

# AI Literacy Among University Personnel: A Cross-Sectional Assessment of Teaching and Non-Teaching Staff at a Philippine State University

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**Abstract**— The integration of artificial intelligence (AI) into higher education policy and practice presupposes a workforce that understands its foundational principles; however, empirical data on AI literacy among university personnel remain scarce particularly in the Global South. This study assessed the AI literacy of selected teaching ( $n = 62$ ) and non-teaching personnel ( $n = 14$ ) at Bicol University, Philippines, using a validated 31-item instrument ( $\alpha = 0.855$ ) spanning five conceptual domains: AI fundamentals, machine learning processes, data literacy, societal implications, and ethics. Descriptive statistics, one-way ANOVA, and item difficulty analyses were employed for data analysis. Results revealed a uniformly moderate literacy levels across both groups (teaching:  $M = 12.66$ ,  $SD = 5.25$ ; non-teaching:  $M = 13.79$ ,  $SD = 4.95$ ), with no statistically significant difference between them ( $p = 0.693$ ). Item-level analysis uncovered a consistent pattern: personnel demonstrated stronger grasp of conceptual and ethical dimensions of AI (items  $\geq 0.50$  difficulty index) but struggled with procedural and technical content, particularly machine learning workflows and model evaluation (items  $< 0.40$ ). These findings challenge assumptions about faculty technological advantage and point to a shared literacy gap that cuts across occupational roles. Implications for differentiated professional development and institutional AI readiness are discussed.

**Keywords**— *AI literacy, university personnel, higher education, Philippines, psychometric assessment, professional development*

## I. INTRODUCTION

The accelerating diffusion of artificial intelligence across sectors—from healthcare diagnostics to administrative automation—has placed unprecedented demands on higher education institutions, not merely as sites of AI research but as organizations whose personnel must navigate AI-mediated workflows in teaching, governance, and student services [1]. While substantial attention has been devoted to preparing students for an AI-transformed labor market, a quieter question has gone largely unexamined: “*how well do the people who run universities actually understand the technology they are increasingly expected to adopt?*”

This question carries particular urgency in the Global South, where resource constraints, uneven digital infrastructure, and limited access to professional development create conditions markedly different from those assumed by AI literacy

frameworks developed in North American and European contexts [2]. The Philippines, with its extensive state university system serving millions, offers a revealing case. National policy mandates increasingly reference AI integration, yet little empirical work has examined whether the institutional workforce possesses the foundational literacy required to implement such mandates meaningfully [3].

The existing literature on AI literacy has expanded rapidly in recent years, but it remains concentrated on two populations: K–12 and undergraduate students [4], [5]. Studies examining faculty tend to focus on their pedagogical use of AI tools rather than their conceptual understanding of the technology itself [6]. Research on non-teaching university personnel—administrative staff, librarians, technical support workers—is virtually absent, a gap that is difficult to justify given these groups’ roles in institutional data management, procurement of AI-enabled systems, and policy implementation.

Several conceptual frameworks have attempted to define what AI literacy entails. Long and Magerko [7] proposed a set of competencies spanning recognition, understanding, evaluation, and ethical reasoning about AI systems. Laupichler et al. [8] developed a knowledge-based instrument specifically targeting conceptual understanding across domains including machine learning, data representation, and societal implications. These frameworks share a recognition that AI literacy is not reducible to tool proficiency; it encompasses the ability to reason about how AI systems work, what their limitations are, and what ethical considerations their deployment raises.

Yet frameworks alone cannot reveal the texture of what people actually know. Aggregated scores can mask important patterns—someone might understand that AI raises ethical concerns while being unable to articulate how a training dataset shapes model behavior. Item-level analysis, though less commonly reported, can expose these differential strengths and weaknesses, providing the diagnostic granularity needed for targeted intervention design.

