AI-Ready but Inclusion-Aware? Faculty Readiness to Use Artificial Intelligence for Inclusive Pedagogy in Philippine Higher Education Institutions

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ABSTRACT:

This study examined faculty readiness to use Artificial Intelligence (AI) for inclusive pedagogy among faculty members across Philippine Higher Education Institutions (HEIs). Anchored in the Technology Acceptance Model and the Universal Design for Learning framework, the study employed a descriptive-correlational-with-predictive design using a researcher-developed and validated survey instrument. Faculty readiness was operationalized across five dimensions: AI Literacy, Perceived Usefulness, Perceived Ease of Use, Attitude toward Inclusive Pedagogy, and Institutional Support, with Inclusive AI Teaching Readiness as the outcome variable. Results revealed that faculty demonstrated a high level of readiness across all dimensions, with Perceived Usefulness and Institutional Support ranked highest. No significant differences in inclusive AI teaching readiness were found across any of the demographic variables examined. The predictor dimensions did not significantly predict the outcome variable in hierarchical regression analyses, with Attitude toward Inclusive Pedagogy showing the strongest directional tendency among the predictors. These null predictive findings suggest that faculty across Philippine HEIs have reached a broadly shared plateau of declared readiness that has not yet translated into differentiated inclusive practice — a condition shaped by compressed score distributions and the complexity of the factors driving actual teaching behavior, which linear models alone cannot fully capture. Future studies employing structural equation modeling and mixed-methods approaches are recommended to more precisely illuminate these relationships. The study contributes evidence-based grounding for designing faculty development programs and shaping institutional and national policies that advance the integration of AI and inclusive education in Philippine higher education.

Keywords: artificial intelligence, inclusive pedagogy, faculty readiness, Universal Design for Learning, Philippine HEIs, Technology Acceptance Model.

INTRODUCTION

The rapid integration of Artificial Intelligence (AI) in higher education has fundamentally altered the landscape of teaching and learning, presenting both unprecedented opportunities and complex pedagogical challenges. Across the globe, academic institutions are increasingly deploying AI-powered tools — from adaptive learning platforms and intelligent tutoring systems to automated feedback generators and predictive analytics — with the primary intent of enhancing instructional efficiency and student outcomes (Zawacki-Richter et al., 2019; Holmes et al., 2022). Yet beneath this wave of technological enthusiasm lies a critical and largely unresolved question: are faculty adequately prepared to harness AI not merely as a tool for general instruction, but specifically in service of inclusive pedagogy — that is, teaching that is deliberately designed to reach every learner, regardless of ability, background, or circumstance?

Inclusive education, broadly defined as the practice of ensuring equitable access to quality learning for all students, including those with disabilities, diverse learning needs, and marginalized identities, has long been enshrined in global education policy frameworks. The United Nations Sustainable Development Goal 4 (SDG 4) explicitly calls for inclusive and equitable quality education, while UNESCO's Education 2030 Framework for Action identifies inclusion as a foundational principle of transformative educational practice (UNESCO, 2015). In the Philippine context, the Commission on Higher Education (CHED) has similarly affirmed its commitment to inclusive education through CMO No. 23, s. 2000, which provides guidelines on the admission and support of students with disabilities in higher education institutions, alongside CMO Nos. 74–77, s. 2017, which mandates the integration of special and inclusive education foundations into pre-service teacher education programs. Despite these policy imperatives, the practical translation of inclusive principles into AI-augmented classrooms remains a significant gap — particularly in developing-country contexts where institutional readiness, technological infrastructure, and faculty competencies vary considerably.

Faculty occupy a pivotal position at the nexus of AI adoption and inclusive practice. As the primary designers and facilitators of learning experiences, their readiness — defined here as a composite of AI literacy, attitudes toward inclusive pedagogy, perceived usefulness and ease of use of AI tools, and the institutional support available to them — directly shapes whether AI integration serves the full diversity of the student population or inadvertently deepens existing educational inequities. Research has consistently shown that technology adoption in education is not neutral: when implemented without deliberate attention to equity and accessibility, AI systems can replicate and even amplify systemic biases, disadvantaging students with disabilities, non-native language speakers, and those from low-income backgrounds. Venkit and Wilson (2021), for instance, demonstrated that common sentiment analysis and toxicity detection models associate disability-related terms with consistently negative connotations, raising serious concerns about the uncritical deployment of such tools in educational settings. Similarly, Whittaker et al. (2019) documented how AI systems, when trained on biased data, systematically reproduce ableist assumptions in ways that harm users with disabilities.

