

# A tridimensional model of AI literacy: An empirical analysis of student performance and demographic patterns in higher education

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This study moves beyond theoretical frameworks to empirically analyse artificial intelligence (AI) literacy among undergraduate students, identifying distinct performance profiles to inform educational interventions. Using a validated, performance-based instrument, we assessed the functional, technical and socio-critical competencies of 353 students at a private university in Mexico. Our analysis revealed three distinct student profiles: lower performance (n = 85), mid-range proficiency (n = 158) and higher competence (n = 107). A critical finding across all profiles was a significant deficit in the socio-critical dimension, with only 2.6% of students demonstrating outstanding ability. Furthermore, the profiles varied significantly by gender and academic stage, challenging traditional assumptions about technology literacy. These findings provide an evidence-based typology for diagnosing student needs and developing targeted, equitable educational strategies to foster comprehensive AI literacy in higher education.

*Implications for practice or policy:*

- Curriculum leaders should view AI literacy as a transversal competence, integrating ethical and critical reflection across curricula.
- Educators and instructional designers must apply differentiated instruction based on learner profiles, recognising that AI literacy development is complex and challenges assumptions about gender and academic progression.
- Policymakers should promote validated assessment tools to replace anecdotal evidence with empirical data, guiding institutional strategies and resource allocation for AI education.

*Keywords:* artificial intelligence literacy, higher education, psychometric validation, cluster analysis, student performance profiles, quantitative research

## Introduction

Artificial intelligence (AI) is a multidisciplinary field focused on developing systems that perform human-like tasks such as learning, reasoning and problem-solving (Anand et al., 2023; Lexcelent, 2019). Generative AI (GenAI) creates content via neural networks (Hwang et al., 2024), learning autonomously from data and user input (Knoth et al., 2024). A key GenAI approach involves large language models using machine learning to generate text, images and audio (Barbon et al., 2024).

In the educational sphere, GenAI is producing a significant impact, especially in higher education. Its implementation promises to transform pedagogical approaches through personalised and adaptive learning, with the aim of improving academic outcomes (Tzirides et al., 2024). However, its integration also poses relevant challenges, such as the preservation of academic integrity, management of algorithmic biases, model transparency, data protection and ethical implications (Bai, 2024; Daly et al., 2024). Therefore, the acquisition of competencies in GenAI literacy emerges as a key skill for both students and

teachers, facilitating critical, autonomous and responsible participation in AI-mediated environments (Daly et al., 2024; Knoth et al., 2024).

AI literacy is still emerging (Su et al., 2023). Coined by Konishi in 2015, it refers to recognising AI's advantages and limitations and using it cautiously. Burgsteiner et al. (2016) applied the term in the iRobot curriculum to teach basic AI in Austrian schools (Kandlhofer et al., 2016). Long and Magerko (2020) proposed a broader definition, promoting critical evaluation and collaborative AI use, an influential contribution supported by McLean and Osei-Frimpong (2019) and McCoy et al. (2023). These developments show that AI literacy, shaped by the rapid evolution of AI technologies, is now considered a fundamental skill for future societal integration (Choi, 2020).

Against this backdrop, this study presents the design, validation and application of a novel multidimensional instrument to assess GenAI literacy in higher education, aiming to inform equitable, context-sensitive interventions through an empirically grounded typology of literacy levels.

### **Theoretical framework**

Based on a systematic review of recent literature on AI literacy, three key perspectives can be identified that allow us to understand the complexity and scope of this emerging competence in the educational context. Functional, technical and socio-critical perspectives should not be understood as isolated categories but as interrelated approaches that address different dimensions of knowledge, use and critical reflection on AI-based technologies. Each of these three perspectives is developed below, in dialogue with the main findings and theoretical contributions gathered in the research. Nevertheless, despite the growing body of literature, current conceptualisations remain fragmented, and empirical studies are often disconnected from each other, making it difficult to establish a comprehensive and unified theoretical framework for AI literacy.

Functionally, AI literacy means using and understanding AI tools in everyday life without needing technical expertise. Lee (2021) views users as active agents improving their lives with AI. Ng et al. (2021) and Laupichler et al. (2024) have emphasised evaluating and applying AI critically. Higher education is key to training students in AI fundamentals (Ayanwale et al., 2024). Long and Magerko (2020) identified 17 competencies of AI literacy, organised into five overarching themes: understanding what AI is, what it can do, how it works, how it ought to be used and how it is perceived by people —encompassing the cognitive, ethical and socio-technical dimensions of human–AI interaction.

The Busan Office of Education (2019) has supported this practical and ethical use. Key competencies include applying AI in daily tasks (Ng et al., 2022), a basic understanding of AI mechanisms (Ma & Chen, 2024), evaluating results for bias and reliability (Ryall & Abblitt, 2024); interacting with intelligent systems (Ayanwale et al., 2024) and recognising AI-generated content (Ryall & Abblitt, 2024). A key limitation of the functional approach lies in its assumption of universal digital familiarity and access, often absent in fields other than science, technology, engineering and mathematics and in under-resourced settings. Moreover, its reliance on self-reported behaviours, rather than demonstrated competencies, undermines predictive validity.

Beyond the functional view, AI literacy also requires a technical perspective involving a deeper understanding of algorithms, models and mechanisms (Touretzky et al., 2019). This allows users not only to apply AI but also to evaluate its limitations and potentially adapt or create AI systems (Tzirides et al., 2024). Core technical competencies include understanding how AI works and is trained (Ryall & Abblitt, 2024), designing algorithms and fostering analytical thinking (Biagini et al., 2024). Although some define developing AI as a separate skill, others integrate it into literacy (Lintner, 2024; Mansoor et al., 2024). However, training gaps persist, especially in humanities (Laupichler et al., 2022; Lee, 2021), compounded by structural inequalities affecting access to AI knowledge. Studies report knowledge gaps in fields such as library science (Hossain et al., 2025) and added barriers in the Global South due to digital inequality (Van Wyk, 2024). Technical competencies in design and cultural studies include machine learning, neural networks and data analysis (Schauer & Simbeck, 2024). A transversal skill across all contexts remains the

ability to evaluate AI outputs critically. Despite growing interest, the operationalisation of technical competencies remains inconsistent, with limited consensus on core skills and few validated instruments suited to interdisciplinary academic contexts. Most measures originated in Global North settings, raising concerns about their cultural transferability and broader applicability.