This study therefore attempts to address three gaps in the current literature. First, it provides empirical data on AI literacy among university personnel in a Philippine state university, a context underrepresented in existing research. Second, it

examines both teaching and non-teaching staff, allowing comparison across occupational roles that are rarely studied together. Third, it moves beyond aggregate scoring to conduct item-level difficulty analysis, revealing the specific conceptual domains where literacy is strong and where it falters. The guiding research questions of this work are:

- RQ1. *What are the AI literacy levels of teaching and non-teaching personnel at Bicol University?*
- RQ2. *Is there a statistically significant difference in AI literacy between these two groups?*
- RQ3. *Which specific AI knowledge domains present the greatest conceptual difficulty for university personnel?*

## II. METHODOLOGY

### A. Research Design and Participants

This study employed a cross-sectional descriptive-comparative design as authorized under Administrative Order No. 177 s. of 2025. The target population comprised selected teaching and non-teaching personnel at Bicol University, a premier state university in the Bicol Region, Philippines. A total of 76 personnel participated: 62 teaching personnel (faculty members across multiple colleges and departments) and 14 non-teaching personnel (administrative and support staff). The broader survey, which also included students ( $n = 1,110$ ), was administered university-wide; however, the present analysis focuses exclusively on personnel responses to examine workforce-specific literacy patterns.

Participation was voluntary and conducted through an online survey platform. No exclusion criteria were applied beyond active employment at the university at the time of data collection. The sample of teaching personnel represented diverse disciplinary backgrounds, including STEM, social sciences, humanities, and professional programs. Non-teaching personnel encompassed roles in administration, research support, and campus operations.

### B. Survey Instrument Deployed

AI literacy was measured using a 31-item multiple-choice knowledge test adapted from the instrument developed by Hornberger et al. [9]. The items span five conceptual domains: (1) AI fundamentals and applications, including definitions, recognition of AI systems, and distinctions between weak and strong AI; (2) machine learning concepts, covering supervised and unsupervised learning, training processes, and model evaluation; (3) data literacy, addressing training-test data partitioning, data visualization, and recommender systems; (4) societal implications, including predictive policing, labor displacement, and the black box problem; and (5) ethical and legal dimensions, encompassing fairness, transparency, accountability, and regulatory challenges. Each item was scored dichotomously (1 = correct, 0 = incorrect), yielding a maximum possible score of 31.

The instrument demonstrated good internal consistency across the full sample ( $\alpha = 0.855$ ). Reliability was acceptable for both teaching personnel ( $\alpha = 0.791$ ) and non-teaching personnel ( $\alpha = 0.753$ ). Cronbach's alpha-if-item-deleted analysis

confirmed that all 31 items contributed positively to the overall construct, with no single item substantially degrading reliability when removed. These psychometric properties confirmed the instrument's suitability for the present analysis.

### C. Data Analysis Implemented

Descriptive statistics (means, standard deviations, ranges) were computed for each personnel group. Group differences in total AI literacy scores were evaluated using one-way analysis of variance (ANOVA). Item difficulty indices—defined as the proportion of respondents answering each item correctly—were calculated for both groups and classified following standard psychometric conventions: easy ( $\geq 0.80$ ), moderate (0.40 - 0.79), and difficult ( $< 0.40$ ) [9]. All analyses were conducted in Python using standard statistical libraries [10].

## III. RESULTS

### A. Respondent Profile

As summarized in Table I, the study involved a total of 76 respondents drawn from both teaching and non-teaching personnel of the institution. The majority were teaching faculty, comprising 62 respondents or 81.6% of the total sample, while the remaining 14 or 18.4% were non-teaching staff. Among the teaching group, representation was drawn from 20 academic departments. Chemical Engineering and Mathematics posted the highest number of respondents with 7 each, accounting for 11.3% of the teaching group per department. Business Administration and Education followed with 6 respondents each or 9.7%, while Biology contributed 4 or 6.5%. Electrical Engineering, Civil Engineering, Mechanical Engineering, and Architecture each had 3 respondents or 4.8%. The remaining eleven departments — Nursing, Social Sciences, Forestry, Fisheries, Accountancy, English and Literature, Psychology, Economics, Political Science, Communication, and Tourism — were each represented by 2 respondents or 3.2%, reflecting a broad yet proportionate cross-section of the academic units within the institution. The distribution of respondents across departments suggested that the sampling procedure was designed to achieve inclusive representation of all academic units, ensuring that the perspectives captured in this study reflect the diverse disciplinary composition of the teaching workforce. The inclusion of non-teaching personnel further broadens the scope of the study, allowing for a more comprehensive understanding of the institutional context under investigation.

