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ORIGINAL RESEARCH

University Students' Engagement with Artificial Intelligence: A Cluster Analysis of Learner Profiles in AI Literacy

Luis Medina-Gual[1] · **José-Luis Parejo**[2]

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Abstract

The rapid integration of artificial intelligence (AI) technologies in higher education has created new opportunities and challenges for student learning. This study examines how university students engage with AI in their learning processes by identifying distinct learner profiles based on their AI literacy, experiences, actions, and perceptions of faculty modeling. Using cluster analysis on a sample of 353 undergraduate students from a private university in Mexico, we identified three distinct profiles through principal component analysis and K-means clustering: "Critically Engaged Navigators" (32%), "Pragmatic Technicians" (37%), and "Emerging Users" (32%). The analysis reveals significant differences in learning exposure, social learning patterns, autonomous learning strategies, responsible AI use, and perceptions of faculty modeling across clusters. These findings have important implications for differentiated pedagogical design, faculty development programs, and the development of adaptive educational technologies that can support diverse learner needs in AI-enhanced educational environments. The study contributes to the growing literature on AI literacy while providing practical insights for educators seeking to optimize AI integration in higher education contexts.

Keywords Artificial intelligence · AI literacy · University students · Cluster analysis · Learner profiles · Faculty modeling

✉ José-Luis Parejo
joseluis.parejo@uva.es

Luis Medina-Gual
luis.gual@ibero.mx

1 Universidad Iberoamericana (Ibero-American University), Mexico City, Mexico

2 Department of Pedagogy, University of Valladolid, Plaza de La Universidad, 1, 40005 Segovia, Spain

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1 Introduction

The proliferation of artificial intelligence (AI) technologies in educational contexts has fundamentally transformed the landscape of teaching and learning in higher education (Almulla, 2024). As generative AI tools such as ChatGPT, Claude, and other large language models become increasingly accessible to students, universities worldwide are grappling with questions about how to effectively integrate these technologies into their pedagogical practices while maintaining academic integrity and fostering meaningful learning experiences (Stojanov et al., 2024). The emergence of AI in education represents not merely a technological shift, but a paradigmatic transformation that requires a nuanced understanding of how students engage with, perceive, and utilize these tools in their academic endeavors (Song et al., 2025)

Recent research has highlighted the critical importance of AI literacy as a foundational competency for 21st-century learners. AI literacy encompasses multiple dimensions, including knowledge and understanding of AI systems, practical skills in using AI tools effectively, ethical considerations in AI deployment, and the ability to critically evaluate AI-generated outputs (Medina-Gual & Parejo, 2025; Zhou & Schofield, 2024). However, the development of AI literacy among university students is not uniform, with significant variations observed across different demographic groups, academic disciplines, and institutional contexts (Wang & Gao, 2024). Understanding these variations is essential for developing targeted educational interventions and support systems that can address the diverse needs of student populations.

The concept of learner profiles has emerged as a valuable framework for understanding the heterogeneity in student engagement with digital technologies (Er et al., 2024). Learner profiles provide a comprehensive view of students' characteristics, preferences, behaviors, and competencies, enabling educators to design more personalized and effective learning experiences (Zhou & Schofield, 2024). In the context of AI literacy, learner profiles can help identify distinct patterns of engagement, revealing how different groups of students approach AI tools, what factors influence their adoption and use (Jin et al., 2025). This understanding is particularly crucial as institutions seek to implement AI-enhanced learning environments that are inclusive, equitable, and pedagogically sound.

2 Theoretical Framework

2.1 AI Literacy and Its Dimensions

The theoretical foundation of AI literacy has evolved rapidly as researchers attempt to define and measure this emerging competency. Ng et al. (2021) proposed a comprehensive framework that identifies four core dimensions of AI literacy: knowledge and understanding of AI, use and application of AI, AI ethics and evaluation, and AI creation. This framework has been widely adopted and adapted by subsequent researchers, with some proposing additional dimensions such as AI self-management and discovery (Laupichler et al., 2023). The multidimensional nature of AI literacy reflects the complexity of human-AI interaction and the need for holistic approaches to AI education.

Recent empirical studies have provided valuable insights into the current state of AI literacy among university students. A multinational assessment revealed significant variations in AI literacy levels, influenced by prior technology experience, academic discipline, and cultural context (Jin et al., 2025). Similarly, research by Darvishi et al. (2024) demonstrated that AI assistance can have differential impacts on student agency, depending on how students approach and utilize AI tools. These findings underscore the importance of understanding individual differences in AI engagement rather than assuming uniform adoption patterns across student populations.

The concept of AI self-efficacy has emerged as a critical factor influencing students' engagement with AI technologies (Chiu et al., 2025). Students with higher AI self-efficacy are more likely to experiment with AI tools, persist through challenges, and develop more sophisticated usage strategies (Kong et al., 2023). Conversely, students with low AI self-efficacy may avoid AI tools altogether or use them in superficial ways that do not contribute to meaningful learning (Laupichler et al., 2023). This relationship between self-efficacy and engagement highlights the need for educational interventions that not only provide technical skills but also build students' confidence and motivation to engage with AI technologies.