Finally, AI literacy also includes a socio-critical dimension, emphasising the ethical and equitable use of AI. This approach maximises societal benefits while mitigating risks such as bias, exclusion and power imbalances, which exemplify the ethical and social challenges that the socio-critical dimension of AI literacy seeks to address (Ayanwale et al., 2024; Hwang et al., 2024; Ryall & Abblitt, 2024). Research shows that algorithmic bias can reinforce social inequalities (Tzirides et al., 2024; Van Wyk, 2024), often due to non-inclusive training data (Boateng & Boateng, 2025). Moreover, the opacity of AI systems creates black box effects that limit transparency and accountability (Bai, 2024).

Lack of transparency in AI systems limits critical evaluation and accountability. AI may also deepen inequalities, concentrating wealth and excluding communities (Biagini et al., 2024; Van Vyck, 2024). Risks include privacy, security, intellectual property, content authenticity and job impacts (Ryall & Abblitt, 2024). GenAI may spread misinformation and affect academic integrity (Daly et al., 2024; Hossain et al., 2025; Vindaca et al., 2024). To address these, ethical frameworks must ensure equity, transparency, accountability and security (Biagini et al., 2024). AI literacy training supports informed and responsible interaction with technology (Lee, 2021) through actions such as integrating ethical discussions into curricula, evaluating result accuracy and bias, promoting inclusive and socially responsible design and raising awareness of misinformation risks, which exemplify the educational strategies fostering critical engagement with AI (Ryall & Abblitt, 2024; Salhab, 2024).

Bai (2024) has called for national policies and ethics codes for AI in education. Development should also consider accessibility and human-centred design (Lérias et al., 2024). The socio-critical perspective remains largely marginalised in curricular practice and is seldom reflected in empirical assessment tools. This creates a significant evaluative gap, as most instruments prioritise technical and functional skills while overlooking learners' ability to interrogate power, ethics and epistemic injustice in AI.

At the international level, various good practices and experiences have been documented in the development of AI literacy in higher education. Tzirides et al. (2024) analysed the impact of using GenAI tools, such as automated reviewers and image generation platforms, in postgraduate courses taught at a public university in the United States of America. The results indicated that, after their participation, the students were more familiar with and comfortable using GenAI technologies and demonstrated a greater ability to understand and critically evaluate their educational applicability. In a complementary way, Kong et al. (2024) evaluated courses designed to strengthen the conceptual understanding of AI among university students with diverse academic profiles. The participants felt empowered by the significant advances achieved in their conceptual understanding and AI literacy. Along the same lines, Biagini et al. (2024) found that a transversal AI literacy course improved student understanding and empowerment and strengthened their ethical awareness concerning these technologies. A study developed in collaboration between universities in Finland and Hong Kong (Korte et al., 2024) examined the evolution of conceptions of AI literacy of international students in the context of a global media education course. The findings showed a significant increase in knowledge of AI and appreciation of its importance in education and society. For their part, Ayanwale et al. (2024) explored the dimensions of AI literacy among prospective teachers at a Nigerian university, concluding that a deep understanding of AI predicts positive outcomes in its use, ethical awareness, content creation and problem-solving. In the same vein, Medina-Gual and Parejo (2025), in a study conducted with Mexican university students, emphasised the need to integrate AI training into higher education, identifying distinct learner profiles and a strong relationship between AI familiarity and perceived educational benefits.

Although these international experiences demonstrate promising pedagogical approaches, they frequently lack robust evaluation frameworks or validated instruments that could be generalised across institutional and cultural boundaries. Moreover, the literature continues to reflect a strong Global North

orientation, with limited empirical attention to contexts in the Global South where structural, infrastructural and linguistic barriers significantly shape how AI literacy is understood and enacted.

Research into AI literacy has yielded a diverse range of assessment instruments, reflecting the conceptual breadth of this emerging competence. These tools vary considerably in scope and focus, encompassing functional, technical, critical and sociocultural dimensions (Table 1). Although instruments such as the Artificial Intelligence Literacy Scale (Wang et al., 2023), the Scale for the Assessment of Non-Experts' AI Literacy (Laupichler et al., 2022) and the Meta-Artificial Intelligence Literacy Scale (Carolus et al., 2024) provide valuable insights into core competencies, they often exhibit limitations in terms of contextual adaptability, theoretical integration and empirical validation across diverse educational settings. Many instruments are designed for specific domains (e.g., medical AI or secondary education), thus limiting their generalisability and cross-contextual applicability. Moreover, a significant number of scales, such as the Attitudes Toward Artificial Intelligence Scale (Sindermann et al., 2021), the Medical Artificial Intelligence Readiness Scale for Medical Students and the General Self-Efficacy in the use of Artificial Intelligence (Morales-García et al., 2024), emphasise attitudes or self-efficacy, often at the expense of deeper cognitive and ethical engagement with AI systems. Although newer instruments like the Artificial Intelligence Literacy Questionnaire (Ng et al., 2022) and the Biagini Questionnaire (Biagini et al., 2024) incorporate ethical and socio-critical dimensions, they remain fragmented and lack alignment with a unified theoretical framework. The absence of comprehensive models that integrate both technical understanding and critical-reflexive practice constitutes a notable gap in the literature. This analysis highlights an urgent need to move beyond fragmented models and towards a holistic, critically grounded framework. There is a pressing demand for instruments that are both theoretically robust and sensitive to the socio-educational contexts in which AI is deployed. The present study responds to this gap by proposing a new assessment framework and instrument, based on an integrative review of existing models and supported by empirical evidence gathered from culturally diverse higher education contexts.