Despite the growing body of literature on AI integration in higher education, studies that specifically examine faculty readiness through the lens of inclusive pedagogy remain scarce. Existing research tends to either focus on general technology acceptance (Davis, 1989; Teo, 2011) or address inclusive education separately from AI adoption, leaving a conceptual and empirical gap at their intersection. This gap is especially pronounced in the Philippine higher education context, where studies on AI in teaching and learning are only beginning to emerge and where inclusive education — despite CHED's policy directives — continues to face implementation challenges related to faculty preparation, resource availability, and institutional culture. Raguindin and Ping (2025), in a Delphi study involving Filipino in-service teachers, found that teachers

express a persistent lack of preparedness for inclusive practices, attributing this deficit to insufficient specific competencies, limited training exposure, and inadequate institutional support.

This study addresses that gap by examining faculty readiness to use AI for inclusive teaching in Philippine HEIs and identifying which dimensions of readiness significantly predict inclusive AI teaching practice. Anchored in Davis's (1989) Technology Acceptance Model (TAM) and the Universal Design for Learning (UDL) framework developed by CAST (2018), the study adopts a descriptive-correlational with predictive design. The findings are expected to contribute to the growing discourse on AI-enabled inclusive education, provide empirical evidence to inform faculty development programs, and offer policy-relevant insights to CHED, HEI administrators, and curriculum developers committed to building more equitable and future-ready higher education systems.

Statement of the Problem

This study determined the level of faculty readiness to use Artificial Intelligence for inclusive pedagogy in Philippine Higher Education Institutions. Specifically, it sought to answer the following questions:

1. What is the demographic profile of the respondents in terms of sex, age, educational attainment, employment status, academic rank, years of service, type of HEI, and teaching discipline?

2. What is the level of faculty readiness to use AI for inclusive teaching along the dimensions of: (a) AI literacy; (b) perceived usefulness; (c) perceived ease of use; (d) attitude toward inclusive pedagogy; and (e) institutional support?

3. Is there a significant difference in faculty readiness across demographic variables?

4. To what extent do the dimensions of faculty readiness correlate with and predict inclusive AI teaching practice?

THEORETICAL FRAMEWORK

This study is anchored on two complementary theoretical and pedagogical frameworks: Davis's (1989) Technology Acceptance Model (TAM) and the Universal Design for Learning (UDL) framework developed by CAST (2018). Together, these frameworks provide robust conceptual scaffolding for examining how faculty perceive, adopt, and deploy AI tools to support inclusive teaching practice.

Technology Acceptance Model (TAM)

The Technology Acceptance Model, originally proposed by Davis (1989) and subsequently refined by Venkatesh and Davis (2000), is one of the most widely validated theoretical frameworks for explaining and predicting individual acceptance and use of information technology. Rooted in Ajzen and Fishbein's (1980) Theory of Reasoned Action, TAM posits that an individual's intention to use a technology is primarily determined by two cognitive beliefs: perceived usefulness — the degree to which a person believes that using a particular technology will enhance their performance — and perceived ease of use — the degree to which a person believes that using a technology will be free of effort. These two constructs, in turn, are influenced by external variables such as individual characteristics, system features, and contextual factors, all of which shape actual technology use behavior.

In this study, TAM serves as the primary lens for understanding faculty decisions to adopt and integrate AI tools into their teaching practice. Subsequent extensions, including TAM2 (Venkatesh & Davis, 2000) and the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003), incorporated additional predictors such as social influence and facilitating conditions, which, in this study, correspond to the institutional support dimension.

Universal Design for Learning (UDL)

The Universal Design for Learning framework, developed by CAST (2018), is built on the foundational premise that there is no single

average learner — individual differences in how students perceive information, engage with content, and express understanding are the norm, not the exception. Drawing on Vygotsky's (1978) concept of the Zone of Proximal Development, UDL offers a proactive pedagogical architecture for designing learning experiences that are accessible and effective for all learners from the outset.

UDL is organized around three core principles: multiple means of representation (the what of learning), multiple means of action and expression (the how of learning), and multiple means of engagement (the why of learning). In this study, UDL serves as the inclusive pedagogy lens through which faculty attitudes and practices are evaluated. Faculty readiness for inclusive AI teaching is interpreted as the capacity and willingness to deploy AI tools in alignment with UDL principles — for instance, using text-to-speech AI for students with reading difficulties, employing AI-assisted multimodal assessment platforms, or leveraging adaptive learning systems to sustain individualized student engagement.