### B. Results of AI Literacy Test

Table II presents the descriptive summary of AI literacy scores for both personnel groups. Teaching personnel achieved a mean score of 12.66 out of 31 (40.8% accuracy), while non-teaching personnel scored slightly higher with a mean of 13.79 (44.5% accuracy). Both groups demonstrated considerable within-group variability, with scores spanning from 5 to 28 (teaching) and 10 to 28 (non-teaching).

The one-way ANOVA revealed no statistically significant difference in AI literacy scores between teaching and non-teaching personnel ( $F = 0.156$ ,  $p = 0.693$ ). This finding indicated that occupational role—and by extension, the presumed academic expertise of faculty—does not confer a meaningful advantage in AI literacy within this institutional context.

TABLE I. PROFILE OF TAPPED RESPONDENTS

Group	Freq.	%
<b>Teaching</b>	<b>62</b>	<b>81.6</b>
Chemical Engineering	7	11.3
Mathematics	7	11.3
Business Administration	6	9.7
Education	6	9.7
Biology	4	6.5
Electrical Engineering	3	4.8
Civil Engineering	3	4.8
Mechanical Engineering	3	4.8
Architecture	3	4.8
Nursing	2	3.2
Social Sciences	2	3.2
Forestry	2	3.2
Fisheries	2	3.2
Accountancy	2	3.2
English and Literature	2	3.2
Psychology	2	3.2
Economics	2	3.2
Political Science	2	3.2
Communication	2	3.2
<b>Non-Teaching</b>	<b>14</b>	<b>18.4</b>

TABLE II. SUMMARY OF AI LITERACY SCORES

Group	N	Mean	SD	Min	Max
Teaching	62	12.66	5.25	5	28
Non-Teaching	14	13.79	4.95	10	28

### C. Diagnostic Tests and Validity

Item difficulty indices were computed for each of the 31 items across both groups. Table III presents a thematic summary organized by conceptual domain, reporting the average difficulty index per domain rather than exhaustive item-by-item values, in keeping with space constraints.

TABLE III. MEAN ITEM DIFFICULTY BY CONCEPTUAL DOMAIN

Domain	Teaching	Non-Teaching	Class.
AI Fundamentals (Q1-Q11)	0.44	0.47	Moderate
Machine Learning (Q12-Q21)	0.38	0.41	Difficult
Data Literacy (Q22-Q26)	0.40	0.43	Moderate
Societal Implications (Q27-Q29)	0.45	0.44	Moderate
Ethics and Legal (Q30-Q31)	0.47	0.46	Moderate

Note: Difficulty index = proportion correct. Classification: Easy  $\geq 0.80$ ; Moderate 0.40–0.79; Difficult  $< 0.40$ .

Several patterns emerged from the item-level data. First, both groups performed best on items addressing ethical principles in AI development, societal challenges, and the general applicability of AI—items that tap into conceptual and normative reasoning rather than technical procedural knowledge. Items asking respondents to identify areas where AI is applied (Q1) or to recognize ethical considerations in AI

development (Q27) yielded difficulty indices above 0.50 for both groups.

Second, the most difficult items for both groups clustered in the machine learning domain. Items concerning weak versus strong AI distinctions (Q8), knowledge representations (Q12), AI decision-making processes (Q14), and model evaluation through test-training data procedures (Q26) consistently fell below the 0.40 threshold. Teaching personnel, despite their academic training, did not outperform non-teaching staff on these technical items—a finding that warrants further examination.

Lastly, the non-teaching group displayed a narrower score range (10–28 versus 5–28) and slightly higher mean, though neither difference reached significance. This pattern suggested a floor effect among some teaching personnel, possibly reflecting the inclusion of faculty from disciplines with minimal technology orientation.

## IV. DISCUSSION

The central finding of this study—that teaching and non-teaching personnel at Bicol University demonstrate equivalent, moderately low AI literacy—carries implications that cut deeper than the numbers might initially suggest. At first glance, a mean accuracy rate hovering around 42% across both groups may appear simply as a deficit to be remedied through training. But the pattern of what personnel know and what they do not reveals something more instructive about the nature of AI understanding in institutional contexts.

