Identifying Distinct AI Literacy Profiles in Higher Education: Implications for Tailored Pedagogical Strategies

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***Abstract*—Understanding how university students engage with Artificial Intelligence (AI) is essential for designing effective educational strategies. Although global interest in AI for education continues to grow, empirical evidence on students' levels and profiles of AI literacy remains limited. This study identifies and characterizes distinct AI Literacy profiles among 392 university students in Mexican higher education. A 25-item instrument, validated through Confirmatory Factor Analysis (CFA), assessed five dimensions of AI literacy: knowledge and skills, emotional engagement, ethical awareness, contextual application, and academic experience. K-means clustering was then applied to identify latent profiles within the student population. Three profiles emerged: disconnected students (44.1%), who showed minimal engagement across all dimensions; curious observers (36.7%), who demonstrated high practical interest but only moderate conceptual understanding; and informed skeptics (19.1%), who displayed strong conceptual and ethical awareness but limited practical application. Cluster membership showed significant associations with gender and computing-related academic background. The findings highlight substantial heterogeneity in students' relationships with AI and underscore the need for differentiated pedagogical approaches. The study provides empirical evidence that a uniform model of AI education is insufficient and emphasizes the importance of addressing diverse learner needs to support the development of capable, critical, and equitable participation in an AI-driven future.**

***Keywords*—Artificial Intelligence (AI) literacy, cluster analysis, higher education, educational technology, artificial intelligence**

I. Introduction

Artificial Intelligence (AI) has rapidly expanded across professional and educational domains, consistently demonstrating its capacity to enhance productivity and support decision-making. Higher education is no exception; however, this accelerated integration of AI also brings important pedagogical, ethical, and cognitive challenges that merit closer examination.

Recent advances in Generative AI (GenAI), particularly large language models such as ChatGPT, have intensified this transformation. Students increasingly rely on these tools for writing, coding, and information retrieval, raising concerns about ethical awareness, responsible use, and critical evaluation [1–3]. Yet, despite the widespread presence of these technologies, empirical research on how university students engage with AI and how this engagement relates to their broader AI literacy competencies remains limited.

As Dijk [4] argues, access to digital technologies does not guarantee knowledgeable, critical, or ethical use. This reasoning applies directly to AI. Since late 2022, AI has become increasingly accessible through low-cost or free applications that run effortlessly on mobile devices, reducing most access barriers. The central challenge now lies in ensuring effective and ethical use. As Wang *et al.* [5] note, individuals need not master technical AI foundations to be considered AI literate; rather, AI literacy refers to the ability to use AI tools competently, critically, and responsibly.

Previous studies have proposed multiple frameworks and instruments to conceptualize and assess AI literacy (e.g., Ng *et al.* [1, 2]; Ding *et al.* [3]; Laupichler *et al.* [6, 7]). However, most focus on validating theoretical dimensions or isolated skills, with limited attention to how these competencies coexist within distinct learner profiles. Addressing this gap, the present study conceptualizes AI literacy as a multidimensional construct shaped by cognitive, affective, ethical, and contextual factors. Using cluster analysis, it empirically examines heterogeneity in students' engagement with AI, thereby linking psychometric validation with educational application. The resulting typology offers an interpretable framework for inclusive curriculum design in higher education.

This study focuses on university students from diverse academic fields who increasingly use generative AI tools, such as ChatGPT, in their academic work. It profiles students according to five dimensions of AI literacy: (1) knowledge and skills, (2) affective engagement, (3) ethical awareness, (4) contextual application, and (5) academic experience. It also examines how these dimensions relate to demographic and contextual variables, including gender, area of study, and university type.

The study addresses two research questions:

1) What distinct profiles of AI literacy can be identified among university students?
2) How are these profiles associated with external variables such as area of study, gender, and university type?

Aligned with these questions, the study pursues three objectives:

1) to identify distinct AI literacy profiles;
2) to describe the characteristics that distinguish these profiles; and
3) to determine the demographic and contextual factors that predict profile membership.

Through these aims, the study contributes theoretically by substantiating the multidimensional configuration of AI literacy and demonstrating how learner profiles emerge from the interplay of cognitive, emotional, ethical, and contextual elements. Practically, it provides evidence-based guidance for designing inclusive, differentiated AI literacy curricula that address variations in engagement, motivation, and ethical awareness when students interact with AI tools.