The ethical dimension of AI literacy has received particular attention in recent literature, as concerns about academic integrity, bias, and responsible AI use have become more prominent (Francis et al., 2025). Research has shown that students' ethical awareness and decision-making regarding AI use vary significantly, with some students demonstrating sophisticated understanding of ethical considerations while others show limited awareness of potential risks and responsibilities (Zhou & Schofield, 2024). The development of ethical AI literacy requires not only knowledge of ethical principles but also the ability to apply these principles in complex, real-world situations where the boundaries between appropriate and inappropriate AI use may be ambiguous (Carolus et al., 2024).

2.2 The Role of Faculty Modeling in AI Literacy Development

Faculty modeling has emerged as a crucial factor in shaping students' attitudes, behaviors, and competencies related to AI use in educational contexts (Hughes et al., 2016). Social learning theory suggests that students learn not only through direct instruction but also through observation of their instructors' behaviors, attitudes, and practices (Bandura, 1977). In the context of AI literacy, faculty modeling involves instructors demonstrating thoughtful, ethical, and effective uses of AI tools in their teaching, research, and professional practices (Zhou & Schofield, 2024). This modeling can significantly influence students' perceptions of AI legitimacy, their willingness to engage with AI tools, and their understanding of appropriate AI use in academic contexts.

The concept of faculty modeling extends beyond simple demonstration of AI tool use to encompass the modeling of critical thinking, ethical reasoning, and reflective practice in AI-enhanced environments. Effective faculty modeling involves making visible the decision-making processes that guide AI use, discussing the limitations and potential biases of AI systems, and demonstrating how to integrate AI tools with human expertise and judgment (Kong et al., 2023). This type of modeling helps students develop not only technical skills but also the metacognitive awareness necessary for responsible and effective AI use (Laupichler et al., 2023).

However, research has also revealed significant challenges in faculty modeling of AI literacy. Many faculty members report feeling unprepared to guide students in AI use, citing concerns about their own AI competencies, uncertainty about institutional policies, and concerns about academic integrity. A recent study found that faculty attitudes toward AI in higher education are mixed, with some embracing AI as a valuable educational tool while others express concerns about its impact on student learning and academic standards (Francis et al., 2025). These mixed attitudes can create inconsistent messages for students and may contribute to the development of diverse learner profiles with varying levels of AI engagement and competency.

2.3 Cluster Analysis and Learner Profiles in AI Education

The application of cluster analysis to understand learner diversity in AI education has gained increasing attention as researchers seek to identify meaningful patterns in student engagement and competency (Er et al., 2024). Cluster analysis provides a data-driven approach to identifying groups of students with similar characteristics, behaviors, or outcomes, enabling researchers to move beyond simple demographic categorizations to more nuanced understanding of learner diversity (Hao et al., 2025). In the context of AI literacy, cluster analysis has been used to identify distinct profiles based on various factors including AI knowledge, usage patterns, attitudes, and self-efficacy (Carolus et al., 2024).

Recent studies have demonstrated the value of cluster-based approaches for understanding AI literacy among university students. For example, research by Wang and Gao (2024) used cluster analysis to identify distinct profiles of students based on their AI literacy levels and lifelong learning orientations, revealing important relationships between AI competency and broader learning dispositions. Similarly, a study focusing on university instructors used cluster analysis to identify different profiles of AI literacy among faculty members, providing insights into the factors that influence instructor readiness to integrate AI into their teaching practices.

The identification of learner profiles through cluster analysis has important implications for educational practice and policy. Different learner profiles may require different types of support, instruction, and resources to develop AI literacy effectively (Zhou & Schofield, 2024). For example, students with high technical skills but low ethical awareness may benefit from targeted interventions focused on responsible AI use, while students with limited technical experience may require more foundational support in AI tool use and application (Kong et al., 2023). Understanding these profile differences can inform the development of adaptive learning systems, differentiated instruction strategies, and targeted support programs.

However, the application of cluster analysis to AI literacy research also presents methodological challenges. The multidimensional nature of AI literacy means that cluster solutions may vary depending on which dimensions are included in the analysis and how they are weighted (Laupichler et al., 2023). Additionally, the rapid evolution of AI technologies means that learner profiles identified at one point in time may not remain stable over time, requiring longitudinal approaches to understand how profiles develop and change (Jin et al., 2025). Despite these challenges, cluster analysis remains a valuable tool for understanding the complexity of student engagement with AI technologies.

2.4 Study Rationale and Objectives

Although research on AI literacy and student engagement with AI technologies has expanded, significant gaps persist in understanding how students develop and apply AI competencies in authentic educational contexts. Prior studies have often examined isolated dimensions of AI literacy or used predefined classifications, potentially missing meaningful, experience-based engagement patterns (Carolus et al., 2024). Moreover, limited attention has been given to how faculty modeling influences students' AI literacy development, despite evidence of its central role in shaping learning outcomes. Addressing these gaps, the present study employs a data-driven cluster analysis to identify learner profiles across multiple dimensions of AI engagement—such as learning sources, usage behaviours, ethical awareness, and perceptions of faculty modeling—thereby revealing naturally occurring engagement patterns and the underexplored relationship between instructor practices and AI literacy development (Hao et al., 2025; Hughes et al., 2016).

The general objective of this study is to analyze how university students engage with artificial intelligence in their learning by identifying different learner profiles based on their AI literacy, experiences, actions, and perceptions of faculty modeling. Specifically, this study aims to:

1. Identify student profiles based on their AI learning sources, usage behaviors, and perceptions of faculty modeling through cluster analysis.
2. Compare the identified clusters in terms of demographic characteristics including gender, academic field, and stage of academic program.
3. Discuss how these profiles can inform teaching strategies, faculty development programs, and the design of adaptive learning tools for AI-enhanced educational environments.