Table 1  
*International compilation of instruments for measuring AI literacy*

Instrument	Authors	Key features
Scale for the Assessment of Non-Experts' AI Literacy	Laupichler et al. (2022)	Technical understanding, critical evaluation, practical application
Artificial Intelligence Literacy Scale	Wang et al. (2023)	Competence in the use of AI; validated in English and Turkish
Meta-Artificial Intelligence Literacy Scale	Carolus et al. (2024)	Based on competence models and psychological metacompetencies
Artificial Intelligence Literacy Questionnaire	Ng et al. (2022)	Affective, behavioural, cognitive and ethical dimensions
Hornberger Test	Hornberger et al. (2023)	Multiple choice; based on Long and Magerko's (2020) competencies
AI Literacy Concept Inventory Assessment	Zhang et al. (2024)	Conceptual inventory for secondary school students
Pinski and Benlian Scale	Pinski & Benlian (2023)	Socio-technical knowledge and experience with AI
Attitudes Toward Artificial Intelligence Scale and Medical Artificial Intelligence Readiness Scale for Medical Students	Sindermann et al. (2021); Karaca et al. (2021)	Attitudes and readiness for medical AI
Biagini Questionnaire	Biagini et al. (2024)	Dimensions: knowledge, operational, critical and ethical
Artificial Intelligence Literacy Scale for Chinese College Students	Ma & Chen (2024)	Designed for Chinese university students
ChatGPT Scale	Chan & Zhou (2023)	Based on expectancy-value theory

Instrument	Authors	Key features
General Self-Efficacy in the use of Artificial Intelligence	Morales-García et al. (2024)	Spanish version on self-efficacy with AI

Source: Own elaboration based on the analysis of AI literacy assessment instruments.

This analysis highlights an urgent need to move beyond fragmented models and towards a holistic, critically grounded framework for AI literacy. Responding to this gap, the present study pursued three interconnected research objectives. A foundational aim was to psychometrically validate a new multidimensional instrument designed to measure AI literacy through performance-based tasks across functional, technical and socio-critical competencies. This step is crucial for establishing a reliable and robust basis for assessment. Building upon this validated instrument, the second objective lay in validating the conceptual framework proposed and thereby creating an empirical typology of AI literacy levels within the higher education context. Finally, we examined how these competency profiles vary according to key demographic and academic variables, specifically gender and academic stage, to uncover patterns that can inform the development of targeted and equitable educational interventions.

## Methodology

### Sample and data collection

The data for this study was collected as part of a standardised institutional assessment programme designed to track the development of various competencies throughout students' degree programmes. In accordance with the university's established ethical guidelines, students provide general informed consent upon enrolment for their anonymised data to be used for academic research purposes. This general consent was explicitly reaffirmed at the time of the instrument's administration, where both students and faculty were informed of the study's objectives and the voluntary nature of participation. It was emphasised that performance on the assessment would have no impact on students' course grades or academic standing, ensuring that participation was free from coercion. All data were fully anonymised prior to analysis to guarantee participant confidentiality.

### Instrument and procedures

We developed the present instrument based on the review of the literature, which revealed no objective assessment instrument addressing AI literacy from a competency-based perspective across the functional, technical and socio-critical dimensions. In this sense, we developed a performance-based instrument based on a comprehensive review of the literature to assess AI literacy. The instrument was designed to measure three dimensions of AI literacy: functional, socio-critical and technical. The assessment consisted of 107 items (Table 2) with varying difficulty levels to capture a wide range of competencies. The instrument was administered during regular class sessions, with faculty members providing standardised instructions to ensure consistency in data collection.

Table 2  
*Structure of the AI literacy test at the university level*

Dimension	Total items in dimension	Subdimension	Items in subdimension	No. of items presented in the test	No. of items per dimension presented in the test
Functional	23	Knowledge of user interface	6	2	10
		Prompt engineering	8	4	
		Basic operation	4	2	
		Simple problem-solving	5	2	
Socio-critical	45	Understanding of power and hegemony	7	2	12

Dimension	Total items in dimension	Subdimension	Items in subdimension	No. of items presented in the test	No. of items per dimension presented in the test
Technical	39	Awareness of bias	10	2	14
		AI demystification	7	2	
		Empowerment for action	7	2	
		Responsible AI	7	2	
		Impact on employment	7	2	
		Comparison of AI models	5	2	
		Access to information, supervision, and lifelong learning	6	2	
		Understanding of AI Capabilities and variability	6	2	
		Understanding of bias and objectivity	5	2	
		Truthfulness, explainability and comprehension	6	2	
		Costs and tokenisation	4	2	
		Advanced large language model techniques	4	1	
		Prompting techniques	3	1	
		Total	107		

To uphold the security and long-term validity of this performance-based assessment, the full item bank remains proprietary. Nevertheless, in the interest of methodological transparency, we have provided illustrative examples of test items for the functional, technical and socio-critical dimensions in Appendix A (<https://doi.org/10.5281/zenodo.17552648>). These items were professionally translated from the original Spanish to demonstrate how each competency was measured. The full instrument can be made available to qualified researchers for non-commercial academic use, subject to a formal data-sharing agreement.

The 107 items were screened with a one-parameter Rasch model, which converts ordinal responses into linear ability estimates and flags misfitting items, a feature valued in educational technology measurement (Sumintono, 2017; Wang et al., 2020). A log-odds (logit) scale was retained for diagnostics; an expected-a-posteriori reliability of .70 meets the conventional criterion for adequate group-level decisions (Bond & Fox, 2015).

To examine potential method bias, we specified a common latent factor (Podsakoff et al., 2003) loading on all parcels; a negligible comparative fit index (CFI) would indicate limited social-desirability influence. Next, a second-order confirmatory factor model tested whether the three first-order competencies converged into a single AI-literacy factor. Indicators were parcelled (three per dimension) following Little et al. (2002) and estimated with robust maximum likelihood under full-information treatment of missing data (Brown, 2015). Fit was judged against Hu and Bentler's (1999) benchmarks (CFI and Tucker-Lewis index  $\geq .95$ ; root-mean-square error of approximation  $\leq .06$ ).

For stakeholder readability, logits were linearly rescaled to a scholastic assessment test-style metric ( $M = 1000$ ,  $SD = 200$ , range = 400–1600) in line with best-practice guidelines on user-friendly score transformations (College Board, 2019; Ekstrand et al., 2022). Performance cut points – developing ( $< 0$  logits), proficient (0–1.5), outstanding ( $\geq 1.5$ ) – were set with the bookmark method, which blends

empirical difficulty ordering with expert judgement of three academics, two of whom are experts in AI for education and one in assessment of learning (Lewis et al., 1996).

Finally, learner profiles were explored through cluster analysis of the rescaled functional, technical and socio-critical scores ( $N = 353$ , satisfying the  $\geq 5 \times$  variables heuristic). Three algorithms – k-means, partitioning around medoids (medoid-based) and Ward’s hierarchical method – were benchmarked. Convergent evidence from silhouette width, elbow and gap statistics supported a three-cluster solution that balanced cohesion and separation (Charrad et al., 2014; Rousseeuw, 1987). K-means was retained for its stability and pedagogical transparency, mirroring recent AI literacy profiling studies (Alvarez-García et al., 2024; Helm & Hesse, 2025). Analyses used R 4.3.2 (TAM, eRm, factoextra, NbClust; R Core Team, 2023).

