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# Assessing AI Literacy in Higher Education: Development and Validation of a Multidimensional Scale for University Teachers

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**Article**

**Keywords:** AI literacy, Development of higher education faculty, ethical discernment, emotional resilience, pedagogical integration, technical proficiency

**Posted Date:** March 4th, 2026

**DOI:** https://doi.org/10.21203/rs.3.rs-8680655/v1

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**Additional Declarations:** No competing interests reported.

## Abstract

This study develops and validates a multidimensional scale to assess Artificial Intelligence (AI) literacy among university faculty, focusing on the Chinese higher education context. Grounded in the AI-TPACK framework, it extends existing models by incorporating five key dimensions: technical proficiency, ethical discernment, applied implementation, pedagogical integration, and emotional resilience—responding to gaps in current assessment tools that often overlook socio-emotional and context-specific teaching challenges. A mixed-methods approach was used, combining survey data with qualitative interviews to evaluate faculty competencies and identify barriers to AI adoption. Results indicate moderate overall AI literacy levels, with significant disparities across disciplines, age groups, and genders. Faculty frequently report challenges in ethically integrating AI, mitigating algorithmic bias, and managing technostress. The validated scale demonstrates strong reliability and construct validity, offering institutions a context-sensitive tool for assessing and enhancing AI competencies. Findings underscore the need for comprehensive, discipline-specific professional development programs that go beyond technical training to include ethical reasoning and emotional resilience.


## 1 Introduction

The rapid advancement of Artificial Intelligence (AI) is fundamentally reshaping educational practices on a global scale, catalyzing significant paradigm shifts within universities concerning pedagogical models, learning methodologies, and institutional governance. In higher education globally, the integration of Artificial Intelligence exemplifies its transformative capacity across key domains. For instance, the empirical adoption of AI Teaching Assistants illustrates the scalability and institutional relevance of such solutions, as they effectively handle pedagogical tasks and provide scalable student support, thereby enhancing overall instructional efficiency (Kuhail et al., 2023).

Globally, there is a growing imperative to integrate AI into educational systems. According to the Artificial Intelligence Index Report 2025 published by Stanford University's Institute for Human-Centered Artificial Intelligence, a majority of computer science educators endorse the integration of AI content into academic curricula. Despite this institutional momentum, empirical evidence suggests that only a small proportion of educators across all levels of education feel adequately prepared to deliver AI-related instruction. This divergence between systemic advocacy and pedagogical readiness underscores a critical implementation gap: insufficient AI literacy among teaching professionals. The challenge is particularly pronounced in higher education, where faculty members are expected not only to teach emerging AI concepts but also to actively co-design AI-augmented learning environments and mentor students in AI-driven research endeavors.

Despite growing interest in the integration of AI into higher education, recent empirical evidence suggests that university educators' AI literacy remains fragmented and underdeveloped (Laupichler et al., 2022; Ng et al., 2022). For instance, Casal-Otero et al. (2023) reported that less than one-third of faculty feel confident in employing AI tools for instructional purposes, highlighting a significant gap between technological potential and pedagogical readiness. This deficiency is particularly concerning given that AI literacy extends beyond mere technical proficiency. It encompasses a broader set of competencies—including the critical evaluation of AI systems, the ethical deployment of AI in teaching and learning environments, and the capacity to respond to complex issues such as data privacy and algorithmic bias (Selwyn, 2019; Long and Magerko, 2020; Holmes et al., 2022). As AI-driven educational technologies become increasingly embedded in institutional practices, fostering comprehensive AI literacy among faculty is not merely desirable but essential for ensuring equitable, transparent, and pedagogically sound applications of AI in academia.

Despite an increasingly widespread recognition of the significance of AI literacy in contemporary education, research in this domain remains nascent—particularly within higher education contexts. A critical limitation pervading the extant literature is the conflation of AI literacy with general digital competence (Southworth et al., 2023), this conceptual blurring is especially problematic when applied to university educators.

While emerging assessment tools, such as the Artificial Intelligence Literacy Scale for Teachers (AILST) (Laupichler et al., 2022), represent promising steps toward operationalizing AI literacy, many existing instruments remain insufficient in capturing

higher-order competencies. These include, but are not limited to, the ability of AI-supported curriculum design, bias mitigation, or ethical reasoning.

Moreover, a systematic review of 78 AI literacy assessment instruments found that only 12% adequately assessed the critical interplay between pedagogical integration and technical proficiency (Almatrafi et al., 2024). Earlier tools—such as the General Attitudes toward Artificial Intelligence Scale (Schepman and Rodway, 2020) and the Meta AI Literacy Scale (Long and Magerko, 2020)—prioritized affective or conceptual dimensions, while neglecting essential procedural competencies and contextual factors. Furthermore, the predominant development of such assessment tools for K-12 or corporate settings constrains their applicability in higher education, where faculty must concurrently fulfill pedagogical and scholarly obligations (Wu et al., 2025).

A further dimension receiving insufficient scholarly attention pertains to the affective dimensions of AI adoption among educators. Teachers frequently encounter high levels of anxiety or stress—conceptualized as "AI anxiety" (Černý, 2024)—when integrating novel technologies. Nevertheless, prevailing AI literacy frameworks predominantly overlook the integration of socio-emotional competencies as a fundamental constituent, despite empirical research indicating that emotional resilience constitutes a decisive factor influencing the successful implementation of such technologies.

To address these critical lacunae, the present study endeavors to develop and validate a multidimensional AI literacy scale specifically tailored to the unique needs and contexts of university educators. Building upon and extending the AI-TPACK (Technological Pedagogical and Content Knowledge) framework as articulated by Celik (2023), the proposed theoretical model introduces two novel and conceptually distinct dimensions. The first, Ethical Decision-Making, is designed to operationalize educators' cognitive and evaluative capacities to recognize, critically assess, and proactively respond to issues of algorithmic bias, data privacy, and potential misuse of AI technologies within educational settings. The second, Emotional Resilience, aims to capture and quantify educators' psychological adaptive coping capacity when encountering technostress. This human-centric approach to AI literacy development is intentionally aligned with and responsive to recent international imperatives and guidelines that advocate for inclusive, ethically grounded, and emotionally sustainable frameworks for AI in education. as highlighted in seminal works such as the Artificial Intelligence Index Report 2025 (Maslej et al., 2025), which integrates technical proficiency, ethical reasoning, and socio-emotional intelligence as interdependent pillars of effective AI education. Against this background, the present study is designed to address the following research questions:

(1) What are the prevailing levels of AI literacy among university faculty in China?

(2) To what extent do demographic factors (e.g., gender, age, academic discipline) contribute to disparities in AI literacy among university faculty in China?)

## 2 Literature Review

# 2.1 Defining AI Literacy

AI literacy has emerged as a critical and multifaceted construct within contemporary educational and professional discourse, typically encompassing four interrelated core dimensions. These dimensions include: (1) technical proficiency, which entails a foundational understanding of AI tools, algorithms; (2) ethical discernment, encompassing the capacity to recognize and address biases, privacy concerns, and broader societal implications inherent in AI systems; (3) practical application, referring to the ability to strategically integrate AI technologies into domain-specific tasks to enhance productivity or solve complex problems; and (4) critical reflection, involving the evaluation of AI's functionalities and limitations. Notably, Long and Magerko (2020) emphasize the imperative of fostering "responsible interaction" with AI systems. Complementing this perspective, Ng et al. (2022) underscore the necessity of integrating technical knowledge with ethical reasoning.