Through these objectives, the study advances theoretical understanding of AI literacy development while offering practical insights for educators, administrators, and policymakers seeking to optimize the integration of AI technologies in higher education.

3 Methodology

3.1 Participants and Data Collection

The study involved n = 353 undergraduate students from a large private university in Mexico. Sampling followed a stratified random, census-like procedure targeting two strata, early semesters (1–3) and advanced semesters (7–9), to ensure balanced representation of students at two critical academic stages. Participation was embedded in the university's entry/exit assessment, and students were informed that anonymized data could be used for research and provided informed consent prior to participation. Faculty staff administered the test, ensuring to follow a protocol for application.

The eligible population consisted of all students enrolled in the targeted courses within the two strata during the assessment window; all invited students completed the protocol, yielding a 100% completion rate within the invited cohort and no attrition. The age range of participants was 17–26 years (granular ages were not recorded). Sex was distributed as follows: male = 157, female = 188, prefer not to respond = 4. As the primary objective was to conduct exploratory analyses (PCA and clustering) to identify latent patterns, no a priori hypotheses regarding demographic differences were tested.

This temporal division provides a natural contrast: early-semester students were already exposed to generative AI (e.g., ChatGPT) during high school, whereas advanced-semester students encountered these tools primarily at university, where no intentional AI-related courses were yet in place. The university is organized into three academic divisions grouping related degree programs—Social Sciences (64.4%), Science, Arts and Technology (29.9%), and Humanities and Communication (5.7%)—and assessments were administered in mandatory core courses (early semesters) or capstone/final courses (advanced semesters) coordinated with program directors. The distribution across divisions mirrors institutional enrollment, with a comparatively smaller share from Humanities reflecting population structure rather than sampling bias.

3.2 AI Literacy Scale: Conceptualisation, Dimensions, and Validation

Accurately gauging AI literacy necessitates an instrument that captures its multifaceted character while remaining psychometrically sound. Building on extant frameworks that conceptualise AI literacy as a synthesis of operational skills, conceptual understanding, and critical awareness (Ng et al., 2021), the present study employed a scale specifically designed for higher-education settings and originally developed within the university's institutional assessment program for entry and exit evaluations. At the time of the study, this instrument had not yet been published in peer-reviewed outlets, although manuscripts reporting on other sections are currently under review with different emphases.

The measure comprises three interrelated dimensions. The functional dimension appraises students' capacity to recognise everyday AI applications, interpret their outputs, and deploy them to address practical tasks without requiring advanced technical expertise. The technical dimension assesses comprehension of the algorithms, data structures, and modelling principles that underpin AI systems, emphasising competencies such as algorithmic thinking, data analytic reasoning, and the ability to adapt or innovate AI solutions (Wang & Gao, 2024). Complementing these, the sociocritical dimension evaluates ethical and societal discernment, including awareness of algorithmic bias, privacy, equity, and transparency, thereby foregrounding the broader ramifications of AI deployment (Darvishi et al., 2024). Together, the three dimensions yield a holistic portrayal of AI literacy that integrates practical performance, conceptual depth, and critical reflexivity.

To secure reliability and validity, the scale was developed through a systematic review of international instruments and theoretical models, ensuring balanced coverage of the functional, technical, and sociocritical strands. Item functioning was examined with a unidimensional Rasch model, which demonstrated satisfactory internal consistency (Expected A Posteriori [EAP] reliability = 0.703). The item difficulties were well-distributed, ranging from −3.41 to +2.30 logits, with a mean of −0.13, suggesting the test is well-centered for the target population and effectively captures a wide spectrum of latent ability (Bond & Fox, 2015). Furthermore, item fit statistics were robust, with 93.5% of the items (100 out of 107) falling within the acceptable Infit and Outfit thresholds. This strong model fit, supported by a Test Information Curve that peaks around the average ability level, confirms the instrument's unidimensional integrity and its capacity to provide reliable measurements across the proficiency continuum. Resulting scores were mapped onto three proficiency levels (Developing, Proficient, and Outstanding) using the bookmark method with the participation of three academic experts. This procedure afforded nuanced diagnostic insight into student competencies.

Subsequent k-means cluster analysis drew on these validated scale scores to identify distinct learner profiles, permitting a fine-grained characterisation of engagement patterns that extends beyond aggregate means (Hair et al., 2019). To facilitate interpretation, the original logit scale was preserved with a mean of 0 and a standard deviation of 1. Examples of items had been added in Appendix 1.