## Results

### Sample description

This study was conducted at a large, private university in Mexico with a longstanding academic tradition of over 80 years. The site was strategically selected for two primary reasons: first, to contribute empirical data on AI literacy from the Latin American context, a region currently under-represented in the literature (Van Wyk, 2024); and second, because the institution is actively using these assessment results to inform a comprehensive curriculum reform, lending practical significance to the findings. The final sample consisted of 353 undergraduate students, whose demographic characteristics are summarised in Table 3.

Table 3  
*Participant demographics (n = 353)*

Instrument	Authors	<i>n</i>	%
Gender	Woman	192	54.4%
	Man	159	45%
	Non-binary or Prefer not to say	2	0.6%
Academic stage	Early (Semesters 1–3)	205	58.1%
	Advanced (Semesters 7–9)	148	41.9%
Academic division	Social Sciences	228	64.4%
	Science, Art & Technology	105	29.7%
	Humanities & Communication	20	5.7%

Source: Own elaboration.

Participants were selected through a stratified purposive sampling strategy focused on academic stage. The goal was to capture students at two distinct points in their academic journey: the beginning (Semesters 1–3) and the end (Semesters 7–9). For early-stage students, data was collected within common core courses that all students are required to take, following coordination with the responsible academic departments. For advanced-stage students, programme coordinators in each academic division were contacted to facilitate access to students in their final semesters. This census-like approach within the targeted strata resulted in a sample whose distribution across academic divisions (e.g., a majority in social sciences) reflects the natural enrolment composition of the university itself. As will be demonstrated in the results, this disciplinary distribution did not significantly influence the AI literacy profiles, confirming its limited effect on the outcomes. This sampling strategy is particularly relevant given the timeline of GenAI. At the time of data collection, early-stage students would have experienced the mainstream emergence of tools like ChatGPT while in high school, whereas advanced-stage students encountered this technological shift during their university studies. This provided a unique opportunity to explore potential differences in how these two cohorts have developed AI literacy, considering the university had not yet implemented formal, specific AI training for either group.

## Scale validation

A Rasch one-parameter model verified that the 107 performance items behaved as one coherent continuum of AI-literacy ability. The model reached stability quickly and yielded an expected a posteriori reliability of .70, adequate for group-level decisions in educational settings (Bond & Fox, 2015). Item difficulties span from very easy (−3.4 logits) to very hard (+2.3 logits) with a midpoint near zero, meaning the instrument can differentiate students across the full spectrum, from beginners to highly competent users. Roughly 80% of items cluster in the “easy–difficult” band, while 13% challenge the most advanced learners, offering scope for growth tasks in instruction. Figure 1 shows that the test delivers its greatest precision around the average student, precisely where most curriculum decisions are made. Precision tapers, as expected, at the extreme ends; educators should therefore interpret scores at the very top and bottom with a little more caution.

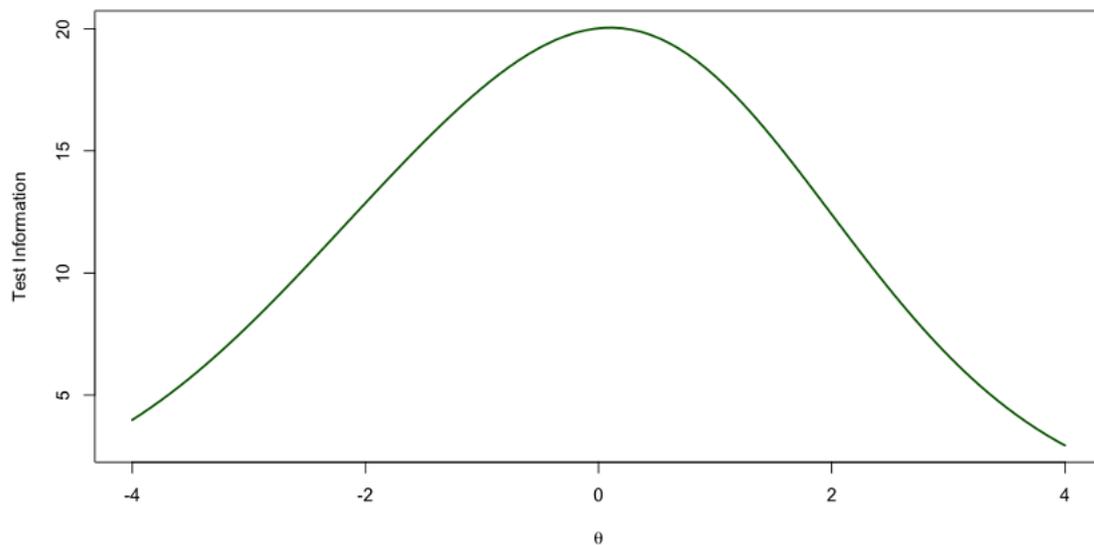


Figure 1. Test information curve

A total of 93% of items met accepted fit criteria, confirming that the questions work consistently and that scores can be trusted for profiling and feedback. Full diagnostics, fit plots, person-item map and classification tables, are available in Appendix B (<https://doi.org/10.5281/zenodo.17552648>) for readers who wish to examine the psychometric detail. Finally, in line with Podsakoff et al. (2003), adding a common-latency factor changed model fit by only  $\Delta CFI = .009$  and explained < 4% of the variance, indicating that social-desirability bias is minimal. In sum, the scale offers a reliable, educator-friendly snapshot of students’ functional, technical and socio-critical command of AI concepts.

## Structural evidence for the three-dimensional competency framework

A correlation heat map (Figure 2) shows moderate overlap between competencies: functional correlates most strongly with technical ( $r = .38$ ), while socio-critical remains more independent ( $r = .28$ – $.29$ ). In practical terms, students who operate AI tools confidently do not automatically demonstrate critical-ethical insight, underscoring the need for explicit socio-critical instruction.

