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Teacher Educators' Readiness and Attitudes Toward Integrating Artificial Intelligence into Teacher-Preparation Curricula

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Abstract

Existing research on AI readiness and attitudes has focused almost entirely on pre-service and K-12 in-service teachers, leaving teacher educators themselves largely out of the picture even though they shape how future teachers come to understand and use artificial intelligence (AI). This study aimed to examine the relationship between AI readiness and teacher educators' favorable attitudes and ethical/pedagogical concerns toward AI integration. A quantitative, correlational design was adopted for this purpose. Data was collected through a construct-based questionnaire administered to teacher educators across public and private colleges (N = 170). The instrument comprised three subscales: AI Readiness (12 items, $\alpha = .74$), Favorable Attitudes (8 items, $\alpha = .71$), and Ethical/Pedagogical Concerns (6 items, $\alpha = .73$). Results showed that AI Readiness was significantly and positively correlated with Favorable Attitudes, $r(168) = .30$, $p < .001$, supporting the study's hypothesis, though the modest effect size ($r^2 \approx 9\%$) indicates readiness is one of several factors shaping attitudes. AI Readiness was also very strongly and positively correlated with Concerns, $r(168) = .74$, $p < .001$, $r^2 \approx 56\%$. Based on these findings, the study recommends that teacher-education administrators establish faculty AI readiness as a distinct professional-development priority, separate from general instructional-technology training, because teacher educators directly model AI use for future teachers, giving their own readiness a consequential, multiplying effect on the profession.

Keywords: AI readiness, teacher educators, technology acceptance model, favorable attitudes, ethical and pedagogical concerns, teacher preparation

Introduction

Background of the Study

Artificial intelligence (AI) is being adopted into education systems worldwide at a pace that has outrun the preparation of the educators expected to use it. Global policy bodies have identified AI as a strategic priority for education, yet the gap between policy enthusiasm and classroom-level readiness remains wide: while a majority of countries now acknowledge AI's strategic importance for education, only a small minority have implemented comprehensive teacher-training programs to support it (Fteiha et al., 2025). This gap is especially consequential in teacher education, where faculty are not simply end-users of AI but are also responsible for modeling its use, its limits, and its ethical boundaries for the next generation of teachers.

Research on AI readiness in education has grown rapidly over the past three years, but it has concentrated almost entirely on two populations: pre-service teacher candidates and in-service K-12 classroom teachers. Large-scale surveys of in-service teachers have shown that readiness is shaped jointly by confidence, perceived usefulness, and prior training, with formal training remaining the single strongest constraint on adoption (Granström & Oppi, 2025). Parallel work on pre-service teachers has found a persistent gap between candidates' enthusiasm for AI and their actual technical competence, alongside a still-forming sense of what AI means for their professional identity as future teachers (Guan et al., 2025). Faculty in higher education more broadly have also begun to receive attention: studies of university lecturers report generally favorable, though uneven, acceptance of AI, shaped by teaching experience, institutional support, and access to professional development (Ayyoub et al., 2025; Ofosu-Ampong, 2024). New instruments, such as the Faculty Artificial Intelligence Literacy and Competency (FALCON-AI) scale, have recently been developed specifically to measure this faculty-level readiness in a role-appropriate way (Song et al., 2026).

Problem Statement

Despite this growing body of work, teacher educators — the faculty who design and deliver teacher-preparation coursework — have received little direct attention in the AI-readiness literature. A scoping review of AI literacy research in teacher education located only a handful of studies addressing teacher educators' own professional knowledge and concluded that teacher-education researchers and practitioners are still poorly represented in how AI literacy is conceptualized and studied (Sperling et al., 2024). The omission matters because teacher educators' own readiness, attitudes, and classroom practices around AI get passed on, whether they mean to or not, to every cohort of pre-service teachers who move through their programs. If teacher-education faculty are not themselves ready to integrate AI thoughtfully, their candidates are unlikely to be either. Yet no published study has directly examined the readiness and attitudes of teacher-education faculty as a distinct population using a role-appropriate, theory-grounded instrument. This study fills that gap.