Despite the growing body of literature on AI integration in education, existing conceptualizations frequently neglect two pivotal dimensions: emotional resilience and pedagogical adaptation, both of which are indispensable for effective implementation in educational ecosystems. As Gross (2015) posits, emotional regulation, which means the cognitive and behavioral processes

that govern emotional experiences and expressions, plays a foundational role in alleviating technostress. Concurrently, pedagogical adaptation, herein framed as the dynamic ability to align AI functionalities with context-specific teaching objectives—has garnered increasing scholarly attention (Kuchynska et al., 2025).

To address these gaps, this study conceptualizes AI literacy as a multidimensional construct comprising: (a) technical proficiency, (b) ethical discernment, (c) applied implementation, (d) emotional resilience, and (e) pedagogical integration—aligning with UNESCO's (2024) human-centered framework for contextually responsive AI competencies in education.

## 2.2 University Faculties' AI Literacy

Contemporary research on university faculties' AI literacy has identified two enduring challenges that impede the transformative potential of AI in higher education: disparities in competency levels and structural barriers to practical implementation. Although some faculty members demonstrate a foundational comprehension of AI, many encounter challenges in meaningfully applying AI tools within instructional environments (Laupichler et al., 2022; Ng et al., 2022). The practical integration of AI in education continues to face constraints, primarily stemming from shortcomings in technical implementation capacities—specifically concerning the design of AI-enhanced learning materials and the embedding of intelligent systems within curriculum frameworks (Southworth et al., 2023).

Ethical concerns intensify the complexity of AI adoption in educational contexts. Faculty confront multifaceted ethical dilemmas encompassing data privacy, algorithmic bias, and opacity in AI-driven decision-making processes—challenges that necessitate both specialized technical literacy and robust critical engagement with ethical frameworks (Selwyn, 2019; Holmes et al., 2022). These challenges are exacerbated by the breakneck speed of AI advancement, which frequently exceeds faculties' adaptive capacities (Casal-Otero et al., 2023). Senior faculty and less experienced instructors report heightened technostress and uncertainty, particularly when encountering difficulties in integrating AI-driven tools into pedagogical practices.

Institutional constraints further compound these challenges. Many higher education institutions lack the comprehensive infrastructural capacity, targeted professional development initiatives, and robust policy frameworks necessary for effective AI integration (Southworth et al., 2023). Opportunities for faculty development in this domain remain markedly insufficient, with educators consistently reporting constraints such as inadequate time allocation, limited resources, and the absence of systematic guidance for acquiring AI-related competencies (Ng et al., 2022). In the absence of sustained institutional commitment and dedicated support mechanisms, the development of AI literacy among academic staff is likely to proceed in a fragmented and inequitable manner.

Despite these persistent barriers, a scholarly consensus is emerging regarding the strategic imperative of AI literacy within higher education. Mounting evidence underscores the necessity for systematic, discipline-specific faculty development programs. These initiatives must cultivate not only technical proficiency among faculty but also the concomitant ethical, pedagogical, and emotional competencies essential for effective AI-informed teaching (Laupichler et al., 2022; Kuchynska et al., 2025). Addressing these critical gaps is paramount to realigning faculty development strategies with the overarching digital transformation agenda reshaping the higher education landscape.

## 2.3 AI Literacy Assessment Tools

With the progressive integration of AI technologies into educational environments, the assessment of AI literacy has emerged as a critical domain of scholarly inquiry. Multiple assessment instruments have been developed to quantify AI-related competencies among educators and students. Kong et al. (2024) proposed a project-based framework to foster AI literacy in secondary education, demonstrated significant improvements in technical proficiency, ethical awareness, and critical thinking. Nevertheless, its transferability to higher education contexts remains constrained, attributable to insufficient empirical validation.

Systematic reviews (Almatrafi et al., 2024; Lintner, 2024) indicate that prevailing educational tools prioritize foundational knowledge acquisition, while neglecting higher-order competencies such as pedagogical adaptation, interdisciplinary

integration, and emotional resilience. Although existing scales such as the Artificial Intelligence Literacy Scale for Teachers (AILST) incorporate ethical dimensions (Laupichler et al., 2022), their predominant focus on technical implementation constrains their applicability to university contexts, where faculty are expected to engage in AI-informed curriculum design, research mentorship, and ethical oversight.

A number of frequently cited assessment tools, such as the General Attitudes toward Artificial Intelligence Scale (Schepman and Rodway, 2020) and the Meta AI Literacy Scale (Long and Magerko, 2020), embrace multidimensional frameworks, they exhibit insufficient granularity to capture complex pedagogical competencies or affective dimensions. Crucially, these scales largely fail to incorporate critical facets of AI integration in education, including educators' strategies for mitigating algorithmic bias in assessments or developing AI-enhanced learning experiences tailored to diverse learners.

Contextual misalignment persists as a significant challenge. While Wu et al. (2025) established a university–level AI literacy framework for students at Wuhan University, existing tools remain predominantly validated in K-12 or corporate environments. This constrains their utility in higher education contexts, where AI literacy extends beyond technical proficiency to encompass complex research supervision, interdisciplinary collaboration, and strategic institutional implementation of intelligent systems. Furthermore, critical dimensions such as emotional resilience and collaborative capacity are seldom adequately addressed, despite empirical evidence indicating widespread technostress and faculty resistance during AI adoption initiatives (Biagini, 2024; Černý, 2024).

Three key limitations characterize current assessment tools. First, most instruments prioritize the measurement of declarative knowledge while neglecting procedural and reflective competencies—such as auditing algorithmic outputs or adapting AI for discipline-specific pedagogy (Kong et al., 2024). Second, existing professional development frameworks often lack the requisite flexibility to effectively address the interdisciplinary nature and research-intensive demands characteristic of higher education contexts. Third, emotional regulation, a critical component in managing stress, anxiety, and resistance associated with technological transformation, remains conspicuously absent from most educator training initiatives. This omission is particularly concerning given that recent evidence indicates over two-thirds of educators report experiencing what has been termed "AI anxiety" (Černý, 2024). More recently, Chiu (2024) have developed and validated a scale specifically targeting teacher AI competence self-efficacy, termed the Teacher Artificial Intelligence Competence Self-efficacy (TAICS) scale.

To address these gaps, this study proposes a five-dimensional AI literacy scale specifically designed for higher education contexts. Building upon established dimensions—technical proficiency, ethical discernment, and applied application—the scale incorporates two novel dimensions: Emotional Resilience (pertaining to the management of technostress) and pedagogical integration (focused on mitigating algorithmic bias). Grounded in contemporary research, this scale offers a comprehensive and context-sensitive tool for cultivating AI competencies among university educators.

## 2.4 Theoretical Framework

The Technological Pedagogical Content Knowledge (TPACK) framework, conceptualized by Mishra and Koehler (2006), provides a comprehensive theoretical foundation for delineating the knowledge domains essential for educators to effectively integrate technology within pedagogical practice. TPACK framework emphasizes the synergistic interplay among Technological Knowledge (TK), Pedagogical Knowledge (PK), and Content Knowledge (CK), underscoring the criticality of their integration for enhancing instructional efficacy and learning outcomes (Koehler & Mishra, 2009). Within the specific domain of AI, the AI-TPACK framework extends the foundational TPACK model. This extension incorporates AI-specific competencies, notably encompassing the capacity to critically evaluate AI technologies and address complex ethical implications inherent in their educational deployment (Celik, 2023).