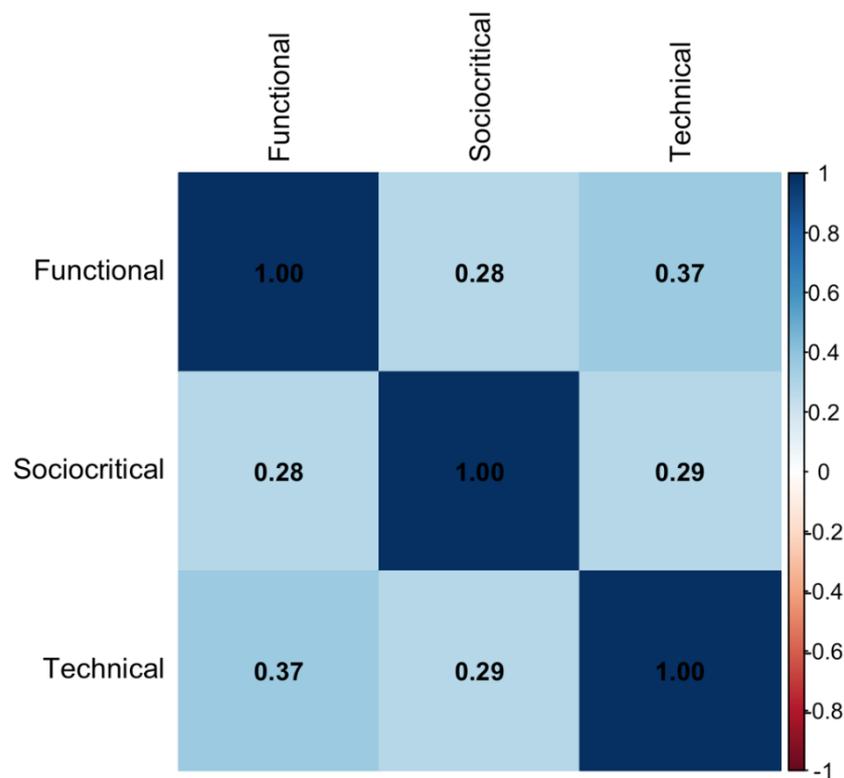


Figure 2. Correlations between Rash dimensions

To check that these competencies still form one higher-order construct, we fitted a second-order confirmatory factor model on nine balanced parcels. The model fits the data (CFI = 1.00; root-mean-square error of approximation = 0.00) based on the recommendations of Hu and Bentler (1999). Standardised loadings obtained (0.76–0.92) confirm that functional, technical and socio-critical skills are distinct yet converge into a single AI-literacy ability, satisfying our second research objective of empirically validating the conceptual framework.

### Rescaling and performance levels

After rescaling logits to a 400–1600 metric, based on the bookmark method, scores were categorised as developing, proficient and outstanding. Roughly one-half of students fell in the developing band across all three dimensions (Table 4), signalling a clear need for foundation-level support. Fewer than 6% reached outstanding, particularly in the socio-critical domain (2.6%), suggesting that ethical-critical aspects of AI remain underdeveloped.

Table 4  
Distribution of performance levels across the individual dimensions – functional, socio-critical and technical – and the overall AI literacy score

Performance level	Functional	Socio-critical	Technical	AI literacy
Developing	48.9%	48.3%	46.6%	45.6%
Proficient	44.9%	49.13%	47.8%	52.4%
Outstanding	6.3%	2.6%	5.7%	2%

A comprehensive global and per-dimension analytical rubric was developed using the bookmark method to evaluate overall performance levels. The following is a brief synthesis of the overall assessment rubrics, including Figure 3 and a detailed explanation in Appendix C (<https://doi.org/10.5281/zenodo.17552648>).

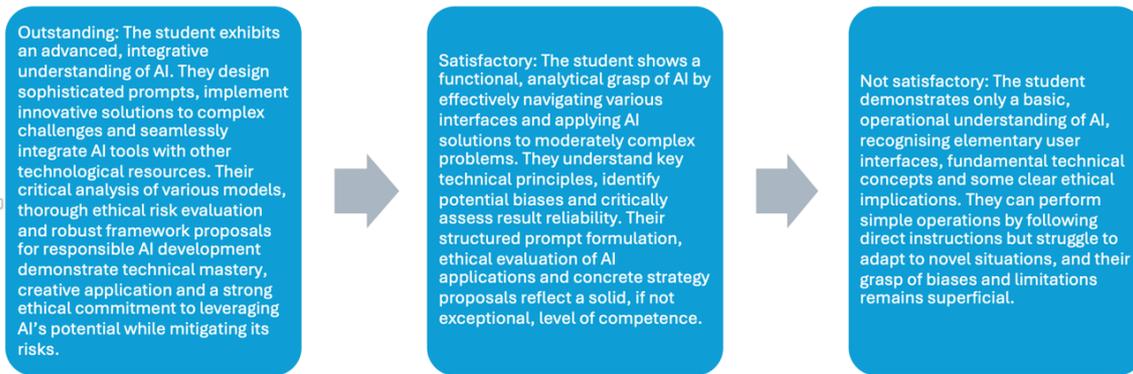


Figure 3. Performance level synthesis from the analytical rubric

### Cluster analysis

The primary objective of this analysis was to develop distinct AI literacy profiles by clustering participants based on their performance across various domains. The silhouette analysis (Figure 4) indicates that a solution with three clusters provided a clear separation between groups. In comparison, both the elbow (Figure 5) and gap (Figure 6) statistic methods corroborated this finding by demonstrating diminishing gains beyond three clusters. Among the tested methods, the k-means algorithm consistently showed superior stability and the highest silhouette values, leading to the adoption of a three-cluster solution.