4 Results

4.1 Self-Reported Scales Validation and Principal Component Analysis

To examine underlying dimensions in students' self-reported experiences with AI in learning contexts, three self-reported scales were administered (five-point Likert scales ranging from 'strongly agree' to 'strongly disagree'). The first scale focused on sources of AI learning, capturing where and how students have learned about AI. The second assessed actions taken when using AI, including ethical considerations and usage strategies. The third scale measured students' perceptions of faculty modeling, or the extent to which instructors exemplify thoughtful and effective uses of AI. In these self-reported scales, no Rasch approach was used. Each set of items was subjected to principal component analysis (PCA) to reduce dimensionality and extract theoretically meaningful components for subsequent analyses. All variables were standardised with a mean of 0 and a standard deviation of 1. The specifics of each PCA are as follows:

- A Principal Component Analysis (PCA) was conducted on eight items representing different sources of learning about AI. After listwise deletion of missing cases, three components with eigenvalues greater than 1 were retained, explaining 56.81% of the total variance.
    - Component 1 (Learning Exposure, 28.91%) reflected generalized engagement across all items. Higher scores indicate broader, non-differentiated exposure to learning about AI across all sources.
    - Component 2 (Learning Sociality, 14.98%) contrasted social/informal sources (e.g., asking others, social media) with structured environments (e.g., university, personal projects). Higher scores on this component represent a greater reliance on social and informal learning channels.
    - Component 3 (Learning Autonomy, 12.92%) distinguished self-directed strategies (e.g., tutorials, online courses) from institutionally supported or incidental learning. Higher scores signify a stronger preference for autonomous, self-directed learning methods.
- A second Principal Component Analysis (PCA) was conducted on eleven items meas-

uring students' reported actions when using AI. Following listwise deletion of missing data, three components with eigenvalues greater than 1 were retained, accounting for 61.28% of the total variance.

- Component 1 (Actions Responsibility, 35.55%) captured critical and ethical dimensions of AI use. Higher scores represent more frequent engagement in responsible and critical practices, such as verifying sources, protecting privacy, and evaluating AI limitations.
- Component 2 (Actions Regulation, 15.09%) reflected intentional management of AI use, contrasting goal-setting and tool selection with more spontaneous practices. Higher scores reflect a more deliberate and structured approach to using AI tools.
- Component 3 (Actions Optimization, 10.64%) represented tactical behaviors focused on enhancing productivity. Higher scores indicate a greater focus on behaviors aimed at refining AI outputs and improving efficiency, such as prompt tuning.

- A third Principal Component Analysis (PCA) was conducted to explore students' perceptions of their faculty's engagement with AI. The analysis included four items related to how instructors use AI, demonstrate its use, support students, and connect AI to future work. A single component with an eigenvalue above 1 was retained, accounting for 71.80% of the total variance. This unidimensional component was labeled Faculty Modeling, and it was oriented such that higher scores indicate a perception of more frequent and effective modeling of AI use by faculty in their educational context.

4.2 Clustering Analysis

To identify meaningful student profiles based on their AI Literacy, we conducted a comparative cluster analysis using three widely recognized algorithms: K-means, Partitioning Around Medoids (PAM), and Hierarchical Clustering with Ward.D2 linkage (Fig. 1). All statistical analyses were performed in R (version 4.3.2) using the packages dplyr, factoextra, cluster, and NbClust. Each method was evaluated across a range of two to ten clusters using three internal validation metrics: silhouette width, within-cluster sum of squares (Elbow method), and the Gap statistic. Based on combined evidence, we selected K-means with three clusters as the optimal solution. As shown in Fig. 1, the average silhouette width peaks at three clusters, while the 'elbow' in the sum-of-squares plot in Fig. 2 also indicates that k = 3 is the point of diminishing returns, confirming it as the most robust solution (Fig. 3).

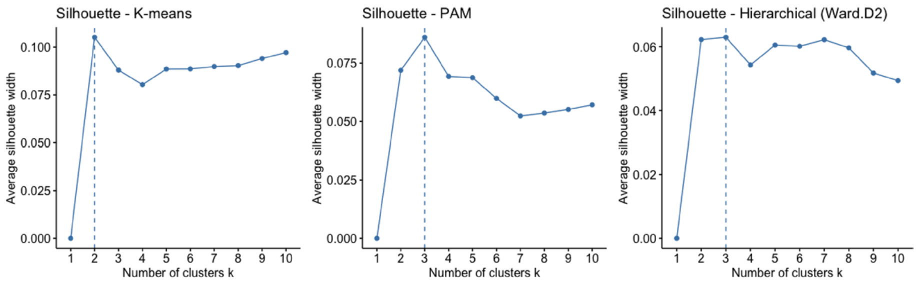

Fig. 1 Comparative cluster analysis using K-Means, PAM, and silhouette-hierarchical (Ward.D2)

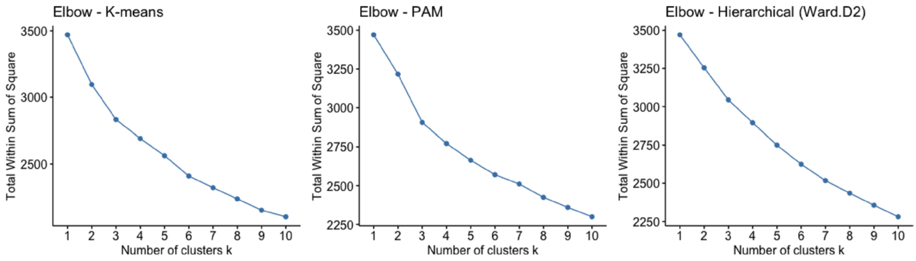

Fig. 2 Comparative cluster analysis using K-Means, PAM, and elbow-hierarchical (Ward.D2)

