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Evaluating AI Literacy Scales in Higher Education: A Systematic Review of Patterns, Gaps, and Research Opportunities from a Socio-Technical Perspective

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Abstract

The widespread adoption of large language models (LLMs) in higher education has intensified the need to assess the extent to which AI literacy scales measure students' readiness for an AI-driven learning environment. However, in the absence of a unified framework to guide construct selection, it remains unclear whether current instruments capture the full spectrum of AI competencies required for effective engagement. This study aims to examine the current literature on AI literacy scales to characterize their scope, identify prevailing constructs, and highlight gaps for future research. To achieve this, the review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology. The search strategy identified 39 AI literacy scales in peer-reviewed journal articles from ScienceDirect, SpringerLink, and IEEE Xplore databases, among other sources. A critical analysis of these scales revealed several gaps, spanning dimensionality, regional representation, assessment methods, theoretical grounding, and population diversity. The findings of this review underscore the importance of joint optimization in scale development to capture the human, technological, organizational, and contextual elements that shape AI literacy in higher education. This study makes two important contributions: (1) it provides a comprehensive account of the current composition of AI literacy scales, and (2) it identifies key gaps and emerging opportunities for refining future instruments.

Keywords

AI Literacy Scale, Higher Education, Socio-Technical Theory

Introduction

The widespread adoption of Large Language Models (LLMs) in higher education has created a need for AI literacy as a core competency for students. AI tools provide benefits such as personalized learning experiences and greater access to educational materials (Almassaad et al., 2024). At the same time, they also pose risks related to misinformation, bias and over-reliance (Almassaad et al., 2024; Dwivedi et al., 2023). As these tools become more integrated into higher education, concerns have arisen about whether students have the necessary skills to engage with them (Dwivedi et al., 2023). A recent global AI student survey indicates persistent gaps in students' preparedness to use AI responsibly (DEC, 2024). In response, researchers have developed various

AI literacy scales to assess students' preparedness to navigate the benefits and risks of AI tools. AI literacy is broadly defined as a skill set required to equip students to understand, apply, assess, innovate and engage responsibly with AI technologies (Mahadewi et al., 2025; Ng et al., 2021; Long & Magerko, 2020).

Measuring AI literacy is critical for understanding how well students have adopted AI. A significant challenge is the fragmented body of literature on AI literacy scales, which offer divergent views on what constitutes AI literacy. Many AI literacy scales have emerged, each with its own definition of AI literacy. The lack of a unified framework to guide the development of these scales makes it difficult to determine whether current instruments capture the full spectrum of AI competencies required for effective engagement.

Several studies have reviewed AI literacy scales. For instance, Lintner (2024) evaluated the quality of AI literacy scales using the COSMIN tool to guide researchers in selecting suitable instruments. Similarly, a review by Biagini (2024) captured the development and validation process of AI literacy scales. Nevertheless, further analysis is warranted, particularly to examine the depth with which constructs are selected and operationalized.

Against this backdrop, the following research questions were formulated:

> **RQ1**- What is the nature and scope of current literature on AI literacy scales in higher education?
>
> **RQ2**- To what extent do existing AI literacy scales in the higher education context capture AI competencies when evaluated through the socio-technical theoretical framework?
>
> **RQ3**- What gaps and opportunities can be identified to refine AI literacy scales for higher education?

This study thus makes several contributions in addressing the research questions; first, it maps the research landscape to understand the nature and scope of studies on the development of AI literacy scales; secondly, it identifies gaps in construct coverage; and thirdly, it aims to explore key emerging opportunities for refining instruments in the future.

Literature Review

Early conceptions of AI literacy framed it as a technical skill relevant mainly to Science, Technology, Engineering, and Mathematics (STEM) disciplines (Rupnik, 2025). This narrow view has since expanded. Ng et al. (2021) conceptualize AI literacy as encompassing four key aspects of understanding, applying, evaluating, and ethically engaging with AI. Long and Magerko (2020) provide a broader set of AI competencies that encompass AI literacy. In their review, AI literacy involves an individual's understanding of what AI is, recognizing its strengths and limitations, co-creating with AI, and applying AI tools in daily life, school, and profession. A study by Hwang et al. (2023) identifies technical abilities, critical awareness, ethical responsibility, and morality as core competencies necessary for college students to engage effectively with AI tools. Anders (2023) describes four key components of AI literacy as awareness, capability, knowledge and critical thinking.