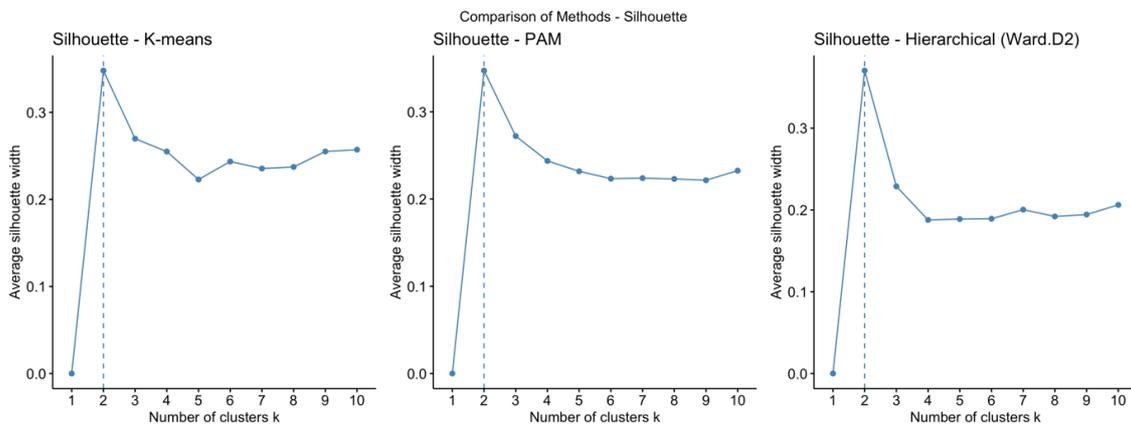


Figure 4. Comparison of methods – silhouette

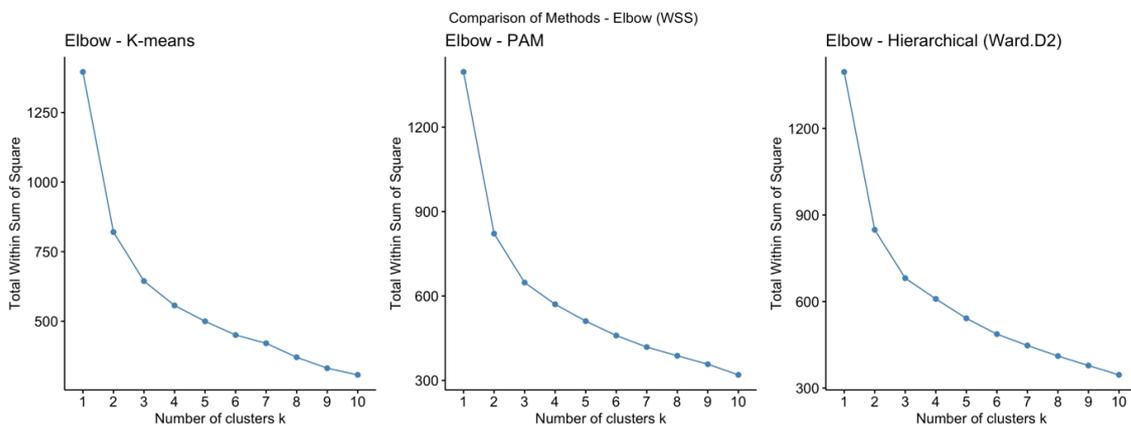


Figure 5. Comparison of methods – elbow (WSS)

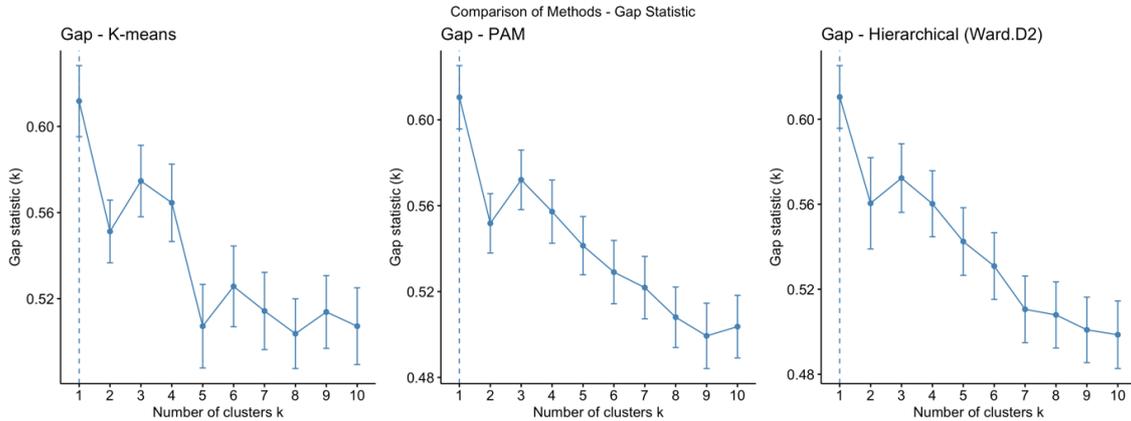


Figure 6. Comparison of methods – gap statistic

After performing the k-means clustering with three clusters, distinct profiles in terms of AI literacy (Figure 7) across the measured dimensions emerged (Table 4). Cluster 1 exhibited mid-range proficiency with average scores around 1041 for functional, 965 for socio-critical, 993 for technical and an overall AI literacy score of approximately 999, comprising 158 participants. In contrast, Cluster 2 was characterised by lower performance across all dimensions, with mean values of about 777 (functional), 845 (socio-critical), 797 (technical) and a total AI literacy score of around 732, representing a group with limited AI literacy skills (85 participants). Finally, Cluster 3 stood out with higher competence, as indicated by mean scores of roughly 1119 for functional, 1179 for socio-critical, 1171 for technical and 1217 overall for AI literacy, consisting of 107 participants.