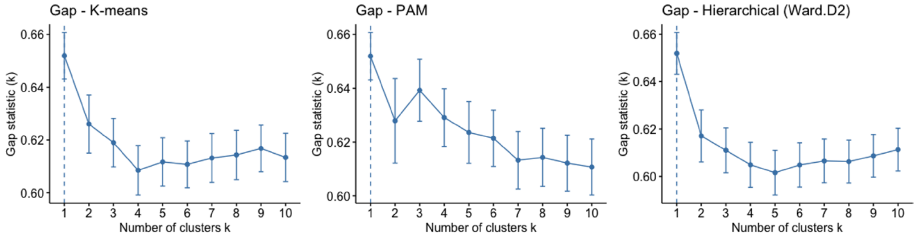

Fig. 3 Comparative cluster analysis using K-Means, PAM, and GAP-hierarchical (Ward.D2)

4.3 Cluster Characteristics and Profiles

The resulting clusters displayed clear differentiation across dimensions of learning, action, and perception. The three-cluster solution revealed distinct learner profiles (Fig. 4). Each point in the figure represents an individual student, positioned according to the first two principal components derived from the AI literacy scales. The x-axis corresponds to Component 1 (Learning Exposure and Sociality), while the y-axis corresponds to Component 2 (Actions Responsibility). A third dimension, Faculty Modeling, is incorporated into the clustering solution but is not directly depicted. The color coding and legend indicate the three profiles: "Critically Engaged Navigators" (Cluster 1), "Pragmatic Technicians" (Cluster 2), and "Emerging Users" (Cluster 3).

- Cluster 1: "Critically Engaged Navigators" (32%, n = 110) demonstrated high scores in Learning Exposure and Learning Sociality, along with elevated levels of Actions Responsibility and Faculty Modeling. This group reflects students with broad and diverse exposure to AI learning experiences, both formal and informal. They also report engaging in intentional and ethically guided use of AI and perceive their instructors as modeling appropriate practices. This profile suggests a population of agentic and critically engaged learners who may be well-positioned to lead or support peer learning initiatives. Hence, this cluster can be characterized as "Critically Engaged Navigators", reflecting students who actively seek diverse learning opportunities and demonstrate mature, intentional use of AI tools.
- Cluster 2: "Pragmatic Technicians" (37%, n = 128) displayed moderate values across most components, with slightly lower scores in Learning Sociality and Faculty Modeling. Despite this, their epistemic orientations (Functional and Technical) remained

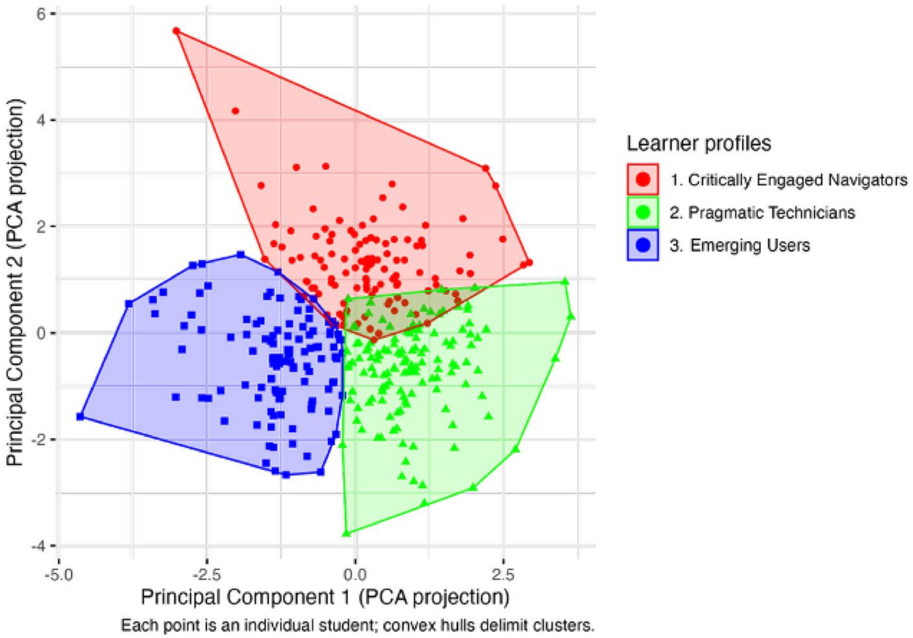

Fig. 4 AI Literacy Learners Profiles (K = 3). K-means clustering solution (K = 3). Each point represents one student case. The axes correspond to the first two principal components of AI literacy (x-axis = Learning Exposure and Sociality; y-axis = Actions Responsibility). Colors denote the three learner profiles: Cluster 1, "Critically Engaged Navigators"; Cluster 2, "Pragmatic Technicians"; and Cluster 3, "Emerging Users."

relatively strong. These students appear to engage with AI in pragmatic terms, focusing on technical aspects while showing lower integration of social learning or critical self-regulation. They may benefit from targeted instructional strategies that emphasize ethical dimensions, collaborative practices, and intentional tool selection. Therefore, this cluster represents "Pragmatic Technicians," students who engage with AI as a useful tool but may benefit from more structured opportunities to reflect ethically and collaborate socially.

- Cluster 3: "Emerging Users" (32%, n = 110) was characterized by consistently low scores across all components, especially in Learning Exposure, Actions Responsibility, and Faculty Modeling. This profile may indicate limited access to AI-related learning opportunities, low self-regulation, and minimal institutional support. Students in this group may lack both internal and external resources for meaningful AI engagement. Their perceptions of faculty modeling were particularly low, suggesting that instructor behaviors and visibility may play a key role in either facilitating or inhibiting engagement with AI in this segment of the student population. As such, this group may be understood as "Emerging Users," reflecting students who may be at risk of exclusion from AI-enhanced learning environments without targeted institutional support.