### A. The Conceptual-Procedural Divide

The most striking pattern in the data is the asymmetry between conceptual and procedural knowledge. Both groups demonstrated reasonable competence with items addressing what AI is, where it is applied, and what ethical concerns it raises. These are the aspects of AI literacy most accessible through general media exposure, public discourse, and informal learning—the kinds of knowledge one acquires by reading news coverage of algorithmic bias or encountering chatbot interfaces in daily life [11].

By contrast, items probing how AI systems actually work—how models are trained, how data is partitioned, how predictions are evaluated—proved substantially more difficult. This conceptual-procedural gap is consistent with the distinction drawn in the recent AI literacy literature between generic and domain-specific literacy [12]–[15]. As the AI Literacy Heptagon framework proposed by Hackl et al. [16] makes clear, technical and applicational dimensions of AI literacy require qualitatively different pedagogical strategies than ethical and social dimensions. Our data empirically confirm this theoretical distinction: the workforce can discuss AI’s societal footprint but cannot reason about the mechanisms producing that footprint.

This pattern has practical consequences that extend well beyond test performance. The ability to reason about AI at the procedural level is precisely what is needed when personnel are asked to evaluate vendor claims about AI-powered tools, to assess whether an AI-driven student advising system is functioning appropriately, or to participate meaningfully in institutional discussions about AI adoption [3]. Conceptual

awareness without procedural understanding creates a workforce that can discuss AI in the abstract but cannot critically engage with it in practice—a gap that have been identified as one of the most pressing challenges facing higher education institutions seeking to integrate AI responsibly [17].

### B. The Faculty Assumption

Perhaps the most counterintuitive finding is the absence of a literacy advantage among teaching personnel. The assumption that faculty, by virtue of their academic training and scholarly habits, would outperform administrative staff on a knowledge assessment proved unfounded. This result resonates with recent empirical work by Mah and N. Groß [18], whose study of faculty AI use and self-efficacy identified four distinct faculty profiles—optimistic, critical, critically reflected, and neutral—and found that the majority of faculty across profiles lacked confidence in their AI understanding, with most expressing interest in professional development. Our data extend this finding by showing that the literacy gap is not merely subjective (felt inadequacy) but objectively measurable.

The disciplinary heterogeneity of the faculty sample partly explains this pattern. Teaching personnel at the university include not only computer scientists and engineers but also psychologists, nurses, artists, and education specialists. For faculty outside STEM and computing disciplines, AI may be no more familiar than it is for administrative staff—and in some cases less so, if non-teaching personnel encounter AI tools through operational systems (e.g., automated scheduling, procurement platforms) that faculty do not routinely use. This interpretation aligns with empirical evidence showing that AI literacy is significantly higher among university students and faculty with a technical or STEM background, and that disciplinary affiliation is a consistent predictor of AI competence — with students and staff from non-technical fields demonstrating substantially lower AI knowledge scores [9].

Furthermore, the nature of academic expertise may itself be a factor. Faculty are trained to develop deep knowledge within narrow disciplinary domains. AI literacy, however, is inherently interdisciplinary — its foundational understanding requires integrating knowledge from computation, mathematics, statistics, ethics, philosophy, and law [19], [20]. Celik [21] has argued persuasively that effective AI integration requires not just technological knowledge but an interconnected web of technological, pedagogical, and ethical understanding — the Intelligent-TPACK framework. In this view, isolated disciplinary expertise is insufficient; what matters is the capacity to synthesize technical, pedagogical, and content knowledge in the specific context of AI. Our faculty sample's performance suggests that this synthesis is largely absent, even among those with advanced degrees.

### C. Proposed Intervention Framework

The empirical patterns identified in this study—uniform moderate literacy, the conceptual-procedural gap, the absence of role-based differences—collectively point toward a structured intervention model. Drawing on several established frameworks in the literature, we propose a three-phase, role-differentiated AI Literacy Development Program (ALDP) that universities in similar contexts may adapt. The design draws on the UNESCO AI Competency Framework for Teachers [22], the AI Across the

Curriculum model developed at the University of Florida [23], and the Intelligent-TPACK framework [21], synthesizing elements of each into a coherent intervention architecture suited to the resource realities of institutions in the Global South.

