement AI-based resources within complex disciplinary and pedagogical contexts (Kasneci et al., 2023; Ouyang & Jiao, 2021). This process demands a range of competencies that go beyond basic digital literacy, including instructional design capabilities, the ability to critically evaluate algorithm-generated outputs, and the capacity to align technological affordances with intended learning outcomes (Koehler et al., 2013; Uerz et al., 2018). Consequently, identifying the competencies that most strongly predict faculty members' effective integration of AI technologies is not merely a theoretical issue but an important empirical priority for higher education institutions and professional development initiatives (Crompton & Burke, 2023; Lawless & Pellegrino, 2007).

Among the competency dimensions most frequently associated with successful technology adoption, pedagogical readiness has consistently been identified as a foundational predictor of how faculty integrate digital technologies into their teaching practices (Angeli & Valanides, 2009; Mishra & Koehler, 2006). Pedagogical readiness—understood as the capacity and willingness of educators to redesign instructional strategies in response to emerging technological affordances—enables faculty to move beyond superficial tool usage toward more meaningful and transformative technology-enhanced teaching practices (Kimmons & Hall, 2017; Koehler et al., 2013). Empirical research across various higher education contexts has shown that faculty members who demonstrate strong pedagogical adaptability are more likely to experiment with, adopt, and sustain innovative technology-supported learning activities (Porter & Graham, 2015; Scherer et al., 2019). The Technological Pedagogical Content Knowledge (TPACK) framework provides a widely recognized theoretical lens for examining the dynamic relationship between pedagogy, technology, and disciplinary knowledge in teaching practice (Mishra & Koehler, 2006; Rosenberg & Koehler, 2015; Voogt et al., 2012).

Alongside pedagogical adaptability, technical readiness—defined as an educator's confidence in using, troubleshooting, and adapting digital and AI-supported tools within authentic instructional contexts—has been identified as a strong predictor of technology integration in education (Compeau & Higgins, 1995; Venkatesh et al., 2003). Grounded in Bandura's (1986) social cognitive theory, technical self-efficacy influences not only whether faculty members attempt to use new technologies but also how persistently they continue using them when they encounter challenges or initial implementation difficulties (Scherer et al., 2019; Teo, 2011). Research applying the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT2) has consistently shown that perceived ease of use and technological confidence mediate the relationship between exposure to emerging technologies and sustained adoption behavior in educational settings (Davis, 1989; Venkatesh et al., 2012). Faculty members who demonstrate strong technical readiness are therefore better positioned to leverage advanced digital and AI capabilities in ways that align with disciplinary learning goals and instructional needs (Crompton & Burke, 2023; Tan et al., 2022).

Beyond readiness constructs, AI literacy and ethical awareness have been increasingly recognized as essential, yet conceptually distinct, dimensions of faculty competence for the responsible integration of artificial intelligence in education (Long & Magerko, 2020; Ng et al., 2021). AI literacy refers to the cognitive capacity to understand the basic principles underlying AI systems, critically evaluate their outputs, and determine their suitability for specific educational purposes (Selwyn, 2019; Zawacki-Richter et al., 2019). Ethical awareness, in contrast, relates to educators' sensitivity to issues such as algorithmic bias, data privacy, academic integrity, and the broader societal consequences of deploying AI technologies in educational environments (Floridi et al., 2018; Miao et al., 2021; UNESCO, 2021). Although these dimensions are theoretically foundational, emerging empirical studies suggest that their influence on technology integration behavior may operate more indirectly—providing the cognitive and ethical foundations through which pedagogical and technical readiness are enacted—rather than functioning as direct predictors of adoption (Crompton & Burke, 2023; Tan et al., 2022).

Professional development programs represent the primary institutional mechanism through which universities seek to enhance faculty competencies in emerging technologies such as artificial intelligence. However, empirical evidence regarding their effectiveness reveals a more complex picture (Darling-Hammond et al., 2017; Guskey, 2002). Some studies indicate that professional training programs do not automatically lead to increased classroom technology integration; instead, they may increase educators' awareness of the pedagogical, technical, and ethical challenges associated with emerging technologies, which can sometimes slow adoption in practice (Lawless & Pellegrino, 2007; Scherer et al., 2021). This tension between conceptual knowledge acquisition and practical classroom implementation has often been described as a knowing–doing gap, a concept widely discussed in organizational learning and professional expertise development literature (Eraut, 2004; Pfeffer & Sutton, 2000). Understanding the conditions under which professional development translates—or fails to translate—into instructional practice remains an important research priority within the field of technology and AI integration in education (Crompton & Burke, 2023; Holmes et al., 2019).