Integration of TAM and UDL

While TAM explains the conditions under which faculty are likely to adopt AI tools, UDL defines the pedagogical purpose toward which that adoption should be directed. Their integration creates a two-dimensional framework: TAM addresses the supply side of faculty readiness — whether faculty are motivated and equipped to use AI — while UDL addresses the demand side — whether that use is oriented toward equitable, inclusive learning outcomes. This integration addresses a recognized gap in the literature: existing TAM studies in educational technology research have largely focused on general instructional outcomes, seldom extending their analyses to equity or accessibility dimensions (Scherer et al., 2019). By coupling TAM with UDL, this study advances a more socially conscious and pedagogically grounded model of technology acceptance, particularly relevant to Philippine HEIs navigating the dual imperatives of digital transformation and inclusive education.

METHODOLOGY

Research Design

This study employed a descriptive-correlational with predictive research design. The descriptive component characterized the level of faculty readiness to use AI for inclusive teaching across its five dimensions. The correlational component examined the bivariate relationships among the predictor variables and the outcome variable. The predictive component — operationalized through hierarchical multiple regression — identified the extent to which dimensions of faculty readiness predict inclusive AI teaching practice. This design is consistent with quantitative educational research aimed at explaining and forecasting behavior within a defined population (Creswell & Creswell, 2018).

Research Locale and Respondents

The study was conducted across Higher Education Institutions (HEIs) in the Philippines, with primary data collection concentrated in the CALABARZON region (Region IV-A). To strengthen generalizability, the study also included respondents from other regions through an online survey platform. Respondents were 213 full-time and part-time faculty members from Philippine HEIs — both state universities and colleges (SUCs) and private institutions — who were teaching at the time of data collection and were willing to participate voluntarily. Respondents were recruited through stratified purposive sampling, with strata defined by HEI type, academic rank, and teaching discipline.

Research Instrument

The primary data collection tool was a researcher-developed survey questionnaire comprising eight parts: (I) demographic profile; (II) AI Literacy (7 items); (III) Perceived Usefulness of AI for inclusive teaching (7 items); (IV) Perceived Ease of Use (6 items); (V) Attitude toward Inclusive Pedagogy (8 items); (VI) Institutional Support (7 items); (VII) Inclusive AI Teaching Readiness — the dependent variable (10 items); and (VIII) optional open-ended questions. Parts II–VI used a five-point Likert scale (5 = Strongly Agree, 1 = Strongly Disagree). Part VII used a

frequency/confidence scale (5 = Always/Very Confident, 1 = Never/Not Confident). Items were adapted from Davis's (1989) TAM scale and UDL-informed inclusive teaching scales, and contextualized for the Philippine HEI setting.

Validity and Reliability

Content validity was established through expert review by seven specialists in educational technology, inclusive education, and research methodology, using the Content Validity Index (CVI) with an item-level threshold of ≥ 0.78 (Polit & Beck, 2006). Internal consistency reliability was assessed through pilot testing with 30 faculty respondents using Cronbach's alpha, with a threshold of $\alpha \geq 0.80$ per subscale (George & Mallery, 2003).

Statistical Treatment

Frequency counts and percentages were used to describe the demographic profile (RQ1). Means and standard deviations were used to describe the level of faculty readiness per dimension (RQ2). The Mann-Whitney U test (for sex) and the Kruskal-Wallis H test (for all other demographic variables) were used to examine significant differences in Inclusive AI Teaching Readiness across demographic groups (RQ3). Pearson correlation coefficients and hierarchical multiple regression — with Type of HEI entered as a control variable in Block 1 and the five predictor dimensions in Block 2 — addressed RQ4. Multicollinearity was assessed using the Variance Inflation Factor (VIF) values, with a threshold of VIF < 5. All analyses were conducted at $\alpha = 0.05$.

RESULTS AND DISCUSSION

Demographic Profile of Respondents

Table 1 presents the demographic profile of the 213 faculty respondents. The majority were female (58.7%), aged 40–49 (33.8%), holders of a master's degree (45.1%), and employed on a regular or permanent basis (63.8%). Most held the rank of Instructor (34.7%) with 11–20 years of service (31.0%) and were drawn primarily from state universities and colleges (48.4%) and taught Education-related courses (31.0%). This profile broadly reflects the Philippine HEI faculty landscape, in which master's degree holders constitute the largest segment and SUC faculty make up a substantial share of the national teaching workforce.