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II. LITERATURE REVIEW

A. Defining Artificial Intelligence Literacy

It is essential to clarify the meaning of "literacy" and the rationale for adopting this concept within the context of Artificial Intelligence (AI). Traditionally, literacy refers to the skills of reading and writing that enable access to information, communication, and participation in society. However, contemporary understandings extend literacy beyond basic alphabetization to encompass the social uses of reading and writing across civic, cultural, and educational domains [8]. This broader interpretation aligns with the objective of this study, which seeks to promote conscious, critical, and responsible engagement with AI rather than mere operational proficiency.

While some studies describe AI literacy as a subset of digital literacy, this perspective has increasingly been regarded as limiting. A growing consensus emphasizes the need for a distinct theoretical framework that captures the unique cognitive, ethical, and socio-technical dimensions of AI, while still acknowledging its connection to foundational elements of digital literacy. Early work by Burgsteiner *et al.* [9] and Kandlhofer *et al.* [10] proposed analogies between traditional literacy and an emerging literacy related to understanding and interacting with AI systems.

In this study, AI literacy is defined as a multidimensional construct comprising the knowledge, skills, and attitudes that enable individuals to engage with AI in responsible and effective ways. The emerging AILit Framework [9] conceptualizes these components as interconnected rather than isolated competencies. Other authors describe AI literacy as an aggregation of related literacies—digital, media, information, technology, and social-media literacy—reflecting its interdisciplinary nature and societal relevance.

Two broad points of agreement can be identified in the literature. First, a universal definition of AI literacy remains elusive due to its interdisciplinary scope and applicability beyond technical fields [11–15]. Second, AI literacy encompasses a set of competencies that can be organized into distinct dimensions, each representing clusters of related skills. These dimensions offer a framework for understanding and evaluating how individuals interact with AI systems across cognitive, ethical, and experiential domains.

B. Dimensions of AI Literacy

Multiple studies have proposed different ways of organizing the competencies associated with AI literacy. Long and Magerko [14] suggested a conceptual framework structured around five guiding questions aimed at novice learners: *What is AI? What can AI do? How does AI work? How should AI be used?* And *How do people perceive AI?* Ng *et al.* [2] identified four categories: (1) knowledge and understanding of AI, (2) use and application, (3) evaluation and creation, and (4) AI ethics. Touretzky *et al.* [15] emphasized five "big ideas": perception, representation and reasoning, learning, natural interaction, and societal impact. Zhang *et al.* [16] introduced three curricular components—fundamental AI concepts, ethical and societal implications, and AI careers—while UNESCO's TVETipedia Glossary [13] highlighted four practical domains: engaging with AI, creating with AI, managing AI's actions, and designing AI solutions.

Despite differences in scope and orientation, these frameworks share a common focus on understanding the nature and functioning of AI, its practical uses, and its societal and ethical implications. Some models, such as that of Long and Magerko [14], emphasize conceptual and philosophical foundations, whereas others, such as Zhang *et al.* [16], take a more practice-oriented, curricular perspective. Importantly, most frameworks adopt a non-specialist viewpoint, avoiding the need for programming or advanced technical expertise. Collectively, they serve as reference points for defining the core dimensions of AI literacy across educational and professional contexts.

The categories identified across these studies group related skills and competencies into broader dimensions. Many are aligned with Bloom's Taxonomy [1, 11, 17, 18], which enables hierarchical classification of learning outcomes from foundational understanding to higher-order evaluation and creation.

Table 1 provides a concise comparative overview of representative AI literacy frameworks, summarizing their main focus, key competencies, and theoretical orientation.

Table 1. AI literacy competencies, based on Shiri (2024) [17]

Author	Main Focus	Key Dimensions/ Competencies	Theoretical Orientation
Long & Magerko [14]	Conceptual framework for novices	Understanding AI; Use & Application; Ethical Use	Foundational questions on AI understanding
Ng *et al.* [1]	Educational evaluation of AI Literacy	Know, Use, Evaluate, Create, Ethics	Pedagogical and curriculum-oriented
Rizvi *et al.* [19]	AI teaching and learning in K–12	Applications, Models, Ethical Levels	Instructional progression from practice to reflection
Annapureddy *et al.* [20]	Generative AI Literacy	Knowledge, Use, Ethics, Continuous Learning	Competence-based framework for generative AI

A comparative reading of these frameworks highlights their complementarity and evolution. Long and Magerko [14] emphasized conceptual understanding and reflective thinking; Ng *et al.* [2] translated these ideas into pedagogically *structured categories grounded in Bloom's Taxonomy; Rizvi et al.* [19] incorporated ethical and social considerations; and Annapureddy *et al.* [21] extended the discussion to generative AI and lifelong learning.