Significance of the Study

This study matters for three groups of stakeholders. For teacher-education programs and their administrators, findings can identify concrete gaps in faculty AI competence and attitude that professional-development planning should target, rather than relying on assumptions carried over from the general higher-education or K-12 literature. For teacher educators themselves, the study offers a structured opportunity to reflect on their own readiness relative to peers across institution types and

experience levels. For the broader field of teacher-education research, the study extends technology-acceptance theory — well validated for teachers and, increasingly, for higher-education faculty in general (Scherer et al., 2019; McGehee, 2024) into a population it has not yet reached, contributing empirical evidence to a literature that currently theorizes about teacher educators more than it studies them directly.

Objectives of the Study

The study pursues the following objectives:

1. To assess the level of AI readiness (encompassing self-efficacy, perceived usefulness, and perceived ease of use) reported by teacher-education faculty.
2. To describe teacher-education faculty's favorable attitudes toward integrating AI into teacher-preparation curricula.
3. To examine the relationship between teacher-education faculty's AI readiness and their favorable attitudes toward AI integration.
4. To explore whether AI readiness is related to the ethical and pedagogical concerns teacher educators hold about AI integration.

Research Questions

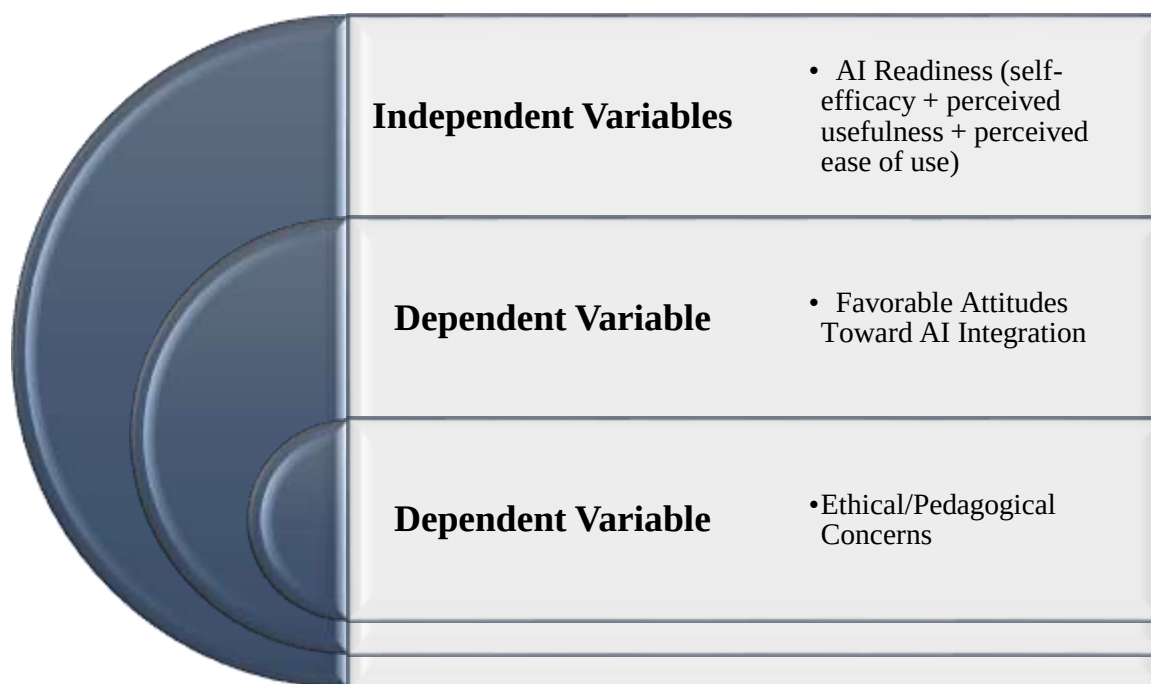
1. What is the level of AI readiness among teacher-education faculty?
2. What is teacher-education faculty's favorable attitudes toward integrating AI into teacher-preparation curricula?
3. Is there a significant relationship between teacher-education faculty's AI readiness and their favorable attitudes toward AI integration?
4. Is AI readiness related to the ethical and pedagogical concerns teacher educators hold about AI integration?

Conceptual Framework

This study's conceptual framework draws on the Technology Acceptance Model (TAM; Davis, 1989), one of the most empirically supported frameworks for explaining educator technology adoption (Granić, 2019; Scherer et al., 2019). The framework centers on three core variables: (1) AI Readiness, a composite construct combining self-efficacy, perceived usefulness, and perceived ease of use, treated as the independent variable; (2) Favorable Attitudes Toward AI Integration, operationalized as educators' overall positive evaluative orientation toward adopting AI tools in instructional practice, the primary dependent variable; and (3) Ethical/Pedagogical Concerns, encompassing educators' reservations about academic integrity, over-reliance, and the pedagogical appropriateness of AI use, a secondary dependent variable.