Table 1 Demographic Profile of Respondents (n = 213)

Variable	Category	f	%
Sex	Male	88	41.3
	Female	125	58.7
Age	Below 30	34	16.0
	30–39	63	29.6
	40–49	72	33.8
	50 and above	44	20.7
Educational Attainment	Bachelor's	11	5.2
	Master's	96	45.1
	Doctorate	79	37.1
	Post-doctorate	27	12.7
Employment Status	Regular/Permanent	136	63.8
	Temporary/Contractual	46	21.6

Variable	Category	f	%
	Part-time	31	14.6
Academic Rank	Instructor	74	34.7
	Assistant Professor	65	30.5
	Associate Professor	41	19.2
	Professor	33	15.5
Years of Service	Less than 5	56	26.3
	5–10 years	53	24.9
	11–20 years	66	31.0
	More than 20	38	17.8
Type of HEI	State University/College	103	48.4
	Private HEI	75	35.2
	Local College	35	16.4
Teaching Discipline	STEM	53	24.9
	Education	66	31.0
	Business/Social Science	43	20.2
	Humanities/Arts	20	9.4
	Health Sciences	31	14.6

Level of Faculty Readiness to Use AI for Inclusive Teaching

Table 2 presents the descriptive statistics for all dimensions of faculty readiness and the outcome variable. All dimensions registered mean within the High range (3.50–4.49), with overall means ranging from 3.71 to 3.85.

Table 2 Descriptive Statistics: Faculty Readiness Dimensions and Inclusive AI Teaching Readiness

Dimension	Mean	SD	Interpretation
AI Literacy	3.71	0.70	High
Perceived Usefulness	3.85	0.60	High
Perceived Ease of Use	3.77	0.64	High
Attitude toward Inclusive Pedagogy	3.74	0.73	High
Institutional Support	3.84	0.63	High
Inclusive AI Teaching Readiness (DV)	**3.72**	**0.68**	**High**

Note. Scale: 4.50–5.00 = Very High; 3.50–4.49 = High; 2.50–3.49 = Moderate; 1.50–2.49 = Low; 1.00–1.49 = Very Low.

Perceived Usefulness registered the highest mean (M = 3.85, SD = 0.60), indicating that faculty generally recognize AI tools as beneficial for instructional delivery and student support. Institutional Support followed closely (M = 3.84, SD = 0.63), suggesting that respondents perceive their institutions as moderately supportive of AI integration. AI Literacy obtained the lowest mean among the predictors (M = 3.71, SD = 0.70), pointing to a comparatively narrower competency in understanding, using, and critically evaluating AI tools — a finding consistent with Zawacki-Richter et al. (2019), who noted that while faculty awareness of AI is growing, deeper critical literacy remains uneven across institutional settings.

The outcome variable, Inclusive AI Teaching Readiness, likewise fell within the High range (M = 3.72, SD = 0.68), indicating that faculty are moderately well-prepared to deploy AI tools in ways that support diverse learners. However, the proximity of all means to the lower boundary of the High range warrants attention: the findings suggest readiness that is present but not yet robust, affirming the need for more targeted faculty development that bridges AI adoption with deliberate inclusive pedagogical practice, as prescribed by the UDL framework (CAST, 2018).

Significant Differences in Inclusive AI Teaching Readiness Across Demographic Variables

Table 3 presents the results of the Mann-Whitney U test and Kruskal-Wallis H tests examining differences in Inclusive AI Teaching Readiness across the eight demographic variables.

Table 3 Differences in Inclusive AI Teaching Readiness Across Demographic Variables

Demographic Variable	Test Used	Statistic	p-value	Decision
Sex	Mann-Whitney U	5673.00	.697	Not Significant
Age	Kruskal-Wallis H	1.796	.616	Not Significant
Educational Attainment	Kruskal-Wallis H	1.005	.800	Not Significant
Employment Status	Kruskal-Wallis H	1.087	.581	Not Significant
Academic Rank	Kruskal-Wallis H	1.992	.574	Not Significant
Years of Service	Kruskal-Wallis H	2.131	.546	Not Significant
Type of HEI	Kruskal-Wallis H	5.163	.076	Not Significant
Teaching Discipline	Kruskal-Wallis H	4.056	.399	Not Significant

Note. Significance level: $p < .05$.