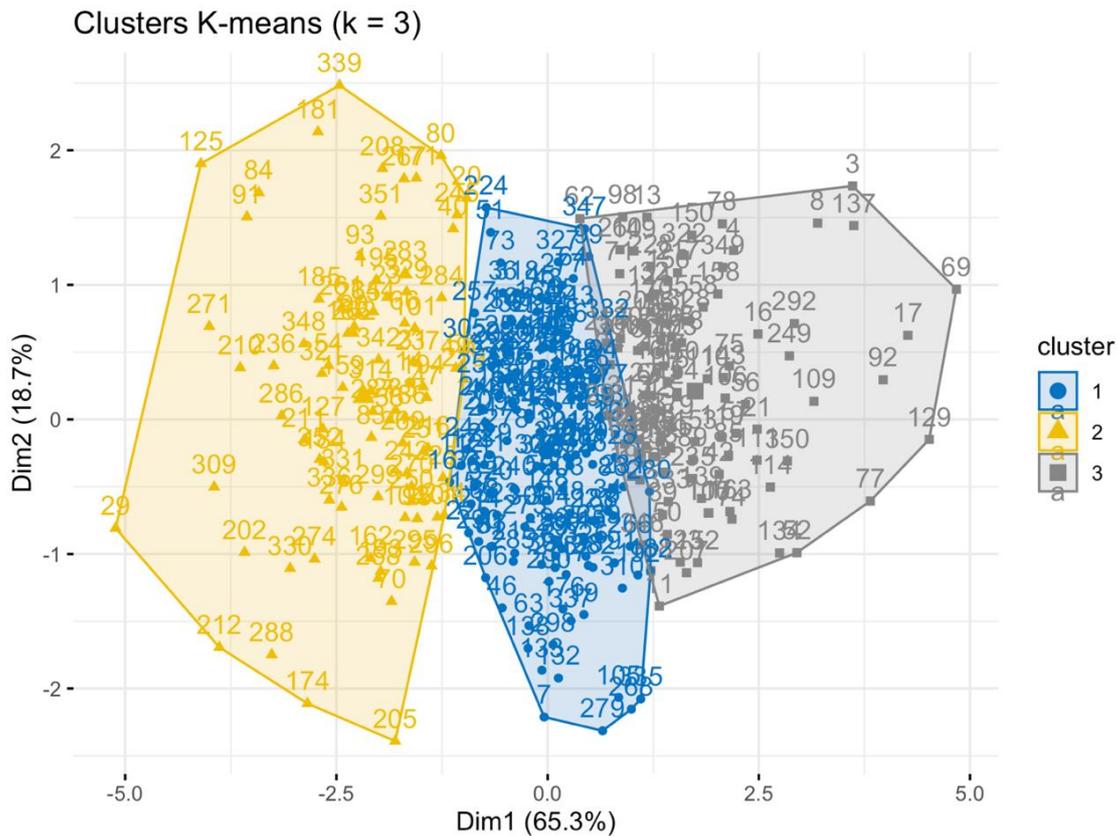


Figure 7. AI literacy competence across clusters based on k-means analysis

Table 5  
*Stratification of AI literacy competence across clusters based on k-means analysis*

Cluster	Mean functional	Mean socio-critical	Mean technical	Mean AI literacy	Size of cluster
1	1041	965	993	999	45.1%
2	777	845	797	732	24.3%
3	1119	1179	1171	1217	30.6%

Complementary analyses to examine the demographic and academic context across the AI literacy profiles (Table 5) revealed significant differences by cluster for both sex ( $\chi^2(4) = 13.405$ ,  $p = 0.009$ , Cramer's  $V = 0.138$ ) and moment/semester ( $\chi^2(2) = 10.954$ ,  $p = 0.004$ , Cramer's  $V = 0.194$ ). For instance, Cluster 1 showed a higher proportion of females (60.1%) compared to males (39.9%), while Cluster 2 had a larger share of males (56.5%) relative to females (41.2%). Similarly, the semester of the student (initial or final) variable indicated that clusters differed in terms of performance phase (with Cluster 3 exhibiting a notably higher percentage in the final category compared to Clusters 1 and 2). In contrast, the distribution of academic division (area of major) did not differ significantly among clusters ( $\chi^2(4) = 4.858$ ,  $p = 0.302$ , Cramer's  $V = 0.084$ ), indicating that the participants' academic divisions are relatively homogeneous across the identified groups.

Table 6  
*Distribution of demographic variables across AI literacy clusters*

Variable	Chi square	Degrees of freedom	$p$ value	Cramer's $V$	Key cluster findings
Sex	13.405	4	0.0095	0.138	Cluster 1: 60.1% female, 39.9% male; Cluster 2: 41.2% female, 56.5% male, 2.4% other; Cluster 3: 56.1% female, 43.9% male.
Moment/semester	10.954	2	0.0042	0.194	Cluster 1: 18.0% final, 82.0% initial; Cluster 2: 20.7% final, 79.3% initial; Cluster 3: 37.7% final, 62.3% initial.
Division	4.858	4	0.3022	0.084	The division distribution shows no significant differences among clusters, indicating a homogeneous allocation across academic sectors.

## Discussion

This study aimed to move beyond abstract notions of AI literacy, seeking to address both the vagueness of existing definitions and the limitations of self-reported measures (Hornberger et al., 2023; Laupichler et al., 2022), by providing an empirical account of student competencies through a newly validated, performance-based instrument. In doing so, it extends the work of Ng et al. (2021) Ng et al. (2022) and Ng et al. (2023), who conceptualised and developed preliminary scales, by offering a validated performance-based tool that overcomes the limitations of self-reported data. The analysis brought to light three distinct profiles among students: those with lower levels of performance, those demonstrating moderate proficiency and those showing high competence. Together, these categories offer a more fine-grained picture of AI literacy in the higher education setting. The results confirm the multidimensional nature of AI literacy and highlight important patterns linked to performance gender, and academic progression, each of which carries meaningful implications for educational practice. These findings lend empirical support to the multidimensional framework articulated by Long and Magerko (2020), affirming that functional, technical and socio-critical dimensions are interdependent yet distinct competencies.

The distribution of students across performance levels presents a sobering picture. With nearly half of the participants classified at the "developing" level and only a fraction (2%) achieving "outstanding" overall proficiency, it is clear that a significant portion of students possess only foundational AI literacy skills. This finding aligns with other research indicating that while students may be frequent users of technology, their deeper competence remains intermediate (Toker Gokce et al., 2024). This is characterised by a basic understanding of AI concepts and an awareness of its social impacts (Lee et al., 2024). The most concerning gap emerged in the socio-critical dimension, where a mere 2.6% of students demonstrated outstanding ability. This highlights a critical lag in educational focus: students are not being sufficiently equipped to grapple with the ethical, societal and power-related implications of AI. This concern strongly echoes the warnings of Daly et al. (2024) and Bai (2024), who emphasised that questions of transparency, bias and academic integrity remain insufficiently addressed within higher education curricula. Such observations reinforce broader scholarly calls to reconceptualise AI literacy as more than the acquisition of functional competencies and technical expertise. Rather, it should be understood as a multidimensional construct that actively cultivates critical reflection and ethical awareness, as argued by Lee (2021), Ryall and Abblitt (2024) and Tzirides et al. (2024).

The findings of this study also align with those of the qualitative research conducted by Sengewald and Tremmel (2024), who observed that, despite the widespread use of AI tools, university students often exhibit limited critical engagement, relying on the outputs without adequately questioning their accuracy, relevance or ethical implications. Along similar lines, the comparative study by O'Dea et al. (2024) revealed that 73% of students in Hong Kong modified at least half of the AI-generated content in their academic work, in contrast to 31% of students in the United Kingdom. Complementing these findings, the study by Knoth et al. (2024) showed that the average quality of the prompts produced by students, as well as that of the generated responses, was considerably low.