The socio-technical theory (Trist & Bamforth, 1951a) provides a robust lens for conceptualizing AI literacy as an interplay between technical and social dimensions. In AI literacy assessment, the technical dimension aligns with task-technology competencies, which assess how well students understand AI technology, including basic AI knowledge, programming proficiency, understanding machine learning techniques, and skills in using AI platforms. Conversely, the social dimension maps onto user and structure constructs. The user competencies emphasize the ethical and cognitive aspects of an individual's engagement with AI. It captures indicators such as ethical reasoning, perception of AI, trust, bias, privacy, attitude, peer influence, and user behavior towards AI. The structure construct includes creating an enabling environment for the student to engage with AI tools effectively through institutional policies, best practices, and access to technology.

Methodology

This review was guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) framework to ensure transparency, replicability, and methodological rigor in the process (Page et al., 2021; Sarkis-onofre et al., 2021). The methodology consists of identification of journal articles, screening of relevant sources, eligibility, and inclusion criteria.

The search for relevant data was done on 16th October 2025 and was limited to journal articles from three academic databases, namely Science Direct, SpringerLink and IEEE Xplore. Google Scholar was also used to ensure a more inclusive search, capturing articles that may not have been indexed in the databases. The keywords used to build the search strings combined key constructs related to “Artificial Intelligence”, “AI Literacy Scale”, “Higher Education” and “Measure”. To improve retrieval, related terms were included for each construct.

The complete search string was as follows: ("Artificial Intelligence" OR "Generative AI" OR "ChatGPT") AND ("AI literacy") AND (scale OR instrument OR test OR questionnaire) AND ("Higher Education" OR university OR college) AND (assessment OR measure OR validate OR validation). However, the search string for the ScienceDirect database was slightly different because the database has a limit of 8 Boolean operators. The search string used was (“Artificial Intelligence” OR “ChatGPT” OR “Generative AI”) AND (“AI Literacy Scale” OR “AI literacy instrument”) AND (“Higher Education”) AND (“Assessment” OR “measure” OR “validation”)

The initial filtering based on year of publication, accessibility, article type, language and keywords in title yielded 787 articles for screening. Duplicates and irrelevant papers based on title and abstract were removed (n=704). Papers that were out of context were also eliminated (n=51). Table 1 shows the list of exclusion criteria.

Table 1
Exclusion criteria

Criterion Name	Exclusion Criterion Explanation
Year	Articles published before 2020
Accessibility	Articles not open Access
Language	Publications not in English language
Type	All journal articles not peer-reviewed
Higher Education	Publications with a population sample not from higher education
Similarity	Publications referencing similar scales. The original publication was retained.

Title of Publication	Publications with titles not containing the keywords and their related terminologies: AI Literacy Scale and Higher Education Students.

To improve retrieval, a snowball search was conducted using the reference lists of other review papers, producing an additional 10 publications (Almatrafi et al., 2024; Biagini, 2024; Laupichler et al., 2022; Lintner, 2024; Mahadewi et al., 2025; Rupnik, 2025). The final search yielded 39 publications included in the study. The PRISMA diagram illustrates the selection protocol, as shown in Figure 1.