Faculty AI integration does not occur in an institutional vacuum; rather, it is systematically influenced by contextual variables such as academic rank, workload distribution, access to technological infrastructure, and the presence of supportive organizational cultures (Anderson, 2008; Fullan, 2007). Senior faculty members often benefit from greater professional autonomy, established peer networks, and accumulated pedagogical confidence, which collectively lower the psychological threshold for experimenting with emerging technologies in their teaching (Ertmer, 1999; Prestridge, 2017). Early-career faculty, in contrast, frequently face competing demands—including heavy teaching loads, research publication pressures, and limited institutional mentoring—that can constrain their capacity for technology-driven innovation (Gómez-Fernández & Mediavilla, 2022; Tondeur et al., 2017). Institutional factors such as administrative encouragement, peer learning communities, and clear technology governance policies have been shown to significantly moderate the relationship between individual competencies and actual technology integration behavior, highlighting that sustainable AI adoption is as much a systemic challenge as an individual one (Scherer et al., 2019; Tondeur et al., 2017).

Despite a rapidly growing body of literature on AI in education, quantitative studies that examine multiple faculty competency constructs simultaneously as predictors of AI integration within a single, methodologically rigorous framework remain comparatively scarce (Holmes et al., 2019; Zawacki-Richter et al., 2019). Most existing investigations rely on descriptive or single-construct designs, which limits their explanatory power and usefulness for informing evidence-based policy and professional development (Crompton & Burke, 2023; Tan et al., 2022). The present study addresses this gap through a cross-sectional quantitative survey of 329 higher education faculty members, modeling AI integration as a function of five interrelated predictors—AI literacy, pedagogical readiness, technical readiness, ethical awareness, and AI-related challenges—while also examining differences by academic rank and formal AI training experience. By employing a reproducible Python-based analytic pipeline, the study further contributes to methodological transparency in educational AI research. Its findings provide both theoretically grounded and practically actionable insights for institutions aiming to foster sustainable, human-centered AI adoption.

2. Materials and Methods

2.1 Research Design

This study employed a quantitative, cross-sectional survey design to examine the competency factors that predict higher education faculty members' integration of artificial intelligence (AI) into their teaching practice.

Quantitative approaches are particularly well-suited for hypothesis testing and modeling theoretically defined relationships among latent constructs in educational and social science contexts (Creswell & Creswell, 2023; Field, 2018). A post-positivist epistemological stance informed the research design, reflecting the assumption that faculty AI competencies and integration behaviors can be meaningfully operationalized, measured, and analyzed through standardized instruments and reproducible statistical procedures (Gorard, 2021; Osborne, 2008).

A structured online questionnaire was administered to faculty members across diverse academic disciplines and institutional affiliations, enabling standardized, scalable data collection on AI-related competencies, readiness dimensions, and integration practices. To maximize analytic transparency and methodological rigor, all data processing, reliability estimation, and inferential modeling were implemented within a fully reproducible Python-based computational pipeline, minimizing human error and ensuring replicability in accordance with open-science standards (McKinney, 2022; Osborne, 2008).

2.2 Participants and Sampling

Participants were recruited from higher education institutions through purposive and snowball sampling strategies targeting active teaching faculty across multiple academic disciplines and career stages. Following data collection, all survey responses were subjected to a rigorous programmatic quality assurance protocol prior to analysis. Column standardization was first applied to eliminate formatting inconsistencies arising during data import, including the removal of special characters, redundant whitespace, and line-break artifacts, thereby ensuring accurate alignment between survey items and their corresponding analytic constructs (McKinney, 2022). All Likert-scale items were subsequently converted to numeric form through controlled coercion, with non-numeric entries treated as missing to preserve measurement validity (Field, 2018).

Missing data were managed using a structured two-step procedure aligned with contemporary psychometric best practices (Newman, 2014): participants with more than 20% missing responses across all items were excluded from analysis, while within-construct person-mean imputation was applied for cases with missing rates at or below this threshold. Following these procedures, a final analytical sample of 329 valid responses was retained, representing a sufficient sample size for the planned multivariate analyses (Hair et al., 2019; Tabachnick & Fidell, 2019).