Figure 1

Conceptual Framework: AI Readiness, Favorable Attitudes, and Ethical/Pedagogical Concerns



Note. Adapted from the Technology Acceptance Model (Davis, 1989) as applied to AI adoption among educators (McGehee, 2024; Scherer et al., 2019).

Review of Literature

If artificial intelligence is reshaping how the next generation of teachers will be trained, it is striking how little attention has gone to the people doing the training. This review traces the current state of research on educators' readiness for, and attitudes toward, integrating artificial intelligence (AI) into teaching, moving from the broader landscape of AI in teacher education down to the narrower, still largely unstudied case of teacher educators themselves, before turning to the theoretical frameworks and barriers that shape how that adoption unfolds and, finally, to the specific gap this study addresses.

AI Readiness and Literacy in Teacher Education: The Broader Landscape

Most existing research on AI readiness in education has centered on pre-service and in-service K-12 teachers rather than on the faculty who train them. Studies of pre-service teachers consistently report a gap between enthusiasm and actual competence: candidates express favorable intentions toward using AI but show limited technical skill and a narrow, tool-focused understanding of what AI integration involves, and many describe a professional identity still in flux around what it means to teach in an AI-influenced classroom (Guan et al., 2025). Similar patterns appear in K-12 in-service populations: a large-scale Estonian survey of nearly 3,900 teachers found that readiness was shaped jointly by confidence,

perceived usefulness, and familiarity with AI tools, with a lack of formal training repeatedly identified as the primary constraint on adoption (Granström & Oppi, 2025). Structural equation modeling work with general and special education teachers in the United Arab Emirates similarly found that attitudes, more than knowledge alone, predicted actual AI-related classroom practice, and that readiness varied by teaching experience and academic role (Fteiha et al., 2025).

A scoping review focused specifically on teacher education found that AI literacy, despite being a fast-growing research topic in education generally, has barely been taken up within teacher-education scholarship itself; of the thirty-four studies it located examining AI literacy in relation to teachers' professional knowledge, very few examined teacher educators as a distinct population, and the authors called explicitly for greater representation of teacher-education researchers in shaping how AI literacy is conceptualized (Sperling et al., 2024). That finding is the starting point for the present study: the readiness literature that motivated this project has largely bypassed the very people who train the next generation of teachers.

Faculty AI Literacy, Attitudes, and Acceptance in Higher Education

A smaller but growing body of work has begun to examine faculty directly, though mostly outside teacher-education contexts specifically. A mixed-methods study of 538 higher-education faculty across disciplines in Palestine found that AI literacy develops through the interaction of perceived usefulness, ease of use, professional development opportunities, peer and community support, and prior technology experience, with qualitative focus-group data suggesting that faculty conceptualize AI literacy as encompassing both functional skill and ethical judgment rather than tool proficiency alone (Ayyoub et al., 2025). A related cross-sectional survey of university lecturers found that a large majority (84%) were willing to accept AI tools for student use, and that acceptance was predicted by teaching experience, institutional support, and general attitude toward AI, even though a meaningful minority remained resistant (Ofosu-Ampong, 2024).

Because existing AI-literacy instruments were developed for the general public, students, or K-12 teachers, they do not capture the role-specific dimensions of faculty work — teaching, research, and service — that shape how instructors actually engage with AI. In response, a recent instrument-validation study developed and psychometrically tested the Faculty Artificial Intelligence Literacy and Competency (FALCON-AI) scale, organized around functional, evaluative, and ethical literacy across four domains of faculty work (Song et al., 2026). The emergence of this new, role-specific instrument signals that the field now recognizes faculty as a population distinct from students or K-12 teachers, but also that validated tools for measuring faculty readiness are only just becoming available; the present study applies that same role-specific lens to teacher educators in particular.