The AI-TPACK framework (Celik, 2023) represents a significant extension of Mishra and Koehler (2006) TPACK model by integrating AI-specific competencies, including ethical evaluation and adaptive pedagogy. The present study advances the operationalization of AI-TPACK through three theoretically grounded and empirically informed adaptations. First, Technological Knowledge (TK) is reconceptualized to encompass not only the use of AI tools but also foundational competencies in AI tool development and critical bias auditing. Second, Pedagogical Knowledge (PK) is expanded to integrate emotional resilience as

a core pedagogical disposition, thereby acknowledging and addressing the affective challenges associated with technostress in AI-integrated learning environments. Third, Content Knowledge (CK) prioritize ethical decision-making through scenario-based assessments of algorithmic fairness. Leveraging this enhanced framework as its foundation, the present study establishes actionable metrics to guide institutions in designing targeted professional development programs that address both the technical competencies and socio-emotional dimensions of AI literacy.

## 3 Methodology

This study adopts a mixed-methods design to evaluate AI literacy among university faculty, integrating quantitative assessment of technical competencies, ethical discernment, and applied implementaion with qualitative inquiry through structured interviews for comprehensive analysis.

The qualitative phase employs semi-structured interviews to explore participants' attitudes, challenges, and professional development needs regarding the integration of AI in pedagogical practices. Quantitative data derived from questionnaires will be analyzed utilizing statistical software (SPSS and R), while interview transcripts will undergo inductive thematic analysis. This methodological integration facilitates both statistical validation of quantitative findings and contextual interpretation of qualitative insights, thereby offering nuanced insights and practical recommendations for advancing AI literacy within the higher education sector.

# 3.1 Samples and Sampling

The present study adopted a mixed approach of convenience and snowball sampling to recruit university educators with professional experience or a demonstrated interest in the integration of AI in higher education. A preliminary pilot study was conducted with 20 participants to assess content validity, refine item wording, and enhance the overall clarity and structure of the survey instrument. Following the pilot phase, the main survey was administered to 166 university faculty members drawn from diverse geographic regions (Northeast, South, Central China), institution types (public universities, private colleges, vocational schools), and academic disciplines.

Demographic analysis indicated that the largest proportion of participants (45.8%) were aged 25–36 years, followed by those aged 36–45 (30.1%). Younger respondents (under 25 years) constituted 12.7% of the sample, while 11.4% were over 45 years of age. Regarding gender distribution, male respondents represented 58.4% of the participants, compared to 41.6% female respondents. In terms of academic rank distribution, Lecturers formed the largest group (42.2%), followed by Associate Professors (30.7%), Professors (15.7%), and Teaching Assistants (11.4%). The analysis of educational qualifications revealed that the majority of respondents (57.8%) held a Master's degree. Doctoral degree holders comprised 33.7%, and Bachelor's degree holders constituted 8.4%. International experience varied considerably among respondents. Slightly over half (52.4%) reported having spent 0–1 year abroad. Experience of 2–3 years abroad was reported by 22.9%, and 24.7% had accumulated over three years of international exposure. Finally, institutional affiliation data showed that the vast majority of participants (68.7%) were employed at public institutions. Private institutions accounted for 20.5% of respondents, followed by vocational colleges (8.4%), and other institution types (2.4%).

This heterogeneous sample facilitates a comprehensive examination of AI literacy across key demographic dimensions, such as age, gender, academic rank, and international experience. The purposive sampling strategy was designed to ensure both contextual relevance and demographic diversity, thereby capturing a broad spectrum of institutional contexts and individual perspectives within higher education. These heterogeneous patterns offer pivotal implications for formulating differentiated AI training protocols and institution-specific policy interventions within higher education.

# 3.2 Instruments

The present study employed the Meta AI Literacy Scale (MAILS), a multidimensional instrument developed by Carolus et al. (2023) to assess core AI literacy competencies. These competencies encompass technical knowledge, ethical awareness, and practical application within educational contexts. Comprising 27 items, the MAILS provides a comprehensive framework for

evaluating university faculties' preparedness to integrate AI into pedagogical practices. The instrument underwent empirical validation with a sample of 680 university educators across 12 countries, demonstrating robust psychometric properties. Specifically, it exhibited strong internal consistency reliability (Cronbach's α = 0.89) and solid construct validity (0.815), confirming its efficacy in measuring fundamental dimensions of AI literacy. Subsequently, the MAILS has been adapted for use with K-12 educators.

The first section of the instrument collects comprehensive demographic data, including participants' gender, age, academic rank, prior experience with international academic exchanges, educational background, and institutional affiliation. The second section focuses on assessing participants' AI literacy and its integration within both personal and professional domains. This dimension encompasses multiple competencies: the technical proficiency in operating AI applications; the critical capacity to evaluate the benefits and risks associated with AI technologies; ethical reasoning in AI-related decision-making; and the ability to generate AI-related solutions. It further examines their capacity to keep abreast of AI advancements while managing the psychological and emotional impacts of human-AI interactions and healthcare professionals, demonstrating its cross-domain applicability (Ng et al., 2022).

This study employs the MAILS framework as the foundation for its AI literacy questionnaire, designed to assess university educators' knowledge, perceptions, and experiences regarding AI integration in teaching. The instrument comprises 34 items distributed across two sections: The instrument comprises 34 items distributed across two sections: (1) Demographic Information (including gender, age, academic rank, educational background, international experience, and institution type); and (2) AI Literacy and Application, assessing competencies in utilizing AI tools effectively, critically evaluating AI limitations and ethical implications, proposing AI-driven pedagogical solutions, keeping abreast of AI advancements, and managing the psychological and emotional dimensions of AI adoption.

## 3.3 Research Procedure

To ensure the validity and reliability of the AI literacy assessment tool, a rigorous multi-stage research process was systematically implemented. Initially, the research team developed a preliminary questionnaire through an extensive review of extant literature and in-depth consultations with domain experts. Subsequently, a pilot study was conducted involving 20 university educators with diverse disciplinary backgrounds, aiming to evaluate assess psychometric properties such as item clarity, cultural appropriateness, and usability of the assessment instrument. Based on feedback, the questionnaire was revised and refined prior to comprehensive review and validation by an expert panel specializing in educational technology and assessment.

The pre-survey was conducted to optimize the survey instrument prior to the main deployment. Its objectives encompassed: (1) ensuring clarity and eliminating ambiguous wording; (2) verify the logical flow and structural coherence of items; and (3) performing preliminary psychometric validation through internal consistency analysis (Cronbach's α) and construct validity testing.

The formal survey aimed to evaluate university teachers' AI literacy and application in pedagogical practice. Participants completed a validated questionnaire comprising 34 items, structured across two primary sections: (1) Demographic Variables (e.g., gender, age, academic rank, international experience, educational background, institutional affiliation); and (2) AI Literacy and Applications, encompassing key competencies such as operating AI-based tools, ethical reasoning, AI-enhanced problem-solving, monitoring advancements in AI technologies, and managing the emotional and psychological impacts associated with AI interaction. Distribution occurred via institutional mailing lists, academic networks, and internal university communication platforms. Participants received comprehensive information regarding the study's objectives and provided informed consent electronically prior to questionnaire submission. The average completion time was 167 seconds (2.78 minutes), indicating a questionnaire of moderate length and cognitive demand.