2.3 Instruments

The survey instrument was organized around eight theoretically derived constructs: AI Literacy, Pedagogical Readiness, Technical Readiness, Ethical Awareness, AI Integration, AI Challenges, Teaching Outcomes, and AI Confidence. Each construct was operationalized through multiple Likert-scaled items, with composite scores calculated as the mean of each construct's constituent items, provided that participants had completed at least 80% of the corresponding items—a threshold established to safeguard the internal consistency and conceptual coherence of the multi-item scales (Hair et al., 2019).

Results indicated satisfactory to excellent reliability across most scales: Pedagogical Readiness ($\alpha = 0.867$), Technical Readiness ($\alpha = 0.862$), AI Integration ($\alpha = 0.863$), Teaching Outcomes ($\alpha = 0.864$), Ethical Awareness ($\alpha = 0.826$), and AI Challenges ($\alpha = 0.832$). Two constructs—AI Literacy ($\alpha = 0.608$) and AI Confidence ($\alpha = 0.668$)—demonstrated lower yet acceptable reliability for exploratory purposes, suggesting conceptual breadth and possible multidimensionality; findings involving these constructs are therefore interpreted with appropriate caution throughout. Outlier detection was applied exclusively to composite variables using standardized z-scores, with cases exceeding $z > 3.29$ excluded prior to inferential analysis (Field, 2018; Osborne, 2008).

2.4 Statistical Analysis

All inferential analyses were conducted within the reproducible Python-based pipeline using core scientific computing libraries: pandas for data manipulation (McKinney, 2022), NumPy for numerical computation, SciPy for statistical operations, and statsmodels for regression modeling (Virtanen et al., 2020). Descriptive statistics—including means, standard deviations, and quartile distributions—were first computed for all composite constructs to characterize the sample's overall AI competency profile (Gorard, 2021). Pearson correlation coefficients were then calculated to examine bivariate associations among constructs, with a correlation heatmap generated to visualize interrelationships and assess convergent validity (Bryman, 2022).

To test the primary research hypotheses, an Ordinary Least Squares (OLS) multiple regression model was estimated with AI Integration as the dependent variable and AI Literacy, Pedagogical Readiness, Technical Readiness, Ethical Awareness, and AI Challenges as predictors. Model outputs—including standardized coefficients, standard errors, t-values, p-values, and 95% confidence intervals—were reported in accordance with current recommendations for inferential transparency (Tabachnick & Fidell, 2019). A moderation analysis was subsequently conducted to evaluate whether Ethical Awareness moderated the relationship between AI Literacy and AI Integration, with the statistical significance of the interaction term (AI Literacy × Ethical Awareness) serving as the primary criterion for establishing moderation (Tabachnick & Fidell, 2019).

2.5 Group Analyses and Ethics

Two complementary group-level analyses were conducted to examine contextual sources of variation in AI Integration. Differences between faculty who had received formal AI training and those who had not were assessed using Welch's independent-samples t-test, selected for its robustness to violations of the equal-variance assumption (Field, 2018). Variation across academic ranks was examined using a one-way Analysis of Variance (ANOVA), with effect sizes reported as Cohen's d and eta-squared (η^2) to characterize the practical magnitude of observed differences (Cohen, 1988).

Regarding ethical considerations, participation in this study was entirely voluntary, and all responses were fully anonymized prior to analysis. No identifying information was collected or retained at any stage of the research process. The study was conducted in strict accordance with institutional ethical guidelines for human subjects research and complied with applicable data protection standards, ensuring that participant confidentiality and research integrity were maintained throughout.

3. Results

3.1 Descriptive Statistics and Construct Intercorrelations

Descriptive statistics for all eight composite constructs are presented in Table 1. Mean scores ranged from 1.96 to 2.54 on the five-point scale, reflecting moderate overall levels of AI-related competency and readiness. AI Challenges yielded the highest mean (M = 2.54, SD = 0.70), suggesting that faculty perceive meaningful barriers to AI adoption as a salient feature of their professional context. Technical Readiness and AI Integration shared equivalent means (M = 2.40), while Ethical Awareness recorded the lowest score (M = 1.96, SD = 0.59), indicating that this dimension remains comparatively underdeveloped across the sample.