Building on this literature, the present study adopts a five-dimensional model that integrates cognitive, affective, and socio-ethical perspectives:

1) knowledge and skills,
2) emotional engagement,
3) ethical awareness,
4) contextual application, and
5) academic experience.

This model allows for a more nuanced characterization of students' AI literacy by incorporating affective and contextual elements that are often overlooked in previous approaches. The integration of Bloom's Taxonomy [21] is particularly valuable because it conceptualizes AI literacy as a continuum, recognizing that individuals may show strength in one dimension while exhibiting gaps in others. Rather than isolating technical specialization, this framework emphasizes balanced development across multiple competencies.

III. Materials and Methods

A. Research Design and Participants

A non-probability snowball sampling method was used to recruit participants. Institutional authorities, faculty members, and researchers were invited to distribute the instrument among their students. This approach was selected to increase the sample size and broaden coverage across the target academic population.

The final sample consisted of 392 university students from multiple higher education institutions in Mexico. Of these, 203 were women, and 189 were men, with ages ranging from 17 to 56 years (M = 20.82, SD = 4.19). Participants represented a diverse set of academic disciplines, including engineering (58.2%), social sciences (35.2%), basic sciences (3.3%), and health sciences (3.3%).

B. Data Collection Instrument

The instrument used in this study was designed to measure university students' levels of AI literacy across five dimensions: (1) knowledge and skills, (2) emotional engagement, (3) ethical awareness, (4) contextual application, and (5) academic experience.

The instrument consisted of three sections. The first gathered demographic information, including university affiliation, academic discipline, age, and gender. The second section contained 47 Likert-scale items, each rated on a five-point scale measuring the intensity or frequency of students' engagement with AI. These items were theoretically organized into five dimensions of AI literacy: 13 items on knowledge and skills, 10 items on emotional engagement, 13 items on ethical awareness, 3 items on contextual application, and 8 items on academic experience.

The third section included eight open-ended questions aligned with these same dimensions. These qualitative items were designed to explore students' perceptions in greater depth and to complement the quantitative data collected in the second section.

For the purposes of this study, only the quantitative responses from the second section were analyzed. The qualitative data from the open-ended questions will be examined in future research.

C. Data Analysis Procedure

The present study analyzed a subset of items from the original 47-item questionnaire using a multi-stage procedure designed to refine the instrument and identify distinct AI literacy profiles. Confirmatory Factor Analysis (CFA) was first conducted on the full set of 47 items to validate the internal structure of the instrument. The CFA was performed using the *lavaan* package with the robust maximum likelihood estimator (MLR), as Mardia's test indicated a non-normal multivariate distribution. Sample adequacy was confirmed (KMO = 0.85; Bartlett's test $\chi^2(300) = 3298.43$, $p < 0.001$), supporting the suitability of the data for factor analysis.

Item refinement followed both theoretical and statistical criteria to ensure conceptual and empirical coherence. Items with standardized loadings below 0.40, cross-loadings of 0.30 or higher, or large standardized residuals ($|SR| > 2.0$) were removed only when their exclusion did not compromise the theoretical coverage of the five dimensions of AI literacy. This process resulted in a 25-item, five-factor subset with adequate fit: $\chi^2(265) = 456.012$; CFI = 0.914; TLI = 0.903; RMSEA = 0.043; SRMR = 0.052. All retained items had loadings above 0.40. Reliability indices demonstrated acceptable to strong internal consistency across dimensions ($\alpha = 0.50$–0.85; $\omega = 0.58$–0.90), confirming the robustness of the refined model.

All analyses were conducted in R (version 4.4.2) using *lavaan* and *psych* for psychometric evaluation and *dplyr*, *cluster*, and *factoextra* for data manipulation and clustering.

K-means clustering was applied to the dataset using the validated 25-item subset, excluding cases with missing responses. To determine the optimal number of clusters, three complementary methods were used: the elbow method to examine the within-cluster sum of squares, the average silhouette coefficient for solutions ranging from two to ten clusters, and hierarchical clustering using Ward's method with dendrogram inspection. Convergence across these approaches indicated that a three-cluster solution was the most stable, interpretable, and theoretically coherent.