4.4 Demographic Composition of Cluster

Table 1 details the mean scores for each cluster, highlighting the clear distinctions between them. For instance, the 'Critically Engaged Navigators' scored significantly higher on Actions Responsibility (1.125) compared to the 'Pragmatic Technicians' (−0.951), underscoring the critical difference in their ethical engagement with AI. Cluster 1 (Critically Engaged Navigators) included students from all divisions in proportions similar to the overall sample, with an even distribution across early and late semesters. They stood out for their high scores in Learning Exposure, Actions Responsibility, and Faculty Modeling. Cluster 2 (Pragmatic Technicians) was predominantly composed of students from Social Studies (69%), with comparatively fewer from Science, Arts and Technology (28%), and showed a slightly higher representation of advanced-semester students (52%). Their profile reflects stronger Technical and Functional scores, though lower Learning Sociality and Faculty Modeling. Cluster 3 (Emerging Users), while more evenly distributed across divisions, was concentrated in late-semester students (77%) and characterized by systematically lower scores across most literacy dimensions, particularly Faculty Modeling and the Sociocritical domain (Table 2).

Table 1 Mean scores of AI literacy dimensions across student clusters

Variable	1. Critically engaged navigators	2. Pragmatic technicians	3. Emerging users
Actions Optimization	0.477	−0.557	0.189
Actions Optimization SE	0.111	0.077	0.089
Actions Regulation	−0.394	0.060	0.317
Actions Regulation SE	0.145	0.078	0.129
Actions Responsibility	1.125	−0.951	0.038
Actions Responsibility SE	0.210	0.123	0.165
Faculty Modeling	0.868	−0.454	−0.291
Faculty Modeling SE	0.126	0.154	0.158
Funcional	0.422	0.461	−1.094
Funcional SE	0.087	0.084	0.086
Learning Autonomy	−0.085	−0.027	0.129
Learning Autonomy SE	0.091	0.096	0.095
Learning Exposure	1.054	−0.968	0.123
Learning Exposure SE	0.121	0.108	0.126
Learning Sociality	0.480	−0.351	−0.057
Learning Sociality SE	0.108	0.086	0.098
Sociocritical	0.313	0.195	−0.562
Sociocritical SE	0.069	0.064	0.074
Technical	0.357	0.351	−0.794
Technical SE	0.082	0.062	0.079

Table 2 Sociodemographic composition of student clusters by academic division, semester progression, and sex

Cluster K3	Division			Sex			Semester of major***	
	Social Studies (%)	Humanities and Communication (%)	Science Arts and Technology (%)	Male (%)	Female (%)	Other (%)	Initial (%)	Final (%)
1	59	7	34	43	56	1	50	50
2	69	3	28	48	50	2	48	52
3	61	8	31	44	56	0	23	77

***Chi-squared, $p < 0.0001$

5 Discussion

5.1 Interpretation of Learner Profiles in AI Engagement

The identification of three distinct learner profiles in this study provides valuable insights into the heterogeneous nature of student engagement with AI technologies in higher education. These profiles extend beyond simple usage patterns to encompass complex interactions between learning behaviors, ethical considerations, social influences, and institutional factors. The emergence of these profiles aligns with recent theoretical frameworks that emphasize the multidimensional nature of AI literacy and the importance of considering individual differences in technology adoption and use.

The “Critically Engaged Navigators” profile represents students who demonstrate sophisticated engagement with AI technologies across multiple dimensions. These students not only seek diverse learning opportunities but also demonstrate mature ethical reasoning and intentional use of AI tools. The high scores on Faculty Modeling among this group suggest that these students are particularly responsive to instructor guidance and may serve as bridges between faculty expectations and peer learning communities.

The characteristics of Critically Engaged Navigators align with theoretical models of self-regulated learning and digital citizenship (Ribble, 2015; Zimmerman, 2002). These students appear to have developed what Darvishi et al. (2024) describe as “agentic” relationships with AI technologies, where they maintain control over their learning processes while leveraging AI capabilities to enhance their academic work. Their high scores on Actions Responsibility suggest that they have internalized ethical frameworks for AI use, potentially serving as positive role models for their peers (Francis et al., 2025). This finding is particularly significant given concerns about academic integrity and responsible AI use in higher education contexts.

The “Pragmatic Technicians” profile represents the largest group in our sample and reflects students who engage with AI primarily as a functional tool rather than as a subject of critical inquiry. While these students demonstrate competence in technical aspects of AI use, their lower scores on Learning Sociality and Faculty Modeling suggest more individualistic and less reflective approaches to AI engagement. This profile is consistent with research by Wang and Gao (2024) on large language models in EFL learning, which found that many students focus primarily on immediate practical benefits of AI tools without developing deeper understanding of their capabilities and limitations.

The prevalence of Pragmatic Technicians in our sample reflects broader patterns observed in technology adoption research, where users often focus on immediate utility rather than developing comprehensive digital literacies (Rogers, 2003). However, this pragmatic orientation is not necessarily problematic, as it may represent an efficient approach to AI use for students with specific academic goals and time constraints (Davis, 1989). The challenge for educators is to help these students develop more critical and ethical perspectives on AI use without undermining their practical engagement with these tools (Venkatesh et al., 2003).