Table 1. Descriptive Statistics for All Composite Constructs

Construct	M	SD	Min	25%	Mdn	75%	Max
AI Literacy	2.15	0.51	1.00	1.83	2.17	2.50	3.67
Pedagogical Readiness	2.13	0.57	1.00	1.88	2.13	2.50	4.00
Technical Readiness	2.40	0.72	1.00	2.00	2.40	2.80	4.40
Ethical Awareness	1.96	0.59	1.00	1.57	2.00	2.29	3.86
AI Challenges	2.54	0.70	1.00	2.00	2.63	3.00	4.50
AI Integration	2.40	0.71	1.00	2.00	2.33	2.83	4.33
Teaching Outcomes	2.02	0.63	1.00	1.67	2.00	2.33	4.00
AI Confidence	2.31	0.68	1.00	2.00	2.33	2.67	4.00

Note. M = mean; SD = standard deviation; Mdn = median. All constructs scored on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree).

Pearson correlation coefficients, visualized in Figure 1, revealed a pattern of positive and statistically significant associations across most construct pairings. The strongest intercorrelation emerged between Pedagogical Readiness and Technical Readiness ($r = 0.75$, $p < .001$), reflecting the close developmental alignment of these two readiness dimensions. Both constructs also demonstrated strong positive associations with AI Integration ($r = 0.62$ and $r = 0.66$, respectively, both $p < .001$). Ethical Awareness and AI Literacy were more moderately correlated with the outcome (r = 0.38 and r = 0.34, p < .001), foreshadowing their non-significant direct effects in the regression analysis.

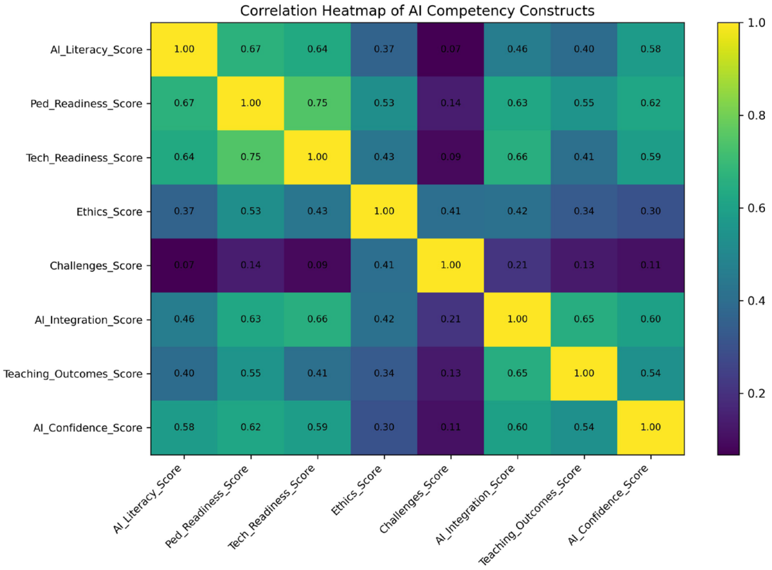

Figure 1. Pearson Correlation Heatmap Among All Composite Constructs. Color intensity reflects the magnitude of the positive association. All displayed correlations are significant at p < .001.

3.2 Predictors of AI Integration

The multiple regression model was statistically significant overall, F(5, 323) = 36.42, p < .001, $R^2 = 0.35$, indicating that the five predictors collectively explained 35% of the variance in AI Integration—a large effect by conventional benchmarks (Cohen, 1988). As shown in Table 2, Technical Readiness was the strongest independent predictor (β = 0.43, p < .001, 95% CI [0.31, 0.56]), followed by Pedagogical Readiness (β = 0.35, p < .001, 95% CI [0.18, 0.52]). These results provide unambiguous support for H1, confirming that technical confidence and pedagogical adaptability exert significant, independent, and substantive effects on faculty AI integration.

AI Challenges also contributed a small but statistically reliable positive effect (β = 0.12, p = .007, 95% CI [0.03, 0.21]), offering partial support for H5: faculty who perceive greater AI-related challenges are not deterred from integration but appear to engage with it more deliberately. By contrast, AI Literacy (β = –0.04, p = .63) and Ethical Awareness (β = 0.05, p = .45) did not emerge as significant direct predictors, suggesting that their influence operates through enabling rather than autonomous behavioral pathways.