Following cluster extraction, statistical validation was carried out to assess the distinctiveness of the resulting profiles. One-way Analyses of Variance (ANOVA) were performed for each of the 25 variables to identify significant mean differences among clusters. Additionally, chi-square (χ^2) tests of independence were used to evaluate associations between cluster membership and categorical variables, including gender, university type, area of study, and whether students' programs were related to computing or education.

Finally, Spearman's rank-order correlations were computed to explore interrelationships among the 25 items. These correlations were visualized through a correlogram illustrating the strength and direction of item-level associations.

D. Determination and Validation of the Cluster Solution

To determine the optimal number of clusters, three complementary methods were applied: the elbow method, the average silhouette coefficient, and hierarchical clustering using Ward's criterion. As shown in Fig. 1, the elbow method indicated that the curve began to flatten at $k = 3$, suggesting diminishing returns in reducing within-cluster variance beyond this point. Fig. 2 presents the silhouette coefficients for solutions ranging from two to ten clusters; although $k = 2$ produced the highest silhouette value, the three-cluster solution offered a more theoretically meaningful interpretation by distinguishing coherent groups such as *The Informed Skeptics* and *The Curious Observers*. The hierarchical dendrogram further supported this configuration by displaying a well-separated three-cluster structure. Based on the convergence of statistical indicators and conceptual interpretability, the three-cluster solution was selected as the most appropriate.

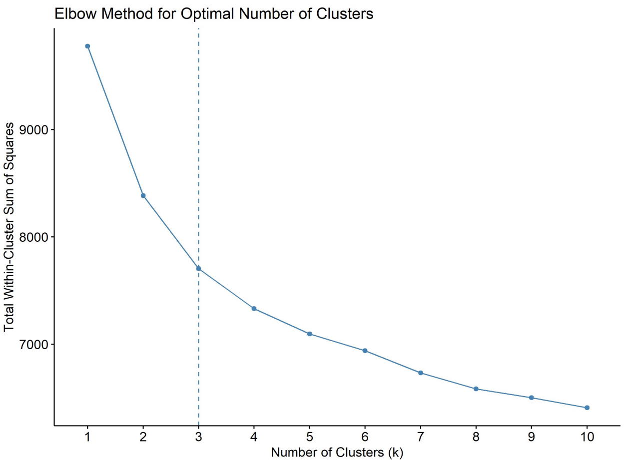

Fig. 1. Elbow method for determining the optimal number of clusters.

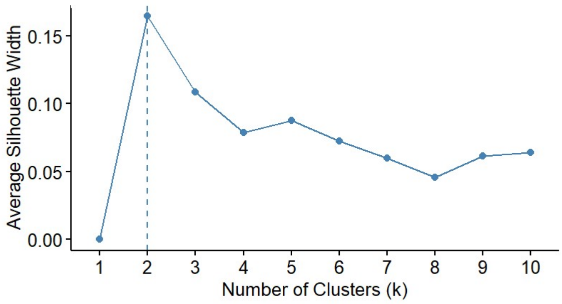

Fig. 2. Average silhouette method for determining the optimal number of clusters.

Table 2. Analysis of Variance (ANOVA) for survey items across three clusters

Variable	F-statistic	p-value
C1	35.4871174	6.9748E-15
C2	47.1635883	4.5738E-19
C3	45.4754261	1.7882E-18
C4	36.9303932	2.0658E-15
C5	45.6977908	1.4935E-18
C16	23.5364081	2.2437E-10
A4	26.2935097	1.9477E-11
A6	16.5122951	1.3092E-07
A8	4.11034283	0.0171199
A10	37.9060092	9.1149E-16
E3	45.6136437	1.5988E-18
E4	55.6979326	5.354E-22
E6	65.0206438	4.3494E-25
E7	69.8484273	1.2064E-26
E8	47.5584891	3.3294E-19
AP1	64.0290325	9.158E-25
AP2	95.3422204	2.0157E-34
AP3	89.4873226	1.0671E-32
EX3	119.995382	2.5638E-41
EX4	118.535415	6.3377E-41
EX5	97.7188953	4.1172E-35
EX6	134.979532	3.0008E-45
EX7	38.4147283	5.9574E-16
EX8	29.1382357	1.6149E-12
EX9	23.4528643	2.4174E-10
EX9	23.4528643	2.4174E-10

Note: The table displays the F-statistic and p-value for each of the 25 survey items, testing for mean differences across the three identified clusters. All F-tests were significant at $p < 0.05$.