The "Emerging Users" profile raises important concerns about equity and inclusion in AI-enhanced educational environments. Students in this group demonstrate limited engagement across all measured dimensions, suggesting potential barriers to AI literacy development that may compound existing educational inequalities (Jin et al., 2025). We label this group 'Emerging Users' to reflect that they are likely in the initial stages of AI literacy development. This term emphasizes their potential for growth with targeted support, rather than suggesting a permanent state of being disconnected from these technologies.

The low Faculty Modeling scores among Emerging Users are particularly concerning, as they suggest that these students may not be receiving adequate institutional support for AI literacy development. Research by Kong et al. (2023) on ChatGPT in higher education found that students' perceptions of institutional support were strongly related to their willingness to engage with AI technologies in academic contexts. The absence of positive faculty modeling may create a cycle where students with limited AI exposure become increasingly disconnected from AI-enhanced learning opportunities.

However, it is important to note that the "Emerging Users" label should not be interpreted as indicating deficiency or inability. Many students in this group may be in early stages of AI literacy development and may benefit significantly from targeted support and scaffolding (Zhou & Schofield, 2024). Research on technology adoption suggests that late adopters often become highly competent users once they overcome initial barriers and develop confidence (Rogers, 2003). The challenge for educational institutions is to identify and address the specific barriers that prevent these students from engaging more fully with AI technologies.

5.2 The Critical Role of Faculty Modeling in AI Literacy Development

One of the most significant findings of this study is the strong relationship between students' perceptions of faculty modeling and their own AI engagement patterns. The Faculty Modeling component emerged as a key differentiator between clusters, with Critically Engaged Navigators reporting the highest levels of perceived faculty modeling and Emerging Users reporting the lowest levels. This finding provides empirical support for theoretical models that emphasize the importance of instructor behaviors in shaping student learning outcomes (Bandura, 1986).

The relationship between faculty modeling and student AI engagement aligns with social cognitive theory, which suggests that learning occurs through observation of others' behaviors, particularly those of respected authority figures (Bandura, 1986). In the context of AI literacy, faculty members serve as important models for how to approach AI technologies thoughtfully, ethically, and effectively (Hughes et al., 2016). When faculty members demonstrate positive attitudes toward AI and model responsible use practices, students are more likely to develop similar attitudes and behaviors.

However, the variation in Faculty Modeling scores across clusters also highlights challenges in current faculty development and institutional support for AI integration. Research has shown that many faculty members feel unprepared to guide students in AI use, citing concerns about their own competencies and uncertainty about institutional policies. A recent study found that while faculty recognize the importance of AI literacy, many lack the training and support necessary to effectively integrate AI into their teaching practices (Francis et al., 2025).

The implications of these findings for faculty development are significant. Traditional approaches to technology training that focus primarily on technical skills may be insufficient for preparing faculty to serve as effective AI literacy mentors (Zhou & Schofield, 2024). Instead, faculty development programs should emphasize the modeling of critical thinking, ethical reasoning, and reflective practice in AI-enhanced environments (Kong et al., 2023). This approach requires not only technical training but also opportunities for faculty to explore their own attitudes toward AI and develop pedagogical strategies for supporting diverse learner needs (Laupichler et al., 2023).

5.3 Implications for Differentiated Pedagogical Design

The identification of distinct learner profiles has direct implications for the design of educational interventions and support systems in AI-enhanced learning environments. Rather than relying on uniform approaches, institutions should tailor strategies to the specific needs and competencies of different groups of students (Zhou & Schofield, 2024). This differentiated approach aligns with principles of universal design for learning and personalized education that have been shown to improve outcomes for diverse student populations (Tomlinson, 2017).

For Critically Engaged Navigators, interventions might focus on leveraging their strong competencies and motivation to foster peer learning and institutional initiatives around AI literacy. These students could be encouraged to serve as peer mentors, contribute to collaborative projects involving AI, or participate in shaping institutional policies on responsible AI use (Kong et al., 2023). Their advanced ethical awareness positions them as potential role models in cultivating reflective and responsible AI practices (Francis et al., 2025).

Pragmatic Technicians, while demonstrating functional competence with AI tools, would benefit from structured opportunities to deepen critical reflection and ethical awareness. Integrating reflective activities into AI-supported learning tasks—for example, requiring students to document their decision-making processes or evaluate the limitations of AI outputs—can strengthen their critical engagement (Laupichler et al., 2023). Collaborative learning arrangements that pair these students with Critically Engaged Navigators may also foster more nuanced and socially informed uses of AI (Johnson & Johnson, 2014).

For Emerging Users, the priority is to build confidence and provide foundational support. Scaffolded introductions to AI tools, explicit instruction on basic concepts, and low-stakes opportunities for practice may help reduce barriers to engagement (Jin et al., 2025). Equally important is to avoid deficit-based approaches, instead emphasizing students' existing strengths and creating inclusive learning environments that encourage gradual participation (Zhou & Schofield, 2024).