At alpha = 0.05, no significant differences were found in Inclusive AI Teaching Readiness across all eight demographic variables. This uniformity of readiness levels across sex, age, educational attainment, employment status, academic rank, years of service, type of HEI, and teaching discipline suggests that the high but moderate level of readiness observed is a broadly shared condition among Philippine HEI faculty — not concentrated in any particular subgroup. Notably, the type of HEI approached did not reach significance (H = 5.163, p = .076), suggesting a possible trend in which faculty from different institutional types may differ marginally in readiness, though this requires further investigation. These results are consistent with the technology adoption literature, which suggests that when an innovation is sufficiently diffused within a professional community, demographic variables lose predictive power over adoption behavior (Teo, 2011).

Correlation Analysis and Predictors of Inclusive AI Teaching Readiness

Table 4 presents the Pearson correlation coefficients between each predictor dimension and Inclusive AI Teaching Readiness.

Table 4 Pearson Correlation Coefficients: Predictor Dimensions vs. Inclusive AI Teaching Readiness

Predictor Dimension	r	p-value
AI Literacy	-.042	.545
Perceived Usefulness	-.010	.882
Perceived Ease of Use	-.008	.914
Attitude toward Inclusive Pedagogy	.125	.069
Institutional Support	-.074	.284

Note. Two-tailed. *p < .05.

None of the five predictor dimensions demonstrated a statistically significant linear correlation with the dependent variable. Attitude toward Inclusive Pedagogy registered the strongest directional association (r = .125, p = .069), approaching but not reaching the conventional significance threshold. This finding is theoretically coherent: faculty who hold more positive, equity-oriented beliefs about inclusive pedagogy are marginally more likely to enact inclusive AI teaching practices, consistent with UDL's emphasis on attitudinal foundations as precursors to inclusive action (CAST, 2018). The near-zero and occasionally negative correlations of AI Literacy, Perceived Usefulness, and Perceived Ease of Use with the DV are addressed in the discussion below.

Table 5 presents the results of the hierarchical multiple regression analysis.

Table 5 Hierarchical Multiple Regression: Predicting Inclusive AI Teaching Readiness

Variable	B	SE	t	p
Block 1: Control Variable (Type of HEI)				
Constant	3.736	.067	55.800	< .001
Private HEI (vs. SUC)	.063	.103	.608	.544
Local College (vs. SUC)	-.219	.133	-1.646	.101
R^2 = .020, Adjusted R^2 = .010, F(2, 210) = 2.090, p = .126				
Block 2: Control + Predictor Dimensions				
Constant	3.774	.624	6.048	< .001
Private HEI (vs. SUC)	.054	.104	.522	.602
Local College (vs. SUC)	-.212	.134	-1.579	.116
AI Literacy	-.052	.068	-.765	.445
Perceived Usefulness	-.020	.079	-.249	.804

Variable	B	SE	t	p
Perceived Ease of Use	.007	.074	.093	.926
Attitude toward Inclusive Pedagogy	.107	.067	1.601	.111
Institutional Support	-.051	.077	-.656	.513
R^2 = .039, Adjusted R^2 = .006, F(7, 205) = 1.173, p = .320; ΔR^2 = .019, F-change(5, 205) = 0.811, p = .543				

Note. n = 213. Unstandardized B coefficients reported. VIF range = 1.01–1.08 (all within acceptable threshold).

Block 1, which entered Type of HEI as a control variable, was not statistically significant (F(2, 210) = 2.090, p = .126, R^2 = .020). Local College faculty showed a negative directional difference relative to SUC faculty (B = -0.219, p = .101), approaching significance and suggesting a possible resource-related disparity. Block 2, which added the five predictor dimensions, yielded a non-significant overall model (F(7, 205) = 1.173, p = .320, R^2 = .039, Adjusted R^2 = .006). The incremental contribution of the five predictors over the control variable was non-significant (ΔR^2 = .019, F-change (5, 205) = 0.811, p = .543). Attitude toward Inclusive Pedagogy remained the closest to significance (B = 0.107, t = 1.601, p = .111). Multicollinearity diagnostics confirmed that these results were not attributable to predictor redundancy: all VIF values were well below the critical threshold of 5 (range: 1.010–1.077).