Table 2. OLS Multiple Regression Coefficients Predicting AI Integration

Predictor	β	SE	t	p	95% CI
(Intercept)	0.30	0.16	1.92	0.056	[–0.01, 0.61]
AI Literacy	–0.04	0.08	–0.48	.630	[–0.19, 0.12]
Pedagogical Readiness	0.35	0.08	4.12	< .001	[0.18, 0.52]
Technical Readiness	0.43	0.06	7.06	< .001	[0.31, 0.56]
Ethical Awareness	0.05	0.06	0.76	.450	[–0.07, 0.17]
AI Challenges	0.12	0.04	2.70	.007	[0.03, 0.21]

Note. β = unstandardized regression coefficient; SE = standard error; 95% CI = confidence interval. Model

Figure 2 presents the scatter plot of actual versus model-predicted AI Integration scores. The close clustering of data points around the diagonal reference line across the full score range confirms adequate model fit and supports the interpretability of the regression coefficients.

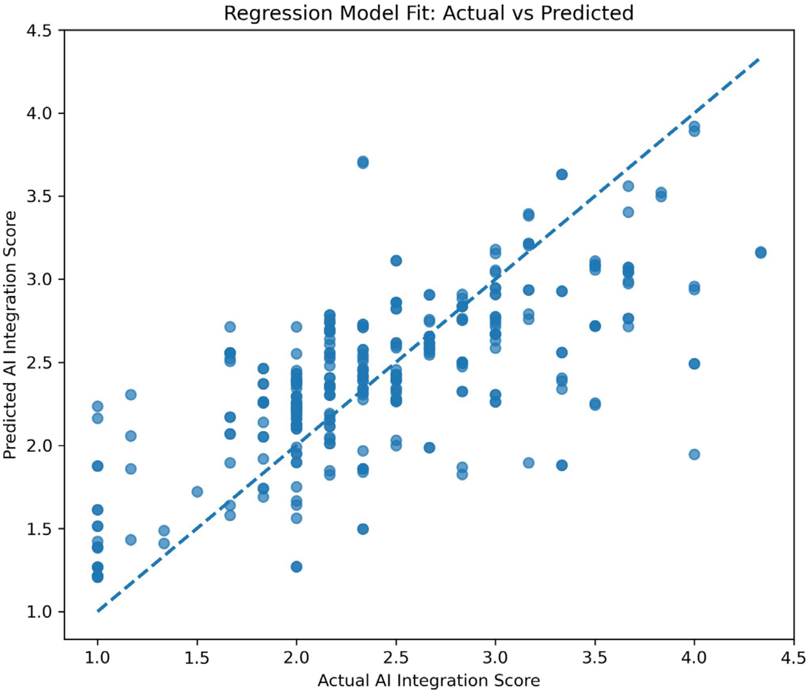

Figure 2. Actual versus Predicted AI Integration Scores. The diagonal line represents perfect prediction.

3.3 Moderation Analysis: Ethical Awareness × AI Literacy

The interaction term (AI Literacy × Ethical Awareness) was not statistically significant (β = 0.04, p = .69, 95% CI [–0.16, 0.24]), as presented in Table 3. Ethical Awareness did not amplify or attenuate the relationship between AI Literacy and AI Integration, and H3 was not supported. Within this model, AI Literacy emerged as a significant positive main effect (β = 0.43, p = .025, 95% CI [0.06, 0.80]), indicating a direct additive contribution when ethical awareness is held constant. These results suggest that literacy and ethics function as independent enabling competencies rather than synergistic moderators of integration behavior.

Table 3. Moderation Analysis: Ethical Awareness as Moderator of AI Literacy → AI Integration

Predictor	β	SE	t	p	95% CI
(Intercept)	0.80	0.41	1.96	.051	[–0.00, 1.60]
AI Literacy	0.43	0.19	2.26	.025	[0.06, 0.80]
Ethical Awareness	0.26	0.23	1.13	.260	[–0.19, 0.71]
AI Literacy × Ethical Awareness	0.04	0.10	0.41	.690	[–0.16, 0.24]

Note. β = unstandardized coefficient. Both predictors were mean-centered prior to computing the interaction term. Non-significant interaction (p = .69) indicates absence of moderation.