Theoretical Frameworks: Technology Acceptance and Adoption Models

The Technology Acceptance Model (TAM) remains the dominant framework for explaining educator technology adoption, including AI adoption. A large-scale meta-analytic structural equation model synthesizing more than one hundred TAM studies and over 34,000 teachers confirmed that perceived usefulness and perceived ease of use reliably predict technology-adoption intentions, although the relative weight of these constructs varies across contexts (Scherer et al., 2019). A systematic review of TAM applications in educational settings likewise concluded that TAM is the most frequently applied and empirically supported model of technology acceptance among teachers and

other educational stakeholders, though most applications extend the original model with context-specific variables such as facilitating conditions or self-efficacy rather than using the bare two-construct version (Granić, 2019). Faculty-specific applications of TAM, including studies of learning-management-system adoption, have similarly found that self-efficacy and facilitating conditions substantially improve the model's ability to predict actual faculty behavior beyond perceived usefulness and ease of use alone (Fathema et al., 2015).

Applied specifically to AI, a meta-analysis of more than sixty educator-acceptance studies extended these TAM-based findings, identifying self-efficacy, perceived usefulness, technological complexity, and ethical concern as the consistent predictors of AI acceptance among educators, while noting that AI introduces amplified resistance compared to earlier educational technologies because of the scale of pedagogical change and ethical uncertainty it demands (McGehee, 2024). This body of work supports using a TAM-informed instrument — capturing perceived usefulness, ease of use, self-efficacy, and facilitating conditions — as the measurement backbone for the present study.

Barriers and Facilitating Conditions

Across both general educational-technology adoption research and the newer AI-specific literature, a consistent set of barriers recurs: insufficient training, limited time, inadequate institutional support and infrastructure, and unresolved ethical or pedagogical concerns about appropriate use (McGehee, 2024; Scherer et al., 2019). Faculty-development scholarship in higher education makes a further point directly relevant to teacher educators: because faculty AI literacy is a prerequisite for teaching AI literacy to students, uneven faculty engagement — ranging from outright avoidance to uncritical rapid adoption — risks producing inconsistent AI instruction that depends on individual instructor enthusiasm rather than being embedded in institutional practice (Liu & Levy, 2026). For teacher educators specifically, the stakes are higher: their own AI attitudes and competence shape not just their personal teaching practice but what pre-service teachers absorb from watching them, and those candidates will carry it forward into K-12 classrooms.

Research Gap and Rationale

Three converging gaps justify the present study. First, the readiness and attitudes literature in education has focused overwhelmingly on pre-service and K-12 in-service teachers; a scoping review found teacher educators' own professional knowledge around AI to be scarcely represented in teacher-education scholarship (Sperling et al., 2024). Second, the small emerging literature on faculty AI literacy and acceptance has largely studied higher-education faculty in general, across disciplines, rather than teacher-education faculty specifically — even though how this group is prepared to use, or avoid, AI has knock-on effects for an entire generation of future teachers. Third, although TAM-based frameworks and newly validated instruments such as FALCON-AI now offer psychometrically sound tools for measuring role-specific faculty AI literacy and readiness (Song et al., 2026), no study has yet directly tested the relationship between teacher-education faculty's AI readiness and their attitudes toward AI integration. The present study addresses this gap with a focused, two-variable design: a single survey of teacher educators, using a TAM-informed instrument, to establish how ready this population is, how favorably disposed they are toward AI integration, and whether the two are related.

Methodology

Research Design

This study employs a quantitative, cross-sectional correlational design. A correlational design was selected because the purpose of the study is to examine the strength and direction of the relationships among three variables — AI readiness, attitudes toward AI integration, and ethical concerns — within a single population at a single point in time, without manipulating any variable. This design is consistent with the majority of published studies on educator technology acceptance, which similarly rely on single-timepoint surveys analyzed through correlation or regression (Granström & Oppi, 2025; Scherer et al., 2019).

Population and Sample

The target population for this study was teacher-educator faculty members who teach education-related courses and are directly responsible for preparing future teachers working in colleges affiliated with University of Punjab across both the public and private sectors. This population was defined broadly because many college-based teacher educators teach across two levels within the same institution: the intermediate (Grade 11–12) level, where Education is offered as a subject, and the undergraduate level (B.Ed. or BS Education programs). Both public-sector and private-sector colleges were included to capture a more representative cross-section of teacher educators than a single-sector sample would allow, while keeping recruitment logistically manageable.