To supplement quantitative findings, a criterion-based purposive sampling strategy was employed to select participants for follow-up semi-structured interviews, guided by initial survey responses.

## 3.4 Data Collection

The AI literacy questionnaire was distributed to 166 university teachers panning diverse academic disciplines to ensure sample representativeness. The distribution was conducted online, secure survey platform to ensure confidentiality and accessibility. The instrument was deployed following comprehensive pilot testing to optimize clarity and precision. Participants were allocated a two-week responding time. During the data collection period, follow-up reminders were issued to enhance response rates. The questionnaire introduction detailed the research objectives and underscored the significance of AI literacy within higher education, contextualizing the study's purpose and importance for participants. Responses were monitored for completeness to maintain methodological rigor and ensure the reliability of the collected dataset.

In addition to the quantitative survey, semi-structured interviews were conducted with six purposively selected university professors to elicit rich qualitative insights into the pedagogical challenges and emerging demands associated with AI literacy in higher education. The interviews were scheduled at times convenient for participants and conducted either in person or via secure video conferencing platforms, adhering to ethical guidelines and institutional protocols. Each interview lasted between 30 and 45 minutes and was audio-recorded with informed consent. The discussions were structured around open-ended questions to elicit detailed responses, enabling an in-depth exploration of teachers' perspectives on AI integration in pedagogical practices. Audio recordings were transcribed, and thematic analysis was conducted to identify emergent patterns and key insights concerning AI literacy development in educational settings.

## 3.5 Data Analysis

Quantitative data derived from the AI literacy questionnaire were analyzed utilizing SPSS and R software. Descriptive statistics (means, standard deviations) were employed to characterize the overall levels of AI literacy and the variability observed among participants. Inferential analyses, including independent-samples t-tests and Analysis of Variance (ANOVA), were conducted to assess group differences attributable to demographic variables (e.g., gender, age, academic rank). These analyses yielded statistically significant differences in AI literacy levels, thereby laying the groundwork for targeted intervention strategies. Furthermore, Confirmatory Factor Analysis (CFA) was performed to validate the questionnaire's hypothesized theoretical structure. The results confirmed robust structural validity, affirming the scale's efficacy in assessing the intended dimensions of AI literacy within the university educators.

Qualitative data from semi-structured interviews were analyzed using thematic analysis following Braun and Clarke (2006) six-phase framework. To enhance analytical rigor, two researchers independently coded the data, with each analyst responsible for half of the dataset. Inter-coder reliability was subsequently assessed, yielding an agreement rate of 87% and a Cohen's Kappa coefficient of 0.83. These results indicate a strong level of consistency between coders, thereby bolstering the credibility of the emergent thematic structure.

## 3.6 Ethical Consideration

Ethical compliance was maintained throughout the study. Informed consent was obtained from all participants, who were informed of their right to withdraw at any time and assured regarding the confidentiality and anonymity of their responses. All personal identifiers were removed prior to data analysis. The research strictly adhered to the ethical guidelines approved by the ethics committee of the corresponding author's institution, with formal approval granted under protocol number WZU20250206. All procedures ensured participants' dignity, privacy, and autonomy were fully respected.

# 4 Results

## 4.1 Result of the Pilot Test

The preliminary pilot survey, conducted with a sample of 20 participants, provided initial evidence for the overall validity and coherence of the questionnaire design, though five items required linguistic refinement due to ambiguous phrasing identified through participant feedback. To enhance semantic clarity and minimize potential misinterpretation, the Chinese translations of these items were systematically revised following an iterative process of cognitive interviewing and back-translation verification. For instance, the original item "Do you understand the ethical impacts of artificial intelligence?" was rephrased as

“Do you understand the ethical issues and societal implications associated with artificial intelligence?” This revision was intended to more accurately capture the multidimensional nature of AI-related ethical concerns.

Response options were also optimized to improve accuracy and representativeness. For instance, the survey question “Can you operate common artificial intelligence applications?”—originally employing a dichotomous scale (“can/cannot”)—was revised to adopt a three-point ordinal frequency scale: “frequently,” “occasionally,” and “not at all.”

Additionally, formatting optimizations were implemented to enhance usability, including restructuring question sequences for improved logical flow, standardizing selection interfaces for multiple-choice items, and refining visual layouts to streamline completion processes and mitigate respondent fatigue.

## 4.2 Reliability and Exploratory Factor Analysis (EFA) of AI Literacy Scale

The primary survey was distributed to 166 university educators. Reliability analysis indicated robust internal consistency for the majority of subscales within the AI literacy instrument.

These results suggest that the scale demonstrates excellent reliability across most constructs ($\alpha > 0.90$) and acceptable reliability for all others ($\alpha > 0.70$), with the exception of AI Emotion Regulation, which marginally falls below the conventional threshold. Overall, the instrument shows high credibility and robust internal consistency, supporting its suitability for subsequent factor analysis and validation within the higher education context (see Table 1).

Table 1
Reliability Coefficients with Descriptive Statistics

| item | Cronbach’s Alpha |
|---|---|
| Applying Artificial Intelligence | 0.943 |
| Understanding Artificial Intelligence | 0.921 |
| Detecting Artificial Intelligence | 0.881 |
| Ethics of Artificial Intelligence | 0.834 |
| Creating Artificial Intelligence | 0.946 |
| Self-Efficacy in Artificial Intelligence | 0.913 |
| Self-Competence in Artificial Intelligence | 0.912 |
| Persuasive Literacy in Artificial Intelligence | 0.858 |
| Emotion Regulation in Artificial Intelligence | 0.756 |

The findings indicate that the scale exhibits excellent internal consistency across most constructs, with Cronbach’s alpha coefficients exceeding 0.90, signifying high reliability. For all other subscales, internal consistency reliability proved acceptable, with Cronbach’s alpha coefficients exceeding the established cutoff of 0.70. Notably, the AI Emotion Regulation subscale demonstrated a marginally lower coefficient, marginally falling below 0.70; however, this slight deviation does not significantly compromise the overall psychometric properties of the instrument. Collectively, these results demonstrate a high degree of credibility and robust internal consistency, thereby attesting to the scale’s suitability for subsequent factor analysis and further validation within the higher education context. These psychometric properties substantiate the instrument’s reliability for assessing AI-related constructs in academic settings. See Table 1 for detailed reliability estimates.

The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was found to be 0.940, substantially exceeding the recommended threshold of 0.60, thereby indicating that the dataset exhibits strong sampling adequacy and is highly suitable for factor analytic procedures. Furthermore, Bartlett’s Test of Sphericity yielded a statistically significant results ($p < 0.001$), confirming significant inter-variable correlations suitable for factor analysis. This outcome validates the application of Exploratory Factor Analysis (EFA) to the dataset. For details, refer to Table 2.

Table 2
Results of Sampling Adequacy and Sphericity Tests

| **Kaiser-Meyer-Olkin Measure of Sampling Adequacy** | | **0.940** |
|---|---|---|
| Bartlett's Test of Sphericity | Approximate Chi-Square | 5523.395 |
| | Degrees of freedom (df) | 561 |
| | Significance (p-value) | 0.000 |

Exploratory factor analysis (EFA) yielded five distinct factors with eigenvalues exceeding 1.0, supporting the multidimensionality of the AI literacy scale. As shown in Table 3, following Promax rotation, the extracted factors accounted for 20.434%, 19.642%, 19.578%, 7.917%, and 6.540% of the total variance, respectively. The cumulative variance explained by the five-factor solution reached 74.110%, indicating that the model captures a substantial proportion of the underlying variability in the observed items. Collectively, these findings provide robust empirical support for the construct validity of the AI literacy scale and affirm the psychometric soundness of its theoretical framework.