3.4 AI Integration Across Academic Ranks

The one-way ANOVA yielded a statistically significant omnibus result, F(4, 324) = 5.57, p < .001, $\eta^2 = 0.06$, supporting H4. As shown in Table 4, Lecturers reported the highest mean AI Integration (M = 2.54, SD = 0.69), followed by Teaching Assistants (M = 2.44, SD = 0.86) and Professors (M = 2.40, SD = 0.68). Assistant Professors (M = 1.98, SD = 0.58) and Associate Professors (M = 2.00, SD = 0.63) reported the lowest integration levels. The small-to-medium effect size ($\eta^2 = 0.06$) indicates that rank-related variation is statistically reliable while remaining one of several contextual influences on integration behavior (Cohen, 1988).

Table 4. Mean AI Integration Scores by Academic Rank

Academic Rank	M	SD	n	SEM
Assistant Professor	1.98	0.58	39	0.09
Associate Professor	2.00	0.63	6	0.26
Lecturer	2.54	0.69	137	0.06
Professor	2.40	0.68	121	0.06
Teaching Assistant	2.44	0.86	26	0.17

Note. M = mean AI Integration composite score; SD = standard deviation; SEM = standard error of the mean.

Associate Professor (n = 6) estimates should be interpreted with particular caution given the small subgroup size.

Figure 3 presents mean AI Integration scores by rank with standard error bars. A progressive increase from Assistant Professor to Lecturer is clearly visible, with Professors maintaining comparably elevated levels. Wider error bars for Associate Professors and Teaching Assistants reflect greater score variability associated with their smaller subgroup sizes.

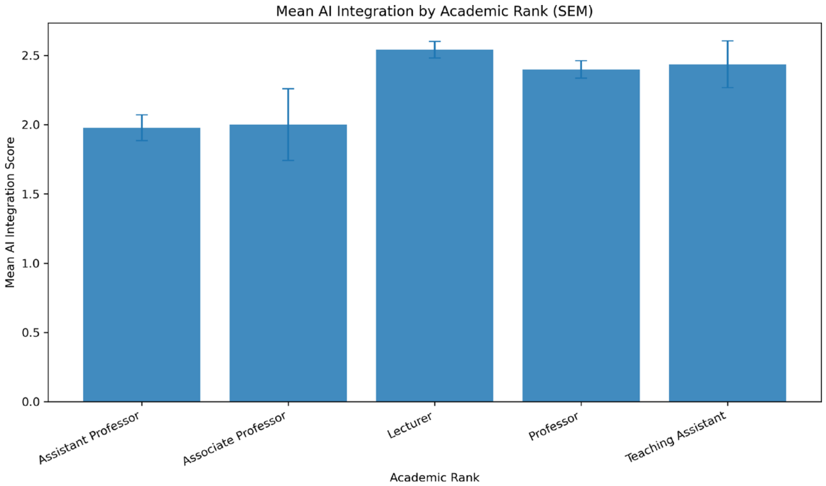

Figure 3. Mean AI Integration Scores by Academic Rank (±1 SEM).

3.5 AI Integration by Formal Training Status: The Training Paradox

H2 predicted that formally trained faculty would report higher AI Integration than untrained peers. The group comparison returned a statistically significant result, t(≈170) = 2.31, p = .022, Cohen's d = 0.21; however, the direction of the difference was opposite to that hypothesized. Trained faculty reported lower mean AI Integration (M = 2.27, SD = 0.65, n = 97) than untrained faculty (M = 2.46, SD = 0.73, n = 232). H2 was therefore rejected in its directional form. Supplementary analysis further revealed that trained faculty perceived significantly more AI-related challenges (M = 2.67 vs. M = 2.49, p < .05), suggesting that formal exposure heightens critical awareness of AI's pedagogical complexity and ethical demands—a knowing–doing gap that may transiently suppress rather than stimulate classroom experimentation.

4. Discussion

The present study examined five competency predictors of faculty AI integration within higher education, yielding results that both confirm and complicate prevailing assumptions in the field. Technical Readiness emerged as the strongest predictor (β = 0.43), followed closely by Pedagogical Readiness (β = 0.35), together explaining 35% of variance in AI Integration. Notably, AI Literacy and Ethical Awareness failed to emerge as significant direct predictors, suggesting their influence operates through indirect enabling pathways rather than autonomous behavioral mechanisms. The unexpected finding that formally trained faculty reported lower integration than untrained peers—alongside higher perceived challenges—points to a knowing–doing gap whereby formal exposure increases critical awareness without proportionally stimulating classroom experimentation. Academic rank differences further confirmed that contextual and career-stage factors shape integration behavior meaningfully.