Once the cluster structure was established, a series of one-way analyses of variance (ANOVAs) was conducted to assess the distinctiveness of the profiles. Each of the 25 Likert-scale items served as a dependent variable, with cluster membership functioning as the three-level independent factor. Table 2 presents the F-statistics and corresponding p-values. All items showed significant differences at $p < 0.05$, and 24 of the 25 reached $p < 0.001$, providing strong evidence that the clusters represent statistically distinct profiles.

To further analyze relationships among the constructs measured in the survey, a Spearman's rank-order correlation analysis was performed on the 25 items. The resulting matrix was visualized in a heatmap (Fig. 3), illustrating the strength and direction of associations both within dimensions and across different aspects of AI literacy.

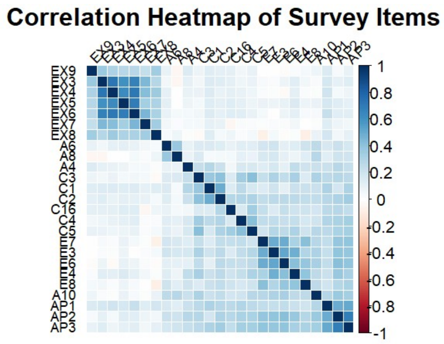

Fig. 3. Heatmap of Spearman correlations among survey items.

IV. Result and Discussion

This section presents the main findings of the study. It begins with the validation of the three-cluster solution and continues with a detailed description of the profiles identified. The analysis then examines the associations between cluster membership and demographic variables. Finally, the section explores intercorrelations among the survey dimensions to provide a broader understanding of how the components of AI literacy relate to one another.

A. Determination and Validation of the Cluster Solution

After establishing the cluster structure, a series of one-way analyses of variance (ANOVAs) was performed to verify the distinctiveness of the three groups. Each of the 25 Likert-scale items served as a dependent variable, with cluster membership functioning as the independent factor. Table 3 reports the F-statistics and corresponding p-values. All items showed statistically significant differences at $p < 0.05$, and 24 of the 25 reached $p < 0.001$, indicating clear and consistent divergence in participants' response patterns. These results provide strong evidence that each cluster represents a distinct profile of AI literacy engagement.

B. Characterization of the Cluster Profiles

The three-cluster solution produced interpretable and theoretically coherent profiles, labeled according to their defining characteristics: Curious Observers, Informed Skeptics, and Disconnected (Table 3; Figs. 4 and 5). The radar chart (Fig. 4) displays the mean scores of the 25 items, allowing direct comparison of patterns across the three profiles. Fig. 5 presents the distribution of participants in a two-dimensional reduced space, showing clear separation among clusters, which supports the stability of the K-means solution and provides the basis for the interpretation of the three profiles.

Curious Observers (n = 144) demonstrated moderate engagement with AI, with intermediate scores in Conceptual Knowledge (C) and Ethical Awareness (E). Their highest means appeared in Academic Experience (EX) items

(EX3–EX8), reflecting optimism and confidence in AI's societal and professional relevance. This group represents exploratory users who display enthusiasm but have not yet developed deeper conceptual mastery.

Table 3. Cluster profile

Cluster	1	2	3
C1	3.159722	3.560000	2.936416
C2	3.000000	3.506667	2.768786
C3	3.062500	3.573333	2.930636
C4	3.090278	3.586667	2.855491
C5	2.833333	3.506667	2.641618
C16	2.500000	3.160000	2.294798
A4	2.625000	3.213333	2.583815
A6	2.881944	3.266667	2.682081
A8	2.923611	3.093333	2.826590
A10	2.965278	3.506667	2.901734
E3	2.972222	3.666667	2.959538
E4	2.687500	3.386667	2.485549
E6	2.916667	3.653333	2.797688
E7	3.090278	3.840000	3.046243
E8	2.659722	3.520000	2.682081
AP1	2.986111	3.560000	2.653179
AP2	2.979167	3.693333	2.774566
AP3	2.993056	3.693333	2.751445
EX3	2.208333	1.680000	1.127168
EX4	2.326389	1.786667	1.231214
EX5	2.361111	1.933333	1.341040
EX6	2.298611	1.800000	1.161850
EX7	2.444444	2.000000	1.601156
EX8	2.798611	2.373333	2.086705
EX9	2.375000	2.266667	1.803468