5.4 Limitations and Future Research Directions

While this study provides valuable insights into learner profiles in AI engagement, several limitations should be acknowledged. First, the study was conducted at a single private university in Mexico, which may limit the generalizability of findings to other institutional contexts, countries, or educational systems. The specific characteristics of the institution, including its resources, student population, and institutional culture, may have influenced the patterns of AI engagement observed in this study (Francis et al., 2025). In this regard, elite and/or religiously affiliated private universities in Mexico, many of which were founded several decades ago and are located in major urban centers, are characterized by medium to large student populations (around 10,000 students). These institutions engage in research activities and offer a wide range of academic programs—spanning undergraduate, master's, and doctoral levels—across diverse fields of knowledge (Medina-Gual et al., 2025). Future research should examine learner profiles across diverse institutional contexts to determine the extent to which these patterns are generalizable.

Second, the cross-sectional design of this study provides a snapshot of student AI engagement at a single point in time but does not capture how learner profiles may evolve over time (Jin et al., 2025). Given the rapid pace of AI technology development and the dynamic nature of student learning, longitudinal studies are needed to understand how learner profiles develop and change throughout students' academic careers (Zhou & Schofield, 2024). Such studies could provide insights into the factors that promote positive profile transitions and the interventions that are most effective for supporting AI literacy development over time.

Third, while this study included measures of student perceptions of faculty modeling, it did not directly observe faculty behaviors or collect data from faculty members themselves (Hughes et al., 2016). Future research should include multiple perspectives on faculty modeling, incorporating both student perceptions and direct observations of faculty AI use practices. Additionally, research examining the relationship between faculty AI literacy and student outcomes could provide valuable insights into the mechanisms through which faculty modeling influences student engagement.

The measurement of AI literacy in this study focused on self-reported behaviors and perceptions, which may be subject to social desirability bias and may not fully capture actual AI competencies (Carolus et al., 2024). Future research should incorporate performance-based measures of AI literacy, such as assessments of students' ability to effectively use AI tools, evaluate AI outputs, and apply ethical frameworks to AI use scenarios (Jin et al., 2025). Such measures could provide more objective indicators of AI literacy and help validate the learner profiles identified through self-report measures.

6 Conclusions

The identification of three distinct learner profiles ("Critically Engaged Navigators," "Pragmatic Technicians," and "Emerging Users") reveals that students' engagement with AI is not uniform and challenges one-size-fits-all pedagogical approaches. The findings reveal substantial diversity in students' approaches to AI learning, reflecting variations in ethical awareness, self-regulation, and exposure to faculty modeling. These results challenge assumptions of uniform AI adoption and underscore the importance of recognizing heterogeneous learner pathways in the design of AI-integrated educational environments.

A central contribution of this research is the empirical evidence linking students' perceptions of faculty modeling with their own levels of AI engagement. This relationship highlights the pivotal role of instructors in shaping students' ethical and reflective use of AI tools. Accordingly, faculty development initiatives should move beyond technical training to include the cultivation of ethical reasoning, critical evaluation, and responsible modeling of AI practices.

The findings also point to the need for differentiated pedagogical strategies that respond to diverse learner needs. Institutions should develop adaptive learning frameworks and inclusive support systems that enable all students—regardless of prior experience or confidence—to participate meaningfully in AI-enhanced learning contexts.

Looking ahead, longitudinal and cross-institutional studies are needed to examine how patterns of AI engagement evolve over time and across different educational systems. As AI technologies continue to transform higher education, sustained inquiry into students' literacy development will be essential to ensure equitable access, responsible use, and meaningful learning outcomes.

By integrating theoretical, empirical, and practical perspectives, this study advances the field of AI literacy research and provides actionable insights for educators, administrators, and policymakers seeking to foster critical, ethical, and effective engagement with AI in higher education.

Appendix

To ensure the integrity and validity of the assessment for future applications, the complete item bank cannot be publicly disclosed. However, we are pleased to share select examples for illustrative purposes. The full set of items can be made available to qualified researchers for validation or academic studies upon formal request.

Functional Dimension

Item (CIU2): "In text generation tools based on artificial intelligence (such as ChatGPT or Gemini), how can a user adjust the tone of the generated responses (e.g., formal, casual)?"

(A) By explicitly stating the desired tone in the initial prompt through clear instructions. (Correct)

(B) By modifying the preferences in the platform's settings menu to establish a default tone.

(C) By activating a customization option within the tool to adjust the response style.

(D) By restarting the conversation to reset the default interaction parameters.

Rasch Statistics:

Difficulty: −1.455 (Easy)

Infit: 0.977

Outfit: 0.988

Technical Dimension

Item (CFV2): "The performance (quality of the response) of an AI model can vary significantly based on which of the following factors?"

(A) How the instructions and prompts are formulated. (Correct)
(B) The number of active users on the platform at one time.
(C) The geographic location from which the query is made.
(D) The specific computer being used to make the prompt.
Rasch Statistics:
Difficulty: −3.418 (Very Easy)
Infit: 0.992
Outfit: 0.897

Sociocritical Dimension

Item (CS6): "What is the most direct societal consequence if a facial recognition system performs less accurately for individuals with certain skin tones?"

(A) It perpetuates discrimination and exclusion. (Correct)
(B) It indicates programming errors that primarily affect its efficiency.
(C) It commits ethical breaches that simply require the model to be improved.
(D) It means the system needs immediate retraining to correct a technical flaw.
Rasch Statistics:
Difficulty: 0.482 (Average)
Infit: 1.061
Outfit: 1.087

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Declarations

Conflict of interest The authors have not disclosed any competing interests.

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