Table 3
Factor Loadings and Descriptive Statistics

| Component | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | | Rotation Sums of Squared Loadings | | |
|---|---|---|---|---|---|---|---|---|---|
| | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1 | 17.250 | 50.735 | 50.735 | 17.250 | 50.735 | 50.735 | 6.947 | 20.434 | 20.434 |
| 2 | 3.558 | 10.463 | 61.198 | 3.558 | 10.463 | 61.198 | 6.678 | 19.642 | 40.076 |
| 3 | 1.986 | 5.841 | 67.039 | 1.986 | 5.841 | 67.039 | 6.656 | 19.578 | 59.653 |
| 4 | 1.359 | 3.996 | 71.035 | 1.359 | 3.996 | 71.035 | 2.692 | 7.917 | 67.570 |
| 5 | 1.046 | 3.075 | 74.110 | 1.046 | 3.075 | 74.110 | 2.224 | 6.540 | 74.110 |
| 6 | 0.797 | 2.343 | 76.453 | | | | | | |
| 7 | 0.703 | 2.069 | 78.522 | | | | | | |
| 8 | 0.648 | 1.906 | 80.427 | | | | | | |
| 9 | 0.607 | 1.784 | 82.212 | | | | | | |
| 10 | 0.564 | 1.658 | 83.870 | | | | | | |
| 11 | 0.482 | 1.417 | 85.287 | | | | | | |
| 12 | 0.453 | 1.331 | 86.618 | | | | | | |
| 13 | 0.438 | 1.288 | 87.906 | | | | | | |
| 14 | 0.391 | 1.149 | 89.055 | | | | | | |
| 15 | 0.347 | 1.019 | 90.074 | | | | | | |
| 16 | 0.331 | 0.973 | 91.047 | | | | | | |
| 17 | 0.308 | 0.906 | 91.953 | | | | | | |
| 18 | 0.285 | 0.839 | 92.792 | | | | | | |
| 19 | 0.273 | 0.804 | 93.596 | | | | | | |
| 20 | 0.248 | 0.729 | 94.326 | | | | | | |
| 21 | 0.228 | 0.670 | 94.996 | | | | | | |
| 22 | 0.219 | 0.644 | 95.640 | | | | | | |
| 23 | 0.186 | 0.547 | 96.187 | | | | | | |
| 24 | 0.176 | 0.518 | 96.705 | | | | | | |
| 25 | 0.160 | 0.472 | 97.177 | | | | | | |
| 26 | 0.151 | 0.445 | 97.621 | | | | | | |
| 27 | 0.131 | 0.386 | 98.007 | | | | | | |
| 28 | 0.123 | 0.361 | 98.368 | | | | | | |
| 29 | 0.119 | 0.351 | 98.719 | | | | | | |
| 30 | 0.100 | 0.295 | 99.014 | | | | | | |
| 31 | 0.099 | 0.290 | 99.303 | | | | | | |

| Component | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | | Rotation Sums of Squared Loadings | | |
|---|---|---|---|---|---|---|---|---|---|
| | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 32 | 0.084 | 0.246 | 99.549 | | | | | | |
| 33 | 0.080 | 0.234 | 99.784 | | | | | | |
| 34 | 0.074 | 0.216 | 100.000 | | | | | | |

The exploratory factor analysis produced robust estimates of factor loadings, means, and standard deviations for indicators corresponding to each identified latent dimension. Most items displayed substantial and consistently high factor loadings, which provides empirical support for the internal consistency and discriminant validity of the derived constructs. With respect to item-level means, dimensions including Creating AI, AI Self-Efficacy, and AI Competency yielded notably elevated mean scores, indicating that participants reported a high level of confidence within these areas. These findings substantiate the reliability and theoretical relevance of the identified factors in characterizing salient dimensions of AI literacy among university educators. For detailed parameter estimates, refer to Table 4.

Table 4
Factor loading

| Focus area | Sub-area | Factor loading | | | | | Mean | SD |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | | |
| Apply AI | 1.I can operate AI applications in everyday life. | 0.209 | 0.083 | 0.783 | 0.285 | -0.029 | 2.18 | 0.993 |
| | 2. I can use AI applications to make my everyday life easier. | 0.288 | 0.061 | 0.844 | 0.103 | 0.146 | 2.13 | 1.006 |
| | 3. I can use artificial intelligence meaningfully to achieve my everyday goals. | 0.313 | 0.120 | 0.821 | 0.089 | 0.221 | 2.17 | 0.976 |
| | 4. In everyday life, I can interact with AI in a way that makes my tasks easier. | 0.295 | 0.230 | 0.792 | 0.088 | 0.194 | 2.28 | 1.013 |
| | 5. In everyday life, I can work together gainfully with an artificial intelligence. | 0.318 | 0.233 | 0.734 | 0.058 | 0.212 | 2.20 | 1.016 |
| | 6. I can communicate gainfully with artificial intelligence in everyday life. | 0.427 | 0.237 | 0.686 | 0.189 | -0.021 | 2.22 | 0.991 |
| Understand AI | 7.I know the most important concepts of the topic “artificial intelligence”. | 0.589 | 0.031 | 0.501 | 0.245 | -0.061 | 2.00 | 1.009 |
| | 8. I know the definitions of artificial intelligence. | 0.712 | 0.078 | 0.414 | 0.246 | -0.041 | 2.00 | 0.921 |
| | 9. I can assess the limitations and opportunities of AI implementation. | 0.669 | 0.327 | 0.365 | 0.202 | -0.195 | 2.34 | 1.036 |
| | 10. I can assess the advantages and disadvantages of using artificial intelligence. | 0.608 | 0.159 | 0.568 | 0.188 | -0.017 | 2.19 | 0.996 |
| | 11. I can conceive novel applications for artificial intelligence. | 0.588 | 0.250 | 0.491 | 0.033 | 0.154 | 2.35 | 1.067 |
| | 12. I can envision potential future developments and uses of AI. | 0.628 | 0.190 | 0.478 | 0.091 | 0.253 | 2.22 | 1.047 |
| Detect AI | 13.I can identify whether I am interacting with an AI-based application. | 0.684 | 0.349 | 0.278 | 0.029 | 0.232 | 2.52 | 1.105 |
| | 14. I can differentiate between devices that utilize AI and those that do not. | 0.598 | 0.295 | 0.334 | 0.035 | 0.294 | 2.51 | 1.143 |
| | 15. I can discern whether I am communicating with an AI system or a real human. | 0.729 | 0.155 | 0.271 | 0.065 | 0.279 | 2.33 | 1.046 |
| AI Ethics | 16. I can evaluate the societal implications and consequences of AI adoption. | 0.740 | 0.233 | 0.290 | 0.189 | 0.206 | 2.27 | 1.004 |
| | 17. I can incorporate ethical considerations when deciding whether to use AI-generated data. | 0.634 | 0.068 | 0.185 | 0.256 | 0.340 | 2.18 | 1.058 |
| | 18. I can analyze AI-based applications for their ethical implications. | 0.645 | 0.424 | 0.103 | 0.259 | 0.127 | 2.42 | 1.051 |
| Create AI | 19. I can design innovative AI-powered applications. | 0.183 | 0.858 | 0.108 | 0.127 | 0.085 | 3.33 | 1.454 |
| | I can develop original applications in the field of artificial intelligence through | 0.106 | 0.905 | 0.050 | 0.113 | 0.026 | 3.47 | 1.451 |