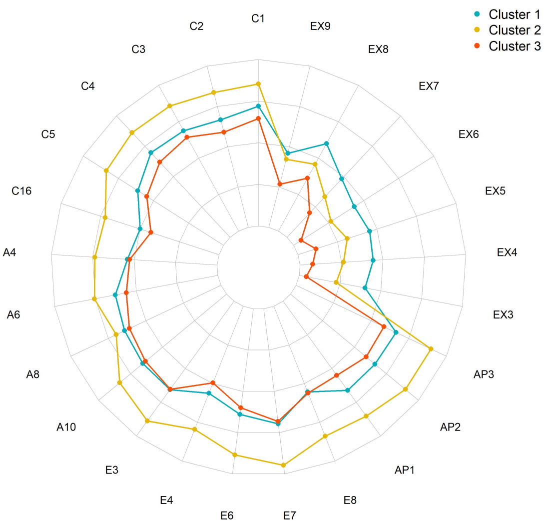

Fig. 4. Combined radar chart of mean scores for the three cluster profiles.

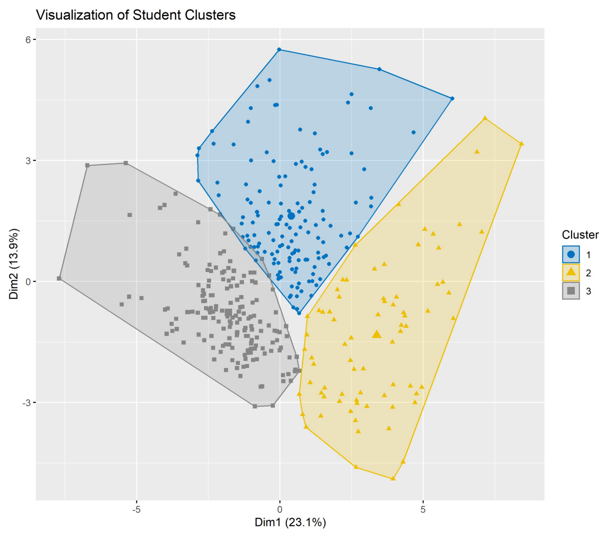

Fig. 5. Scatter plot of the three-cluster solution.

Informed Skeptics (n = 75) exhibited the highest overall engagement, particularly in Conceptual Knowledge and Ethical Awareness (e.g., C2–C4, E6–E7), as well as in Contextual Application (AP). These patterns suggest advanced analytical and ethical competence. Their lower scores on EX items indicate a critical and cautious stance toward AI's broader promises.

The Disconnected group (n = 173), the largest cluster, showed uniformly low means across all dimensions, especially in C and E. Low scores in items such as C1–C5 and E3–E4 point to a limited understanding of AI concepts and minimal ethical reflection. These patterns suggest general disengagement and marginal awareness of AI's academic or professional relevance.

Taken together, these distinctions show that the profiles differ not only in overall levels of engagement but also in the balance among cognitive, ethical, contextual, and experiential dimensions of AI literacy.

C. *Association of Clusters with Demographic Variables*

Chi-square (χ^2) tests of independence were conducted to examine associations between cluster membership and key demographic variables. The results are summarized in Table 4. Statistically significant relationships were identified for gender ($\chi^2(2)$ = 15.06, p < 0.001) and computation-related academic background ($\chi^2(2)$ = 7.47, p = 0.024). No significant associations were observed for the university type ($\chi^2(2)$ = 5.44, p = 0.066), general area of study ($\chi^2(6)$ = 6.92, p = 0.328), and education-related background ($\chi^2(2)$ = 4.82, p = 0.090).

Table 4 presents a summary of the chi-square results, including test statistics, degrees of freedom, and significance levels. These findings indicate meaningful disparities in AI engagement across profiles, suggesting that demographic and disciplinary factors may influence how students interact with and experience AI.