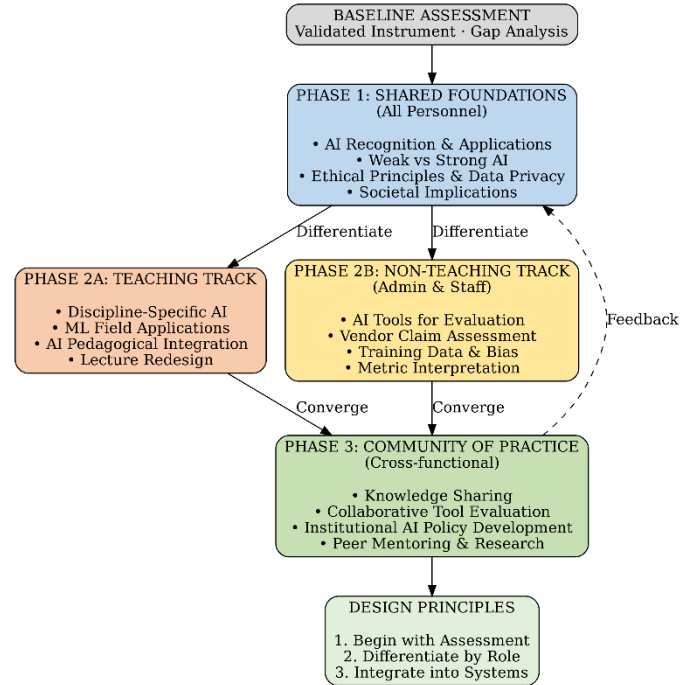


Fig. 1. The AI Literacy Development Program (ALDP): A three-phase proposed intervention framework for university personnel.

**Phase 1: Shared Foundations (All Personnel).** The first phase addresses the common baseline revealed by our data. Since both groups share essentially the same starting point, the initial intervention should be institution-wide, targeting the conceptual and ethical domains where partial understanding already exists. Drawing on the UNESCO framework’s “Acquire” level [22], this phase would involve structured workshops covering five core themes: (a) recognizing AI systems in everyday and professional contexts, (b) understanding the distinction between narrow and general AI, (c) identifying ethical principles governing AI deployment, (d) recognizing data privacy considerations, and (e) evaluating the societal implications of algorithmic decision-making. These workshops should employ active learning strategies—case discussions drawn from the Philippine educational context, scenario-based reasoning exercises, and collaborative problem-solving—rather than lecture-format delivery, consistent with evidence that participatory approaches yield stronger learning outcomes in technology literacy programs [24].

**Phase 2: Role-Differentiated Technical Deepening.** The second phase directly targets the procedural gap through separate tracks for teaching and non-teaching personnel. For faculty, the intervention should be grounded in the Intelligent-TPACK framework [21], which emphasizes the integration of technological knowledge with pedagogical and ethical reasoning. Concretely, this means discipline-specific modules showing how machine learning concepts intersect with faculty members’ own fields: how text classification relates to literary analysis, how predictive modeling applies in agricultural

science, how neural networks function in medical imaging. The University of Florida’s AI Across the Curriculum initiative [23] provides a scalable model here, demonstrating how AI concepts can be infused into existing disciplinary content rather than treated as standalone technical training. The key insight from that model is that faculty engage more deeply with AI when they perceive its relevance to their own scholarly work, rather than as an external imposition.

For non-teaching personnel, the second phase should focus on applied evaluation competencies—what Laupichler et al. [8] describe as the capacity to critically assess AI applications without necessarily building them. This includes understanding what it means when a vendor claims a system uses machine learning, what questions to ask about training data quality and representativeness, and how to interpret basic performance metrics such as accuracy and error rates. Scenario-based learning using real administrative workflows (e.g., automated enrollment systems, AI-assisted document classification) would anchor abstract concepts in familiar professional contexts.