One of the most notable findings of this study relates to the demographic patterns observed within the AI literacy profiles, which run counter to widely held assumptions. Whereas much of the literature on technological literacy has tended to associate higher competence with male students (e.g., Møgelvang et al., 2024), our results suggest the opposite: women were more strongly represented within the mid-range proficiency group, while men appeared disproportionately in the lowest-performing group. This reversal indicates that AI literacy, as a relatively new and multifaceted construct, may not be governed by the same historical gender dynamics that have shaped traditional computing skills. First introduced by Konishi (2015) and subsequently consolidated in the academic debate through Burgsteiner et al. (2016), AI literacy represents an area in which entrenched patterns of technology use may play a less prominent role than capacities such as critical thinking or interdisciplinary approaches to learning. Our findings are consistent with more recent work reporting minimal or context-dependent gender differences (Laupichler et al., 2022; Mansoor et al., 2024), underscoring the need for a more nuanced understanding of gender in this emerging field.

The findings regarding academic stage also require careful interpretation. Although advanced-semester students were more likely to be in the highest-performing cluster, this cannot be attributed solely to more time spent at university. As noted in our methodology, the mainstream explosion of GenAI occurred when our advanced students were already in university, while our early-stage students experienced it in high school (Hwang et al., 2024). The superior performance of advanced students may therefore reflect not just longer academic exposure but also the development of more mature critical thinking skills and greater opportunities to apply AI in specific disciplinary contexts, which accelerates literacy development (Ayanwale et al., 2024; Tzirides et al., 2024).

Finally, the absence of significant differences by academic division is a crucial finding. This contradicts some research suggesting discipline-specific patterns in technology adoption (Mansoor et al., 2024) and strongly supports the argument that AI literacy should be treated as a transversal competence. In its current stage, core AI literacy appears to be a set of cross-cutting skills relevant to all students, regardless of their major. This reinforces the need for AI education to be integrated across the curriculum, rather than being siloed in technical departments (Medina-Gual & Parejo, 2025). Collectively, these findings

underscore the importance of a data-driven, contextualised approach to AI education, moving beyond one-size-fits-all assumptions to address the specific needs and profiles of a diverse student body. By situating this research within Latin America, it directly responds to the concerns raised by Van Wyk (2024) regarding the limited empirical attention devoted to Global South contexts.

## **Conclusion**

This study provides a crucial empirical grounding for the evolving concept of AI literacy in higher education. The psychometric validation and deployment of our multidimensional instrument offer a robust foundation for moving beyond theoretical frameworks and self-reported data towards an evidence-based measurement of student competence. In doing so, our research makes three primary contributions to the field.

This study offers robust empirical support for the tripartite model of AI literacy, affirming the functional, technical and socio-critical dimensions as distinct yet interrelated components of a coherent construct. By identifying three student profiles (lower performance, mid-range proficiency and higher competence), it presents a practical framework for tailoring institutional responses. Notably, the marked weakness in the socio-critical domain reinforces calls to embed ethical and critical reflection within AI education. Furthermore, the demographic patterns observed, particularly in relation to gender and academic stage, challenge conventional assumptions, suggesting that AI literacy, as an emerging field, is shaped by factors beyond traditional trajectories in technology education.

In sum, this study not only provides a validated tool for assessment but also uses it to paint a detailed, evidence-based picture of the current state of AI literacy. The profiles and patterns uncovered here offer a critical foundation for educators and policymakers to design the targeted, equitable and critically aware educational interventions necessary to prepare all students for a future permeated by artificial intelligence.

## **Limitations and future research**

Although this study offers valuable empirical insights, several limitations must be acknowledged. The data were drawn from a single private university in Mexico, whose particular demographic and institutional context may not be generalisable to public institutions or other cultural settings. The use of a purposive sample from a single cohort, although internally robust, limits the external validity and stability of the instrument across diverse student populations. Moreover, the cross-sectional design enables the identification of profiles but precludes causal inference regarding the development of AI literacy over time. Finally, the fast-paced evolution of AI technologies necessitates the continuous updating of the instrument's item bank to ensure ongoing content validity and relevance.

Building on these limitations, several avenues for future research emerge. Cross-institutional and cross-cultural validation efforts are needed to test the generalisability of the instrument. Longitudinal research is essential to move beyond the static snapshot provided by cross-sectional data and to trace the evolution of student competencies over the course of their university education. Such studies could compare cohorts who entered higher education before and after the mainstream adoption of GenAI, offering deeper insight into the impact of this technological shift. Additionally, now that distinct performance profiles have been empirically identified, future studies should focus on designing and evaluating targeted pedagogical interventions, particularly those aimed at strengthening the underdeveloped socio-critical dimension. Finally, further investigation into the contextual variables influencing the gender patterns observed in this study would significantly enhance the understanding of this emerging field.

## **Implications for educational practice**

The empirical identification of distinct AI literacy profiles underscores the need for higher education institutions to move beyond uniform pedagogical models and adopt differentiated instructional

strategies. This typology enables educators to respond more precisely to the varying competencies within their classrooms: students with lower performance require scaffolded, foundational instruction; those with mid-range proficiency benefit from problem-based learning; and higher-competence learners are well-suited for advanced, self-directed projects involving the creation or critical assessment of AI systems. Furthermore, the consistently weak performance across all profiles in the socio-critical dimension highlights the urgent need for curricular reform. Institutions should embed socio-critical perspectives throughout the curriculum, ensuring students across disciplines engage with ethical, social, and political implications of AI in contextually relevant ways. Findings related to gender and academic stage suggest that student support strategies must be data-informed and tailored. A progressive, scaffolded learning trajectory is essential, taking into account both formal instruction and informal exposure to AI. Lastly, the absence of significant differences across academic divisions reinforces the view that AI literacy should be cultivated as a transversal, institution-wide competence.

## Author contributions

**Luis Medina-Gual:** Conceptualisation, Investigation, Writing – original draft, Writing – review and editing; **José-Luis Parejo:** Data curation, Investigation, Formal analysis, Writing – review and editing; **Luis Medina-Velázquez:** Conceptualisation, Writing – review and editing.

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