A purposive (non-probability) sampling technique was used, since the population of teacher educators across public and private colleges is not centrally listed and a full sampling frame was not available; purposive sampling is well suited to studies such as this one, where the goal is to reach a specific, knowledgeable population rather than to generalize from a fully randomized frame (Etikan et al., 2016). Faculty were included if they (a) currently taught at least one education-related course to either intermediate-level or undergraduate-level students, and (b) had at least one semester of teaching experience at their current institution. Institution type (public vs. private) was recorded and reported descriptively, allowing for a simple comparison of respondent composition without treating it as a formal moderating variable. The a priori target sample size was 170 teacher educators, consistent with comparable single-country studies of this design (e.g., Fteiha et al., 2025, N = 161). To reach that target, the questionnaire was distributed to approximately 200 eligible faculty; the achieved sample size was N = 170 teacher educators who completed their responses.

Instrument

Data was collected using a single, structured, self-report questionnaire consisting of four parts. Part I collected demographic and background information, including years of teaching experience, institution type (public college vs. private college), level(s) taught (intermediate and/or undergraduate), subject area, and prior AI-related knowledge (yes/no), all of which were reported descriptively rather than tested as moderators. Part II was a 12-item AI Readiness subscale, adapted from the constructs and operational definitions established in the Technology Acceptance Model (Davis, 1989) and subsequent educator-focused AI-literacy instruments (Song et al., 2026), covering three sub-dimensions: self-efficacy, perceived usefulness, and perceived ease of use (4 items each). Part III was an 8-item Favorable Attitudes Toward AI Integration subscale, adapted from the attitude constructs used in comparable educator-attitude studies (Granström & Oppi, 2025; Ofosu-Ampong, 2024). Part IV was a 6-item

Ethical/Pedagogical Concerns subscale, developed to capture ethical, pedagogical, and practical concerns about AI in teacher preparation — including ethical implications, critical-thinking erosion, bypassing genuine learning, reduced pedagogical creativity, bias/fairness, and data privacy/security — as a construct empirically and conceptually distinct from favorable attitudes. All items used a 5-point Likert format (1 = Strongly Disagree to 5 = Strongly Agree).

Reliability Analysis

Internal consistency was assessed using Cronbach's alpha ($\alpha \geq .70$ considered acceptable), a widely used but sometimes uncritically reported reliability statistic that should be interpreted alongside the number and content of items in a subscale rather than as a stand-alone marker of instrument quality (Taber, 2018). The 12-item AI Readiness subscale demonstrated acceptable reliability ($\alpha = .74$). The 8-item Favorable Attitudes subscale likewise demonstrated acceptable reliability ($\alpha = .71$). The 6-item Ethical/Pedagogical Concerns subscale demonstrated acceptable reliability ($\alpha = .73$).

Data Collection Procedure

The questionnaire was administered online (via Google Forms) to maximize reach across public and private colleges of education within a limited timeframe, alongside paper copies where institutions preferred in-person distribution. College principals were first contacted for permission to approach faculty at their institutions. The survey link, accompanied by a brief description of the study's purpose and an informed-consent statement, was then shared directly with eligible faculty via institutional email or official departmental groups, with principals' assistance in circulating the link where needed. Data collection took place over a period of approximately one month, with a reminder sent approximately two weeks after initial distribution to improve response rate.

Data Analysis

Demographic data (Part I) were summarized using descriptive statistics (frequencies and percentages). AI Readiness, Favorable Attitudes, and Concerns scores were each summarized using means and standard deviations to address Objectives 1 and 2. To address Objective 3, a Pearson product-moment correlation coefficient was calculated between the composite AI Readiness score and the composite Favorable Attitudes score. To address Objective 4 / Research Question 4, a separate Pearson correlation was calculated between AI Readiness and the Concerns composite. Normality was checked prior to each correlation; because all variables met the normality assumption, Pearson correlation was used as the primary test throughout. All analyses were conducted using SPSS, with statistical significance set at $\alpha = .05$.

Ethical Considerations

Participation was entirely voluntary; all respondents were informed of the study's purpose, their right to withdraw at any point without penalty, and the confidentiality and anonymity of their responses before beginning the survey. No personally identifying information was collected; institutional affiliation was recorded only at the level of institution type (public college vs. private college), not by name. Formal permission was attained from principals for this study, consistent with the minimal-risk, anonymous, adult-respondent survey design; standard informed-consent, voluntariness, and confidentiality protections were followed throughout. Data were stored securely and used solely for the purposes of this study.

Results

All results below are based on the sample size (N = 170).