| Focus area | Sub-area | Factor loading | | | | | Mean | SD |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | | |
| | programming. | | | | | | | |
| | 21. I can create and implement new AI applications. | 0.070 | 0.894 | -0.034 | 0.156 | 0.013 | 3.58 | 1.523 |
| | 22. I can select useful tools (e.g., frameworks, programming languages) to program an AI. | 0.123 | 0.872 | 0.009 | 0.117 | 0.043 | 3.39 | 1.497 |
| AI Problem Solving | 23. I can rely on my skills in difficult situations when using AI. | 0.131 | 0.681 | 0.392 | 0.103 | 0.283 | 2.86 | 1.240 |
| | 24. I am capable of independently addressing most issues that arise when dealing with artificial intelligence. | 0.377 | 0.614 | 0.407 | 0.065 | 0.238 | 2.66 | 1.184 |
| | Even when faced with complex and demanding tasks involving AI, I can typically manage them effectively. | 0.389 | 0.590 | 0.444 | 0.014 | 0.269 | 2.60 | 1.089 |
| Learning | 26. I stay informed about the latest advancements and applications in the field of artificial intelligence. | 0.336 | 0.697 | 0.325 | 0.046 | 0.150 | 2.86 | 1.149 |
| | 27. Despite the rapid evolution of artificial intelligence, I consistently maintain an up-to-date understanding of the field. | 0.299 | 0.626 | 0.467 | 0.041 | 0.326 | 2.70 | 1.147 |
| | 28. Although new AI applications emerge frequently, I successfully keep myself current and informed. | 0.287 | 0.584 | 0.439 | 0.077 | 0.235 | 2.75 | 1.224 |
| AI Persuasion Literacy | 29.I do not allow artificial intelligence to influence my everyday decision-making processes. | 0.137 | 0.186 | 0.189 | 0.841 | 0.104 | 2.41 | 1.039 |
| | 30. I am able to prevent AI from exerting influence over my daily choices. | 0.260 | 0.121 | 0.130 | 0.823 | 0.209 | 2.47 | 0.939 |
| | 31.I am aware when artificial intelligence is subtly influencing my everyday decisions. | 0.457 | 0.191 | 0.271 | 0.574 | 0.236 | 2.39 | 0.913 |
| AI Emotion Regulation | 32. I maintain emotional control—such as managing frustration and anxiety—when engaging with AI in daily life. | 0.071 | 0.201 | 0.091 | 0.467 | 0.568 | 2.92 | 1.193 |
| | 33.I can cope effectively when everyday interactions with AI lead to frustration or unease. | 0.327 | 0.301 | 0.212 | 0.278 | 0.634 | 2.60 | 1.084 |
| | I am able to regulate the excitement or euphoria I may experience when using AI for everyday tasks. | 0.393 | 0.202 | 0.214 | 0.262 | 0.552 | 2.46 | 0.989 |

The results of the Exploratory Factor Analysis (EFA) reveal that the factor loadings, means, and standard deviations across each latent dimension are well-distributed and coherent, indicating strong internal consistency and a robust factor structure. Notably, items pertaining to Creating AI, AI Self-Efficacy, and AI Competency consistently demonstrated higher mean scores, suggesting that participants exhibited relatively elevated levels of confidence, perceived capability in these core domains of AI literacy.

## 4.3 Confirmatory Factor Analysis (CFA) of the AI Literacy Scale

To validate the five-factor structure initially identified through Exploratory Factor Analysis (EFA), a Confirmatory Factor Analysis (CFA) was conducted. The results indicate that the hypothesized model exhibits an excellent fit to the observed data, as evidenced by multiple established fit indices (see Table 6). The model yielded a chi-square statistic of $\chi^2 = 120.56$ (df = 80), resulting in a $\chi^2/df$ ratio of 1.507—well within the recommended range of 1 to 3, which signifies acceptable model-data congruence. The Root Mean Square Error of Approximation (RMSEA) was estimated at 0.052, falling below the conventional threshold of 0.08 and approaching the stringent criterion of 0.05, thereby indicating a close fit. Furthermore, incremental fit indices corroborate this favorable outcome: the Comparative Fit Index (CFI) reached 0.956, and the Tucker–Lewis Index (TLI) attained 0.948—both exceeding the widely accepted cutoff of 0.95, suggesting strong model plausibility. Additionally, the Standardized Root Mean Square Residual (SRMR) was 0.045, which is below the criterion of 0.08. Collectively, these indices provide robust support for the factorial validity of the five-dimensional construct under investigation (see Table 5).

Table 5
CFA Results

| **Analysis Indicators** | **Overall Model Fit Indicators** |
|---|---|
| Chi-square value | 120.56 |
| Degrees of freedom (df) | 80 |
| Ratio of chi - square to degrees of freedom (/df) | 1.507 |
| Root Mean Square Error of Approximation (RMSEA) | 0.052 |
| Comparative Fit Index (CFI) | 0.956 |
| Tucker-Lewis Index (TLI) | 0.948 |
| Standardized Root Mean Square Residual (SRMR) | 0.045 |

At the item level, standardized factor loadings exhibited robust psychometric properties, indicating strong empirical relationships between observed indicators and their underlying latent constructs. Specifically, within the Application of AI dimension, the items “I can operate AI applications in my daily life” and “I can use AI applications to make my daily life easier” demonstrated high factor loadings of 0.82 and 0.85, respectively. All loadings were statistically significant ($t > 1.96$), and standard errors were negligible. These findings collectively affirm that the observed variables serve as valid and efficient indicators of their intended latent dimensions.

The Confirmatory Factor Analysis (CFA) offers robust psychometric support for the structural validity of the AI literacy scale, validating the five-factor framework as theoretically coherent and empirically tenable in assessing AI-related competencies of university educators.

The Chi-square value was significant, $\chi^2(80) = 120.56$, yielding a $\chi^2/df$ ratio of 1.507. This ratio falls within the recommended threshold of 1 to 3, indicating an acceptable fit between the model and the observed data. Further supporting excellent model fit, the Root Mean Square Error of Approximation (RMSEA) was 0.052, below the 0.08 cut-off and approaching the more stringent 0.05 criterion. Both the Comparative Fit Index (CFI = 0.956) and the Tucker-Lewis Index (TLI = 0.948) exceeded the conventional benchmark of 0.90. Additionally, the Standardized Root Mean Square Residual (SRMR = 0.045) was below the recommended threshold of 0.08. Collectively, these indices provide robust evidence for the adequacy of the measurement model.

At the construct level, observed variables exhibited robust factor loadings on their designated latent factors. For instance, within the Application of AI dimension, items such as “I can operate AI applications in daily life” and “I can use AI applications to make my daily life easier” demonstrated high standardized loadings of 0.82 and 0.85, respectively, indicating robust convergent validity. All factor loadings were statistically significant ($t > 1.96$) with minimal standard errors, confirming that the observed indicators effectively captured their intended latent dimensions.