These findings align with and extend several established theoretical and empirical traditions. The primacy of Technical Readiness corroborates Davis (1989) and Venkatesh et al. (2003), who demonstrated that technological confidence consistently mediates adoption behavior. The significant role of Pedagogical Readiness resonates with Mishra and Koehler's (2006) TPACK framework and Koehler et al. (2013), who emphasized the inseparability of pedagogical and technological competence. The non-significant direct effects of AI Literacy and Ethical Awareness echo Crompton and Burke (2023) and Tan et al. (2022), who positioned these constructs as foundational enablers rather than direct behavioral drivers. The training paradox replicates dynamics described by Lawless and Pellegrino (2007) and Scherer et al. (2019), while paralleling the knowing–doing gap articulated by Pfeffer and Sutton (2000) and Darling-Hammond et al. (2017), reinforcing that knowledge acquisition does not automatically produce instructional change.

These results carry meaningful practical implications for higher education institutions designing professional development initiatives and AI adoption strategies. Institutions should prioritize faculty development programs that build technical confidence and pedagogical adaptability concurrently, rather than focusing narrowly on conceptual AI literacy or compliance-oriented ethics training. The training paradox finding suggests that professional development must be coupled with structured, low-stakes opportunities for classroom experimentation to bridge the gap between awareness and action. The rank-based differences highlight the importance of differentiated support structures: early-career faculty require mentoring and reduced workload burdens, while experienced faculty benefit from peer learning communities. Institutional governance policies providing infrastructure access and administrative encouragement remain essential for translating individual competencies into sustained, practice-level AI integration.

Several limitations constrain the generalizability of this study's findings. The cross-sectional design precludes any causal inference regarding the directionality of observed relationships between competency constructs and AI integration behavior. The purposive and snowball sampling strategies may introduce self-selection bias, potentially overrepresenting faculty who are already engaged with AI-related discourse. The relatively low Cronbach's alpha values for AI Literacy ($\alpha = 0.608$) and AI Confidence ($\alpha = 0.668$) suggest possible multidimensionality, warranting cautious interpretation of findings involving these constructs. The extremely small Associate Professor subgroup ($n = 6$) limits the reliability of rank-based comparisons for that category. Additionally, the exclusive reliance on self-reported measures introduces common method variance, which may inflate observed associations among constructs sharing the same measurement format.

Future research should address these limitations through longitudinal designs capable of tracking competency development and integration behavior across academic semesters, thereby establishing clearer directional and causal relationships. Mixed-methods approaches incorporating classroom observations and interviews would complement self-report data by capturing the nuanced contextual factors that questionnaires cannot fully operationalize. Researchers should investigate the mechanisms through which AI Literacy and Ethical Awareness exert their indirect effects, potentially through mediation modeling. Comparative cross-institutional and cross-national studies would clarify whether the training paradox is culturally or institutionally specific. Refining AI Literacy instrumentation to address its observed multidimensionality would also strengthen future measurement models, enabling more precise predictions of integration behavior across diverse disciplinary and career-stage contexts.

5. Conclusions

This study provides robust quantitative evidence that Technical Readiness and Pedagogical Readiness constitute the most consequential predictors of faculty AI integration in higher education, while simultaneously revealing that formal training does not straightforwardly accelerate adoption behavior. The counterintuitive training paradox finding is particularly significant, suggesting that knowledge-focused professional development may paradoxically heighten perceived barriers without proportionally enabling practice-level change. Collectively, these findings underscore that sustainable AI adoption in academic contexts is as much a systemic and institutional challenge as an individual competency issue. Universities must therefore move decisively beyond awareness-raising interventions toward experientially grounded, contextually responsive faculty development frameworks that concurrently build technical confidence, pedagogical adaptability, and practical implementation capacity within genuinely supportive organizational environments.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
OLS	Analysis of Variance
TPACK	Technological Pedagogical Content Knowledge
TAM	Technology Acceptance Model
UTAUT2	Unified Theory of Acceptance and Use of Technology (Extended Version)
IRB	Institutional Review Board
SEM	Standard Error of the Mean
CI	Confidence Interval
β	Standardized Regression Coefficient
η^2	Eta-Squared Effect Size
α	Cronbach's Alpha
ICT	Information and Communication Technology
UNESCO	United Nations Educational, Scientific and Cultural Organization

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