Table 4. Summary of Chi-Square tests for association between cluster membership and demographic variables

Variable	X-squared	df	p-value
Gender	15.0604043	2	0.00053663
University type	5.44131001	2	0.06583162
General area of study	6.92385212	6	0.3279468
Computation-related	7.47391309	2	0.02382651
Education-related	4.82211745	2	0.08972026

D. *Correlation among Survey Items*

Spearman's rank-order correlation analysis was conducted on the 25 Likert-scale items to explore the relationships among the survey constructs. The results revealed coherent blocks of positively correlated variables that aligned with the original dimensions. Strong correlations were observed among Conceptual Knowledge items (C1–C16), Ethical Awareness items (E3–E8), and Contextual Application items (AP1–AP3), supporting the internal consistency of these constructs. The full correlation matrix is presented as a heatmap in Fig. 3, illustrating the strength and direction of the associations across all items.

V. Discussion

The objective of this study was to identify and characterize distinct AI Literacy profiles among university students. The subsequent cluster analysis identified three distinct groups: Curious Observers, Informed Skeptics, and Disconnected. This section is devoted to the interpretation of these profiles, the discussion of their implications for higher education, and the delineation of limitations and directions for future research.

A. Interpretation of the Identified AI Literacy Profiles

The three identified profiles demonstrate that AI literacy is not a unitary construct but a multidimensional spectrum that encompasses knowledge, application, ethical reflection, and engagement. Each profile reflects a distinct combination of cognitive, affective, and contextual elements that shape how students interact with AI technologies.

Informed Skeptics, corresponding to the second cluster, exhibited the highest level of engagement. They reported strong conceptual knowledge, frequent use of AI tools, and heightened ethical awareness. Their stance reflects a form of evidence-based skepticism, characterized by analytical caution rather than rejection of AI. This profile aligns with advanced stages of digital literacy, demonstrating a balanced and non-hyperbolic interpretation of AI's capabilities and limitations. The association between this profile and both computational backgrounds and a higher proportion of male students suggests that deeper forms of AI engagement may currently be concentrated within specific demographic groups.

Disconnected, the largest profile, displayed low engagement across all dimensions—knowledge, use, ethical awareness, and expectations. Their consistently low scores indicate passive or minimal involvement with AI. The predominance of female participants within this profile, combined with the lack of associations with any particular academic domain, suggests a broader disengagement trend that may be shaped by gender-related barriers. These findings underscore the need for further research into structural and cultural factors that influence women's participation in emerging AI practices.

Curious Observers, corresponding to the first cluster, occupied an intermediate position. They expressed optimism about AI's potential and demonstrated awareness of its societal impact, yet reported only moderate levels of knowledge and use. Their elevated expectations, coupled with limited conceptual grounding, indicate a learning-by-exposure trajectory in which attitudes and interests precede the development of deeper competencies. As such, this group represents a critical audience for targeted instructional interventions designed to scaffold conceptual understanding and promote responsible engagement.

A particularly noteworthy finding is the significant association between cluster membership and gender: Informed Skeptics were predominantly male, while Disconnected were predominantly female. This pattern suggests that pathways toward engagement or disengagement may not be evenly distributed across demographic groups. The relationship between the Informed Skeptics profile and computational training, but not general academic area, indicates that formal instruction in computing may promote advanced AI literacy more effectively than disciplinary exposure alone.

Beyond demographic distinctions, these results resonate with broader theoretical frameworks such as the digital divide and the engagement gap. As Van Dijk [4] argues, equitable access to technology does not guarantee equitable participation, understanding, or critical use. The three profiles identified in this study illustrate positions along this continuum: from exposure without meaningful engagement (Disconnected), to exploratory use driven by curiosity (Curious Observers), to selective and critical engagement grounded in conceptual and ethical competence (Informed Skeptics). This perspective reframes digital inequality as a matter of participation, agency, and critical literacy, rather than merely access.

The absence of significant associations with university type or general academic area further suggests that AI literacy profiles transcend institutional and disciplinary boundaries. This emphasizes the need for inclusive and interdisciplinary strategies, as students' engagement with AI cannot be predicted solely by their field of study.

A central contribution of this study is the identification of a discrepancy between conceptual knowledge and practical application. The Informed Skeptics challenge the assumption that understanding necessarily leads to frequent use, demonstrating strong conceptual and ethical awareness alongside cautious or selective application. Conversely, Curious Observers exemplify an experiential trajectory in which active experimentation occurs despite limited theoretical grounding. These patterns reinforce the view that AI engagement does not follow a linear continuum; instead, it reflects a multifaceted interplay of cognitive, ethical, and affective factors. Consequently, the findings extend existing typologies by conceptualizing AI literacy as a multidimensional construct shaped by both intellectual and emotional dimensions.