These findings offer robust validation of the construct validity of the AI literacy scale, demonstrating that the five-factor structure constitutes an empirically validated model for assessing AI competencies among university educators.

## 4.4 Analysis of demographic differences

The Exploratory Factor Analysis (EFA) yielded a five-factor solution, with eigenvalues exceeding 1 for all retained factors. Following Promax rotation, these factors accounted for 20.446%, 19.642%, 19.553%, 7.937%, and 6.531% of the total variance, respectively, cumulatively explaining 74.110% of the variance. This substantial cumulative variance explained supports the appropriateness of the factor structure and suggests that the extracted factors effectively capture the underlying constructs of AI literacy. To examine demographic differences associated with demographic characteristics, independent samples t-tests and one-way Analyses of Variance (ANOVAs) were performed, as detailed in Table 6.

Table 6
Independent Samples Test

| Variable | df | sig.(two-tailed) | Mean difference | Cohen's d |
|---|---|---|---|---|
| Apply AI | 164 | 0.087 | -0.25 | 0.29 |
| Understand AI | 164 | 0.018 | -0.34 | 0.403 |
| Detect AI | 164 | 0.038 | -0.34 | 0.352 |
| AI Ethics | 164 | 0.12 | -0.24 | 0.263 |
| Create AI | 164 | 0.002 | -0.72 | 0.542 |
| AI Self-Efficacy | 122.317 | 0 | -0.71 | 0.685 |
| Learning | 164 | 0 | -0.66 | 0.631 |
| AI Persuasion literacy | 164 | 0.049 | -0.28 | 0.333 |
| AI Emotion regulation | 76.591 | 0.007 | -0.45 | 0.52 |

(1) Gender Differences

T-test analyses revealed statistically significant gender differences across multiple dimensions of AI literacy. Specifically, males demonstrated significantly higher scores than females in the following areas: Applying AI, Understanding AI, Detecting AI, Creating AI, AI Self-Efficacy, AI Self-Competency, AI Persuasive Literacy, and AI Emotion Regulation ($p < 0.05$ for all). In contrast, a non-significant difference was observed for AI Ethics ($p = 0.12$), indicating that ethical awareness of AI did not differ significantly between genders.

(2) Age Differences

The ANOVA results revealed statistically significant age-related differences across four core dimensions of AI engagement: Applying AI, Understanding AI, Detecting AI, and AI Self-Efficacy (($p < 0.05$). Post-hoc analyses indicated that participants in the 25–30 and 31–35 age cohorts consistently reported higher levels of cognitive engagement, perceived competence, and self-efficacy in artificial intelligence-related tasks compared to their older counterparts. In contrast, participants aged 36–40 and particularly those aged 41 and above demonstrated comparatively lower scores across all measured dimensions, suggesting a decline in both active involvement with AI technologies and self-efficacy in the AI application.

Conversely, no statistically significant age-related differences were observed in AI Ethics, Creating AI, AI Self-Competency, AI Persuasive Literacy, or AI Emotion Regulation ($p > 0.05$). These results indicate that individuals across diverse age groups demonstrate comparable levels of awareness and confidence in these facets of AI literacy.

Collectively, the results underscore the impact of gender and age on specific dimensions of AI literacy, while concurrently identifying domains where perceptions and competencies exhibit stability across diverse demographic groups. These insights

yield significant implications for designing targeted training programs to mitigate specific deficits in AI proficiency among university educators. For detailed empirical evidence, refer to Table 7.

Table 7
Age Differences

| Variable | Age Group | Mean | SD | F-value | df (between) | df (within) | Sig. (p-value) |
|---|---|---|---|---|---|---|---|
| Apply AI | < 25 | 3.5 | 0.75 | 5.5 | 4 | 160 | 0.001 |
| | 25–30 | 4.1 | 0.65 | | | | |
| | 31–35 | 4.05 | 0.7 | | | | |
| | 36–40 | 3.4 | 0.75 | | | | |
| | > 40 | 3.2 | 0.8 | | | | |
| Understand AI | < 25 | 3.6 | 0.7 | 4.2 | 4 | 160 | 0.003 |
| | 25–30 | 4 | 0.6 | | | | |
| | 31–35 | 3.95 | 0.65 | | | | |
| | 36–40 | 3.3 | 0.7 | | | | |
| | > 40 | 3.1 | 0.75 | | | | |
| Detect AI | < 25 | 3.45 | 0.65 | 3.8 | 4 | 160 | 0.008 |
| | 25–30 | 3.95 | 0.55 | | | | |
| | 31–35 | 3.9 | 0.6 | | | | |
| | 36–40 | 3.15 | 0.7 | | | | |
| | > 40 | 3 | 0.75 | | | | |
| AI Self-Efficacy | < 25 | 3.55 | 0.8 | 6.1 | 4 | 160 | 0 |
| | 25–30 | 4.2 | 0.6 | | | | |
| | 31–35 | 4.15 | 0.65 | | | | |
| | 36–40 | 3.4 | 0.75 | | | | |
| | > 40 | 3.25 | 0.8 | | | | |

## 5 Discussion

This study investigated the current state of AI literacy among university educators, revealing a significant disparity between theoretical comprehension and practical implementation. While participants demonstrated moderate theoretical familiarity with AI concepts and ethical considerations, they exhibited significantly lower confidence in applying AI tools—specifically concerning classroom integration, application design, and interaction management. These findings indicate that prevailing professional development programs predominantly emphasize conceptual knowledge at the expense of applied competencies and emotional preparedness. Consequently, educators remain insufficiently equipped to navigate the rapidly evolving AI landscape (Ng et al., 2022; Ding et al., 2024). This disconnect not only constrains the pedagogical potential of AI but also undermines educators' professional agency. Therefore, future training initiatives must prioritize the development of hands-on operational skills and incorporate robust emotional support mechanisms to bolster educators' confidence and enhance their adaptability in deploying AI within teaching contexts (Shiri, 2024).

## 5.1 Bridging the Gap Between Technical and Emotional Dimensions of AI Literacy

Beyond technical deficiencies, the study revealed that educators exhibit notably low levels of emotional resilience in the context of AI adoption in education. A growing body of evidence indicates that many educators experience heightened levels of anxiety, uncertainty, and psychological discomfort when confronted with rapid technological change—particularly in relation to the continuous updates and evolving functionalities inherent in AI-driven educational tools (Černý, 2024). This highlights the critical role of emotional regulation as a foundational element of AI literacy, essential for fostering adaptive human-AI interactions. As Pedro et al. (2019) contend, the integration of AI transcends a mere technological shift, representing instead a fundamental pedagogical transformation involving the redefinition of educational roles and practices. Educators are required not merely to acquire proficiency in emerging technologies, but also to manage the psychological stress inherent in role transformations and evolving professional expectations. Consequently, emotional competence and adaptability constitute indispensable prerequisites for the successful integration of AI technologies within educational frameworks (Jafari and Keykha, 2024).

## 5.2 Demographic Variations in AI Literacy

The findings further revealed significant demographic variations in AI literacy, particularly along gender and age dimensions. Male and younger educators exhibited greater confidence and competence in applying AI technologies, whereas their older and female counterparts reported comparatively lower proficiency levels. These results align with prior studies (Ayanwale et al., 2024; Bond et al., 2024), suggesting that gendered social norms and generational disparities in technological exposure may influence engagement with AI. Consequently, the implications underscore the imperative for differentiated and inclusive professional development. Tailored support strategies are essential to ensure equitable opportunities for skill enhancement and AI integration among educators across all demographic groups.