Table 1

Demographic Profile of Respondents

Characteristic	Category	n (%)
Institution Type	Public college	85 (50.0%)
	Private college	85 (50.0%)
Years of Teaching Experience	Low (5–6 yrs)	44 (25.9%)
	Mid (7–8 yrs)	66 (38.8%)
	High (9–10 yrs)	60 (35.3%)
	M (SD) years	7.85 (1.47)

Note. N = 170.

Table 1 summarizes the demographic composition of respondents (N = 170). Respondents were evenly split between public (n = 85, 50.0%) and private (n = 85, 50.0%) colleges of education, with a mean of 7.85 years of teaching experience (SD = 1.47). Subject area, level taught, and prior-AI-knowledge showed no variance across respondents and were therefore omitted.

Descriptive Statistics

Table 2

Descriptive Statistics for Study Variables

Variable	M	SD
AI Readiness	3.61	0.47
Favorable Attitudes	3.39	0.63
Concerns	3.56	0.60

Note. 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree).

Table 2 presents descriptive statistics for the three study variables, each classified as Low (1.00–2.33), Moderate (2.34–3.67), or High (3.68–5.00) based on standard 5-point-scale banding. AI Readiness was Moderate (M = 3.61, SD = 0.47). Favorable Attitudes was Moderate (M = 3.39, SD = 0.63), and Concerns was likewise Moderate but toward the upper end of that band (M = 3.56, SD = 0.60), indicating that ethical and pedagogical concern was fairly common among these teacher educators.

Correlational Analysis

Table 3

Pearson Correlation Analysis

Relationship	N	df	r	p
AI Readiness – Favorable Attitudes (H ₁)	170	168	.30**	< .001
AI Readiness – Concerns (RQ4)	170	168	.74**	< .001

Note. ** $p < .001$.

Table 3 presents the results addressing Objectives 3 and 4. AI Readiness was significantly, positively correlated with Favorable Attitudes, $r(168) = .30$, $p < .001$ (H₁ supported), and significantly, positively, and very strongly correlated with Concerns, $r(168) = .74$, $p < .001$ (RQ4). Figures 2 and 3 display these relationships.

Figure 2

Scatterplot of AI Readiness and Favorable Attitudes (N = 170), with linear trend line.

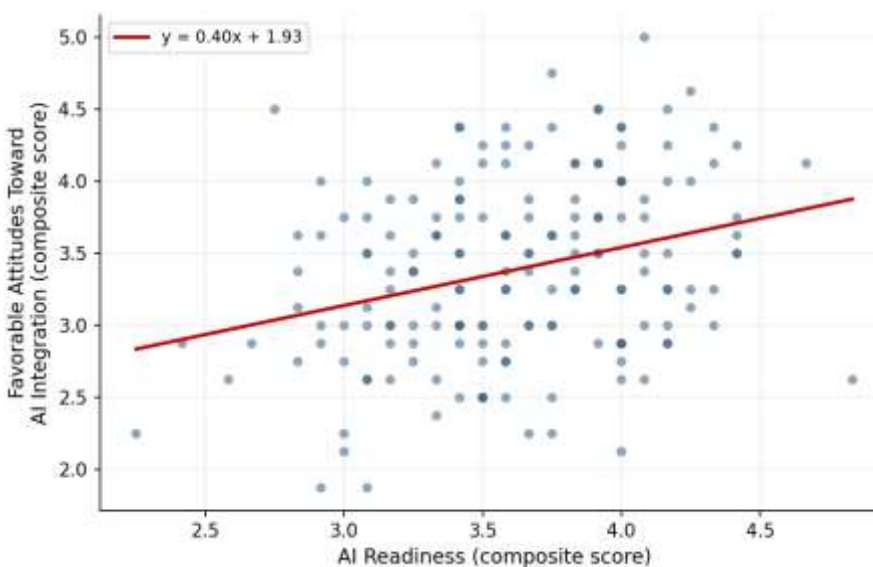
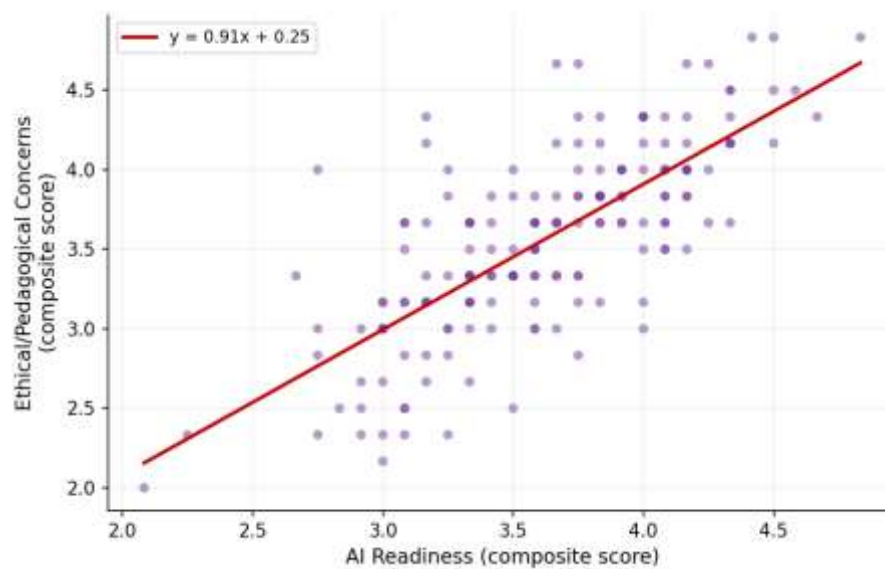