The non-significant regression findings are interpreted through three lenses. First, range restriction is the most parsimonious explanation: with all predictor and outcome means clustered between 3.71 and 3.85, the statistical variance necessary to detect linear predictive effects is severely compressed, producing a ceiling effect that reflects collective declarative readiness without yet revealing differentiated practice. Second, the findings raise questions about model form: inclusive AI teaching readiness may operate as a threshold or interaction phenomenon rather than as a linear additive function of individual cognitive beliefs — possibilities that are better examined through structural equation modeling (SEM) in future studies. Third, unmeasured contextual factors — such as department head influence, peer modeling, student demographics, and CHED policy pressure — may be more powerful situational drivers of inclusive AI teaching practice than the individual-level beliefs captured by TAM, consistent with Scherer et al.'s (2019) meta-analytic finding that TAM's predictive power is substantially moderated by organizational and cultural context.

CONCLUSION AND RECOMMENDATIONS

Conclusion

This study examined faculty readiness to use AI for inclusive pedagogy in Philippine HEIs across five dimensions — AI Literacy, Perceived Usefulness, Perceived Ease of Use, Attitude toward Inclusive Pedagogy, and Institutional Support — and their predictive relationship with Inclusive AI Teaching Readiness. Three principal conclusions emerge.

First, faculty in Philippine HEIs demonstrate a high level of readiness to use AI for inclusive teaching across all dimensions, with Perceived Usefulness (M = 3.85) and Institutional Support (M = 3.84) ranked highest, and AI Literacy (M = 3.71) comparatively lowest. The outcome variable, Inclusive AI Teaching Readiness, similarly registered a High level (M = 3.72), affirming that Philippine faculty have broadly internalized positive orientations toward both AI tools and inclusive pedagogy at the declarative level. However, the proximity of all means to the lower boundary of the High range signals that this readiness, while present, is not yet deeply operationalized.

Second, inclusive AI teaching readiness does not differ significantly across any of the eight demographic variables examined, suggesting a broadly shared readiness plateau across the Philippine HEI faculty landscape. This finding implies that targeted interventions should address systemic and pedagogical conditions rather than demographic segmentation alone.

Third, the five predictor dimensions do not significantly predict inclusive AI teaching readiness in a hierarchical linear regression model, with Attitude toward Inclusive Pedagogy emerging as the only variable with a directional — though non-significant — association ($B = 0.107$, $p = .111$). These null predictive findings, attributable primarily to range restriction and the likely non-linear nature of readiness-to-practice translation, constitute theoretically informative evidence that calls for SEM-based, mixed-methods, and longitudinal follow-up.

Recommendations

For HEI Administrators and Academic Leaders

Given that faculty readiness is uniformly high but not deeply operationalized, institutions may invest in practice-oriented professional development programs that explicitly connect AI tool use with UDL principles. Workshops, learning communities, and peer mentoring initiatives that model inclusive AI teaching in discipline-specific contexts are particularly warranted. Institutions should also develop clear, equity-centered AI policies guiding faculty in deploying AI tools responsibly and inclusively, particularly for students with disabilities and those from marginalized backgrounds.

For CHED and Philippine Education Policymakers

The near-significant difference between local college and SUC faculty in Inclusive AI Teaching Readiness points to a resource disparity warranting policy attention. CHED is encouraged to expand infrastructure support and funding for AI-related faculty development at local colleges. CHED may also consider issuing a dedicated memorandum order that explicitly integrates inclusive AI pedagogy into existing frameworks for quality assurance, faculty qualification standards, and HEI accreditation criteria, building on the inclusive education directives of existing CMOs.

For Faculty Members

Faculty are encouraged to actively deepen their AI literacy beyond general familiarity — particularly their capacity to critically evaluate AI tools for bias, accessibility, and equity implications. Engaging with UDL principles as a framework for lesson planning and assessment design, and advocating within their departments for more robust institutional support for inclusive AI teaching, are practical starting points.

For Future Researchers

Future research may consider: (1) employing Structural Equation Modeling (SEM) to test complex, non-linear relationships among readiness dimensions and inclusive AI teaching practice; (2) adopting mixed-methods designs that complement survey data with classroom observation and focus group discussions; (3) conducting longitudinal studies to track readiness development and its translation into teaching behavior over time; (4) including student outcome variables to examine whether faculty readiness produces more equitable learning experiences; and (5) expanding the sample to cross-regional or national probability samples to strengthen generalizability beyond the CALABARZON region.

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