**Phase 3: Sustained Engagement and Community of Practice.** The third phase addresses a critical gap identified in the literature: the tendency for one-time training to decay without sustained reinforcement [25]. A longitudinal study of AI literacy among U.S. academic library employees found that training participation alone did not significantly enhance AI literacy; what mattered was sustained access to tools, with communities of practice identified separately as a key mechanism for shared learning and sustained development [26]. This finding suggests that the intervention should culminate in the establishment of an institutional AI Literacy Community of Practice (CoP)—a cross-functional group of faculty and staff who meet regularly to share experiences, evaluate new AI tools, discuss emerging ethical challenges, and collaboratively develop institutional AI use policies. The CoP model aligns with the UNESCO framework’s emphasis on continuous professional development and with evidence that peer learning structures are particularly effective in resource-constrained settings where external expert training may be episodic [22].

#### *D. ALDP Generalizability and Institutional Implications*

While this study is situated at a single Philippine state university, the patterns it reveals—and the intervention model it suggests—are likely relevant to a broader range of institutions. The conditions that produce moderate, undifferentiated AI literacy among personnel are not unique to Bicol University: they characterize any institution where AI training has not been systematically provided and where personnel rely on informal exposure. Mikeladze et al. [27] conducted a critical review of AI competence frameworks for educators and found that existing frameworks predominantly adapted European digital competence models and largely failed to specify the resources, infrastructure, and contextual conditions needed to implement AI competency requirements in practice — a gap that is especially consequential for institutions in resource-constrained settings such as those in the Global South. Our proposed ALDP framework addresses this gap by emphasizing low-cost, internally facilitated interventions (communities of practice, scenario-based workshops using existing institutional tools)

rather than resource-intensive approaches dependent on external expertise or specialized infrastructure.

For institutions considering the adoption of such a framework, three design principles emerge from both the literature and our data. First, begin with assessment: an institutional AI literacy baseline should be established before interventions are designed, as the specific domains requiring attention will vary by context. Second, differentiate by role but not by hierarchy: our data show that occupational role does not predict literacy level, but roles do predict the contexts in which AI understanding will be applied. Third, integrate AI literacy into existing institutional structures (faculty development programs, staff orientation, committee deliberations) rather than creating parallel training systems that compete for limited time and resources. This integration approach is consistent with the constructive alignment model proposed by Schofield and Zhou [28], which advocates embedding AI literacy within existing learning outcomes and assessment structures rather than treating it as an add-on.

## V. LIMITATIONS AND FUTURE DIRECTIONS

Several limitations temper the conclusions that can be drawn. The non-teaching sample ( $n = 14$ ) is small, limiting the statistical power of group comparisons and the generalizability of findings for this subgroup. The cross-sectional design precludes causal inference; longitudinal studies tracking literacy changes following interventions would be more informative. The instrument, while validated, only measured declarative knowledge and did not capture applied competencies (e.g., a respondent might correctly identify that training data quality affects model performance without being able to evaluate data quality in practice). Future research should adopt mixed-methods approaches, incorporating qualitative interviews and task-based assessments, to capture the applied dimensions of AI literacy that knowledge tests miss. Additionally, the proposed ALDP framework requires empirical validation. Future studies should implement the three-phase intervention in a quasi-experimental design with pre-post assessment, tracking not only knowledge gains but also changes in confidence, tool adoption, and critical evaluation behaviors. Comparative studies across multiple Philippine state universities would also clarify whether the patterns observed here are institution-specific or reflect broader systemic conditions. Finally, the relationship between AI literacy and actual institutional decision-making about AI adoption—whether more literate personnel make better procurement, policy, or pedagogical decisions—remains an open and practically important question.

## VI. CONCLUSION

In conclusion, this study demonstrated that AI literacy among Bicol University personnel is moderate and uniform across teaching and non-teaching roles, revealing a workforce aware of AI’s implications but lacking the procedural understanding needed for meaningful institutional engagement. These findings therefore challenge the assumption that academic affiliation confers AI literacy advantages and call for institution-wide professional development grounded in established frameworks. In response, the study proposes a three-phase AI Literacy Development Program designed for resource-constrained institutions in the Global South — one built on the

conviction that institutional AI readiness begins not with technology procurement, but with the deliberate cultivation of human understanding.

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