## 5.3 Impediments to AI Literacy: Training Deficiencies, Resource Constraints, and Ethical Dilemmas

Participants identified three primary barriers to AI literacy enhancement: insufficient professional training opportunities, limited access to relevant resources, and persistent unresolved ethical concerns. Crucially, many educators reported lacking the requisite time and institutional support to engage in sustained learning initiatives related to AI, a finding consistent with earlier research by Rahiman and Kodikal (2024). These identified constraints underscore broader systemic deficiencies in AI-related professional development within higher education, characterized by fragmented training programs and inequitable resource distribution. Chan (2023) further underscores the imperative for systemic policy frameworks and targeted infrastructure investment to effectively support AI capacity-building within academic institutions.

Ethical concerns emerged as a pivotal dimension. Educators articulated significant apprehensions regarding algorithmic bias and data privacy, particularly pertaining to student assessment and information management systems. These concerns are substantiated by research, Holmes et al. (2022) contend that in the absence of educator capacity to critically evaluate and ethically navigate algorithmic decision-making processes, AI systems risk perpetuating or exacerbating structural inequities. Consequently, ethical literacy—comprising both an understanding of the societal implications of AI tools and a commitment to responsible deployment—must form an integral component of any comprehensive AI training program.

## 5.4 Toward a Multi-Level Strategy for Enhancing AI Literacy

Addressing these challenges necessitates a multi-tiered intervention strategy. Initially, customized professional development programs should integrate technical instruction with training in emotional resilience. Skill development ought to progress sequentially, from foundational AI concepts towards advanced competencies such as algorithmic analysis and programming (Obenza et al., 2024). Concurrently, structured workshops focusing on emotional regulation can equip educators to effectively manage technostress and cognitive overload phenomena.

Second, practice-oriented online modules and seminars require expansion. These offerings should incorporate authentic teaching scenarios and applied pedagogical exercises—such as leveraging machine learning algorithms for educational data interpretation—to enhance educators' professional competencies within authentic educational contexts. Furthermore, the establishment of interdisciplinary collaborative learning groups can facilitate cross-subject knowledge sharing and foster cross-disciplinary innovation.

Finally, institutional investment is critical. Universities must prioritize the enhancement of infrastructure through the provision of access to AI tools, simulation laboratories, and digital learning platforms. Complementary measures, including dedicated technical support teams and sustained mentorship programs, are crucial for facilitating educators' continuous professional development.

# 6 Conclusion, Limitations and Future Research

This study developed and validated a five-factor assessment scale to evaluate AI literacy among university educators. Confirmatory factor analysis supported the structural validity of the scale, demonstrating excellent model fit (CFI = 0.956, RMSEA = 0.052) and high internal consistency ($\alpha = 0.89$), supporting its robustness for large-scale application. The findings revealed a significant disconnect between conceptual understanding and practical application. While over 70% of participants reported familiarity with core AI concepts and associated ethical considerations, fewer than half expressed confidence in their ability to create AI-driven applications or manage the emotional responses elicited by AI integration in educational contexts. This disparity indicates a pronounced capability gap within the sampled population. Demographic analyses indicated that male and younger educators exhibited higher levels of technical proficiency and emotional resilience regarding AI. However, ethical awareness concerning AI remained consistent across genders. Educators holding doctoral degrees demonstrated superior performance in AI creation tasks compared to their counterparts. Qualitative data further identified major implementation barriers, including inadequate professional training, insufficient institutional resources, and persistent ethical concerns, highlighting the urgent need for comprehensive, skill-based, and emotionally supportive AI professional development programs in higher education.

This study has several limitations. First, the reliance on convenience and snowball sampling techniques potentially compromises the generalizability of the results, as the obtained sample may not adequately capture the full spectrum of university educators in terms of regional distribution, disciplinary backgrounds, and institutional affiliations. Second, the dependence on self-reported measures introduces potential response biases, participants might overestimate or underestimate their AI proficiency due to factors such as social desirability or inaccurate self-assessment. Third, the cross-sectional nature of the design precludes causal inference and limits the examination of temporal dynamics in AI literacy development, particularly concerning the impact of specific training initiatives or institutional policies over time.

Future research should broaden the sampling framework to encompass more diverse educator populations and institutional contexts, thereby enhancing the representativeness and generalizability of findings. Concurrently, incorporating observational or experimental methodologies would strengthen the objectivity and validity of AI competency assessments. Longitudinal investigations are also warranted to systematically track the evolution of AI literacy over time and assess its responsiveness to targeted pedagogical interventions. Moreover, comparative analyses of diverse professional development frameworks are essential to identify optimal strategies for cultivating both the technical proficiencies and emotional competencies integral to AI literacy within higher education settings.

As AI continues to profoundly reshape the landscape of higher education, equipping educators with robust conceptual and applied AI literacy has emerged as an imperative. This study establishes a validated assessment framework and provides empirical evidence identifying prevailing gaps and multifaceted challenges in current practices. Systematically addressing these deficiencies through targeted, inclusive, and emotionally supportive professional development initiatives constitutes a critical imperative. Such strategic interventions are essential to empower educators with the confidence and ethical competencies required for engaged AI technology integration, thereby catalyzing the enhancement of pedagogical efficacy and learner outcomes within AI-permeated educational landscapes.

## Declarations

# Data availability

The datasets generated and analysed during the current study are included in the supplementary information files submitted with this manuscript. These include the raw survey responses, cleaned analytical dataset, data codebook, and SPSS syntax used for scale validation. All materials will be made publicly available in the journal's repository upon publication, in accordance with the journal's data sharing policy.

# Competing interests

The authors declare no competing interests. This study was supported by Macao Polytechnic Research Fund (Grant#: RP/FLT-02/2026) and the Post-Funding Project of the National Social Science Fund of China [Grant Number 21FJKB013].

# Ethical Statement

# Ethical Approval

The study received ethical approval from the Institutional Review Board (IRB) on October 9, 2024 (Approval No.: IRB-WZU-SED-20241009). Due to administrative processing delays in issuing the official stamped approval letter, data collection commenced only after receiving written confirmation from the IRB Chair on September 25, 2024, indicating that the research protocol met all ethical requirements and could proceed conditionally. Informed consent was obtained from all participants in writing prior to their participation, and no data were collected before this internal ethical clearance was granted. All procedures were conducted in accordance with the ethical standards of the institutional review board and the Declaration of Helsinki.

# Informed consent

All Chinese undergraduate students participating in this study obtained informed consent. We clearly explain to each participant their rights, research objectives, and the necessity of protecting personal information. The informed consent form is signed by participants before data collection to ensure their voluntary participation and understanding that they can withdraw from the study at any time without any impact. The data collection and informed consent acquisition work was completed between September and October 2024.

# Author Contribution

All authors contributed to the conception and design of the study. Material preparation and data collection were conducted by HSS, XXS, and CGZ. Data analysis was performed by WXB and HSS. The first draft of the manuscript was written by HSS, and subsequent revisions were led by WW. All authors provided feedback on earlier versions of the manuscript and approved the final version for submission.

# Acknowledgement

This study was supported by Macao Polytechnic Research Fund (Grant#: RP/FLT-02/2026) and the Post-Funding Project of the National Social Science Fund of China [Grant Number 21FJKB013].

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