Figure 3

Scatterplot of AI Readiness and Concerns (N = 170), with linear trend line.



Regression Analysis

Table 4

Regression Model Summary

Model	N	R	R ²	Adj. R ²	F	p
1: Readiness → Favorable Attitudes	170	.30	.088	.083	16.26	< .001
2: Readiness → Concerns	170	.74	.555	.552	209.42	< .001

Table 5

ANOVA: Regression Model Significance Test

Model / Source	Sum of Squares	Df	Mean Square	F	p
Model 1					
Regression	5.948	1	5.948	16.26	< .001
Residual	61.472	168	0.366		
Total	67.419	169			

Model 2					
Regression	33.696	1	33.696	209.42	< .001
Residual	27.032	168	0.161		
Total	60.728	169			

Simple linear regression was used to model each outcome from AI Readiness, providing a predictive complement to the correlational results above. Table 5 presents the model summaries: Model 1 (Readiness predicting Favorable Attitudes) explained 8.8% of the variance, $R^2 = .088$, $F(1, 168) = 16.26$, $p < .001$; Model 2 (Readiness predicting Concerns) explained 55.5% of the variance, $R^2 = .555$, $F(1, 168) = 209.42$, $p < .001$. Table presents the corresponding ANOVA breakdown confirming that both regression models, as a whole, were statistically significant before individual coefficients are interpreted.

Table 6*Regression Coefficients*

Model / Predictor	B	SE	β	T	p
Model 1: (Constant)	1.93	0.36	—	5.31	< .001
AI Readiness	0.40	0.10	.30	4.03	< .001
Model 2: (Constant)	0.25	0.23	—	1.08	.280
AI Readiness	0.92	0.06	.74	14.47	< .001

Note. B = unstandardized coefficient; β = standardized coefficient.

Table 6 presents the regression coefficients. In Model 1, AI Readiness significantly predicted Favorable Attitudes, $B = 0.40$, $SE = 0.10$, $\beta = .30$, $t(168) = 4.03$, $p < .001$: each one-point increase in AI Readiness was associated with a 0.40-point increase in Favorable Attitudes. In Model 2, AI Readiness significantly predicted Concerns, $B = 0.92$, $SE = 0.06$, $\beta = .74$, $t(168) = 14.47$, $p < .001$: each one-point increase in AI Readiness was associated with a 0.92-point increase in Concerns — a substantially larger, more precisely estimated effect.

Discussion

AI readiness and attitudes have been studied extensively among pre-service and in-service K-12 teachers (Guan et al., 2025; Granström & Oppi, 2025) and, more recently, among higher-education faculty in general (Ayyoub et al., 2025; Ofosu-Ampong, 2024). Teacher educators — the people who train those future teachers — had received barely any attention of their own (Sperling et al., 2024), which is the gap the present findings speak to, extending Technology Acceptance Model-based readiness research (Scherer et al., 2019; McGehee, 2024) into this population for the first time.