B. Implications for Educational Practice

The results of this study carry several practical implications for higher education. The presence of a sizable Disconnected group underscores the need for foundational AI literacy curricula in all disciplines, not only in STEM fields. Such initiatives must be inclusive, accessible, and contextually relevant, particularly in light of the gender disparities identified in this study and reported in emerging literature ([22–24]). These findings reinforce the importance of designing learning environments that promote equitable participation and confidence in AI-related tasks.

To translate these insights into practice, differentiated curricular strategies can be developed for each profile.

Disconnected. Introductory workshops can provide essential concepts in artificial intelligence and emphasize hands-on use of simple, accessible tools. These activities should be designed to build initial confidence, reduce anxiety, and offer meaningful early exposure to AI. Examples include guided explorations of everyday AI applications, introductory demonstrations, and scaffolded exercises that promote gradual skill acquisition.

Curious Observers. This group benefits from project-based and collaborative learning that connects personal interest with structured competency development. Activities such as building simple chatbots, practicing prompt engineering, or conducting ethical case analyses can transform curiosity into deeper conceptual understanding. These approaches help students move from exploratory engagement to more informed and critical use of AI tools.

Informed Skeptics: Advanced seminars that address algorithmic bias, data ethics, and AI governance can leverage the strengths of this profile while promoting social responsibility. Structured debates, peer-led sessions, and critical policy reviews support sustained engagement and encourage students to broaden their perspectives. These activities reinforce ethical reflection and provide opportunities to apply conceptual knowledge to real-world issues.

Taken together, these differentiated strategies illustrate how a three-profile model can guide inclusive and adaptive curriculum design. Rather than assuming a single developmental trajectory, AI literacy education can be tailored to accommodate diverse motivational, cognitive, and ethical pathways, supporting learners at multiple stages of engagement.

C. Limitations and Future Research

The present study is subject to several methodological and contextual limitations. The data were collected from university students in Mexico, offering valuable insights into a specific national context but limiting the generalizability of the findings to other educational systems. Future research should replicate this profiling analysis in diverse international settings to assess the robustness and cross-cultural applicability of the identified profiles.

The use of self-reported measures represents another limitation, as these instruments capture perceptions rather than demonstrated competencies. Subsequent studies could incorporate performance-based assessments or behavioral data to evaluate AI literacy more objectively.

Additionally, the exclusion of qualitative responses restricted the exploration of participants' underlying motivations and beliefs. Future work should integrate qualitative analysis of the open-ended responses to enrich the interpretation of the profiles and to deepen understanding of discipline- and gender-related differences.

Finally, the cross-sectional design provides only a static representation of students' AI literacy profiles. Longitudinal and mixed-method approaches would help capture how these profiles evolve over time, offering a more comprehensive account of the development of AI literacy throughout students' academic trajectories.

VI. Conclusion

This study proposes an empirically grounded framework for understanding the heterogeneity of AI literacy among university students. By integrating confirmatory factor analysis with cluster modeling, three distinct engagement profiles were identified, each reflecting specific combinations of cognitive, ethical, and affective elements. This methodological approach represents a novel contribution to AI literacy research, revealing forms of variability that remain obscured in traditional mean-based analyses.

The findings also provide actionable insights for educational practice. Institutions can develop differentiated AI literacy pathways that address the needs of disengaged learners, curiosity-driven experimenters, and critically reflective users. Embedding AI literacy across disciplines through introductory workshops, project-based activities, and advanced ethical discussions can promote equitable participation and foster critical awareness.

Theoretically, the study positions AI literacy as a multidimensional and socially situated construct, extending earlier models that framed it primarily as a cognitive or technical skill. Practically, it establishes a replicable profiling methodology that institutions can use for self-assessment and to guide future curricular innovation.

Future research should expand this work through longitudinal and cross-national studies to examine how AI literacy profiles evolve across educational systems and cultural contexts. Further investigations may also explore how policy frameworks, curriculum design, and teacher preparation shape students' engagement trajectories, allowing for continued refinement of the profiling model introduced here.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

All authors contributed to the study's conception and design. Material preparation, data collection, and analysis were performed by E.M.U., J.I.L.F., and C.C.G. The first draft of the manuscript was written by E.M.U., J.I.L.F., and C.C.G. and all authors commented on previous versions of the manuscript. All authors read and approved the final version of the manuscript and approve it for publication.

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