Addressing Objectives 1 and 2, teacher educators in this sample reported Moderate levels of both AI readiness ($M = 3.61$ of 5) and favorable attitudes toward AI integration ($M = 3.39$ of 5), rather than

the strongly favorable or strongly resistant profile sometimes assumed in policy discussions of AI adoption. This Moderate positioning is itself informative: it suggests that teacher educators are neither uncritically enthusiastic early adopters nor disengaged holdouts, but a population still forming its stance — confident enough with the technology to use it, yet not uniformly convinced it belongs at the center of teacher-preparation curricula. This pattern is broadly consistent with Ofosu-Ampong (2024), who similarly found generally favorable but uneven acceptance among university lecturers, and suggests that teacher-education programs are working with a faculty base that is genuinely persuadable rather than already settled in either direction — which is precisely the population for which the readiness-building interventions discussed below would be expected to have the most leverage.

Consistent with Hypothesis 1 and with the broader TAM literature, teacher educators who reported greater self-efficacy, perceived usefulness, and perceived ease of use around AI tools also reported more favorable attitudes toward integrating AI into their teacher-preparation curricula. This finding aligns with prior work linking readiness constructs to favorable technology attitudes among both K-12 teachers (Granström & Oppi, 2025) and higher-education faculty generally (Ayyoub et al., 2025). At the same time, the effect size observed here ($r = .30$, $r^2 \approx 9\%$) was more modest than the higher correlations sometimes reported in adjacent literatures, suggesting that readiness is one meaningful predictor of favorable attitudes among teacher educators but leaves the large majority of variance unexplained — consistent with McGehee's (2024) meta-analytic observation that AI-specific attitudes are shaped by a wider set of factors (institutional support, ethical concern, disciplinary context) than earlier educational technologies typically required.

AI Readiness was very strongly and positively correlated with Concerns ($r = .74$): teacher educators who report greater confidence, perceived usefulness, and ease of use around AI tools also report substantially higher ethical and pedagogical concern about AI in teacher preparation, not less. An anxiety-about-the-unknown account would predict the opposite — concern clustering among faculty who feel least capable with AI but that is not what the data show. Instead, the faculty who understand AI tools well enough to feel ready to use them appear to be the same faculty who have thought carefully enough about AI to recognize its ethical and pedagogical risks: concern that tracks understanding rather than concern born of unfamiliarity. Training alone, in other words, will not make this concern go away — building readiness may well surface more of it, not less, as faculty become better informed.

Because Concerns was measured with a short, carefully validated 6-item subscale rather than folded into the Favorable Attitudes composite, the study was able to detect this strong, positive relationship with confidence ($\alpha = .73$). This underscores why reliability diagnostics belong in the core reporting of any survey-based study: a thinly measured construct can obscure a relationship that a properly validated subscale reveals clearly.

Recommendations

1. Teacher-education programs should invest in structured, hands-on AI training for faculty, since AI readiness was the strongest actionable predictor of favorable attitudes toward AI integration identified in this study.
2. Training should not be institutes marketed or evaluated as a way to reduce ethical and pedagogical concern; concern rose alongside readiness in this sample, so Training programs

should instead create dedicated, ongoing spaces (e.g., faculty working groups, curriculum-review committees) for faculty to raise and address AI-related ethical and pedagogical concerns as they become more informed.

3. Teacher-education administrators should treat faculty AI readiness as a distinct professional-development priority in its own right, separate from general instructional-technology training, given the specific and consequential role teacher educators play in modeling AI use for future teachers.

4. Pursue experimental or longitudinal designs to test whether AI training interventions causally shift readiness, favorable attitudes, and concern over time, rather than relying solely on the cross-sectional, correlational evidence presented here.

5. Extend this line of research to teacher educators in other institutional and national contexts, given that the present sample was drawn using purposive sampling from a limited set of colleges of education.

Conclusion

Teacher educators, a population largely overlooked in the existing literature, reported Moderate levels of both AI readiness and favorable attitudes toward AI integration (Objectives 1 and 2). In a single survey administration (N = 170), greater AI readiness — encompassing self-efficacy, perceived usefulness, and perceived ease of use — was significantly associated with more favorable attitudes toward integrating AI into teacher-preparation curricula, supporting Hypothesis 1 (Objective 3), and very strongly associated with the ethical and pedagogical concerns faculty expressed about AI (Objective 4). Greater AI readiness among teacher educators, then, goes with both more favorable curricular attitudes and more informed ethical concern — concern is not simply a marker of low readiness here.

Teacher educators' own AI-related beliefs and practices pass, one way or another, to the pre-service teachers they train — which is why supporting their readiness matters well beyond their own classrooms. The recommendations above outline concrete next steps for both teacher-education practice and future research building on this study.

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