Article Selection Protocol

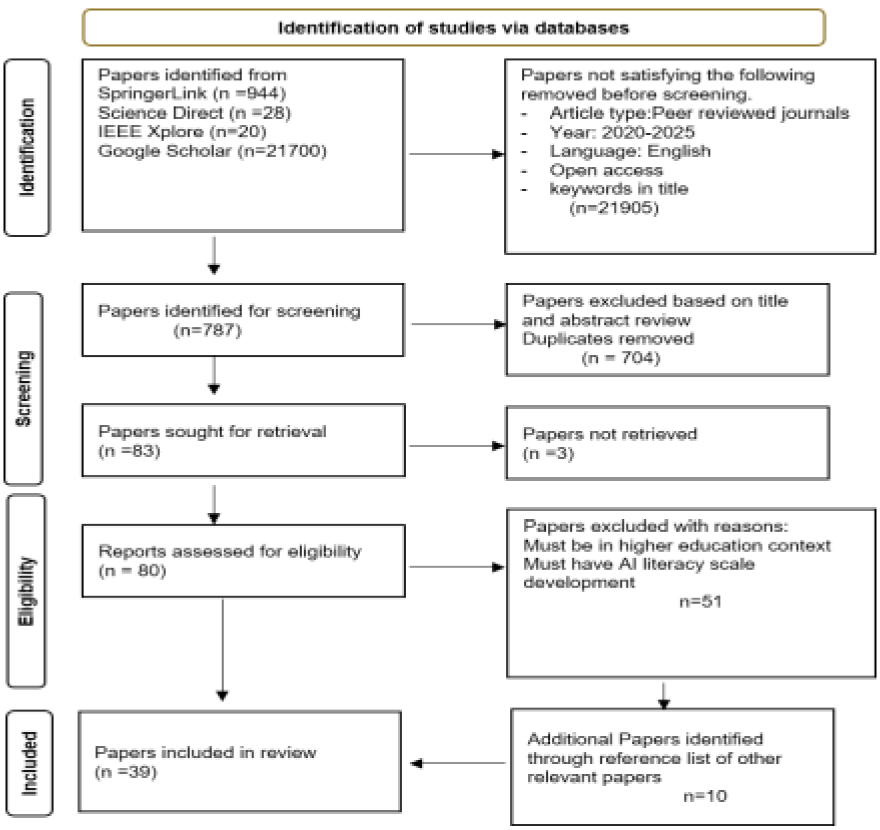

Figure 1
PRISMA diagram of the search and screening strategy (Page et al., 2021).

Results and Synthesis

Characteristics of selected studies

RQ1- What is the nature and scope of current literature on AI literacy scale development in higher education?

To address RQ1, descriptive analysis was conducted to identify publication patterns and examine the characteristics of the literacy scales.

Publications over time

The total number of publications per year was assessed to identify trends in scholarly activity. This pattern reveals how scholarly interest in the development of AI literacy scales evolved.

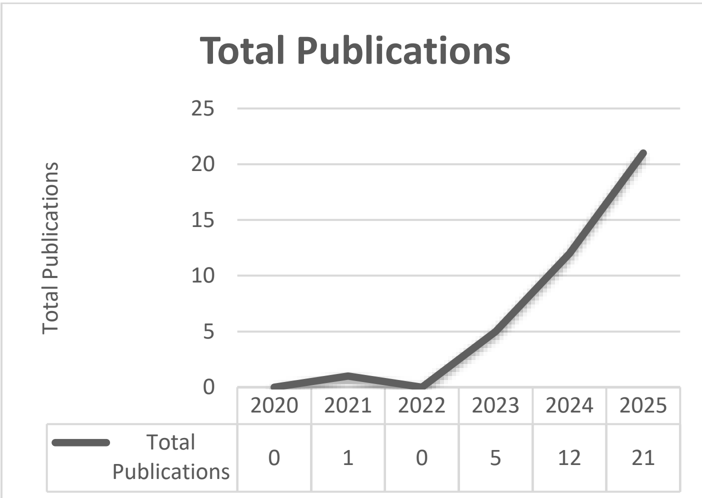

Figure 2: Number of Publications over the period (2020-2025)

The distribution of literature per year as shown in figure 2 shows an upward trend of literature beginning around 2023. From 2020 to 2022 there were few publications on AI literacy scales (n=1) reflecting a period where discussions around AI literacy were yet to gain academic attention. The upward trend from 2023 coincides with the public release of generative AI tools such as ChatGPT, which became popular in institutions of higher learning.

Publications per Region

Figure 3 illustrates the number of publications distributed across the continents.

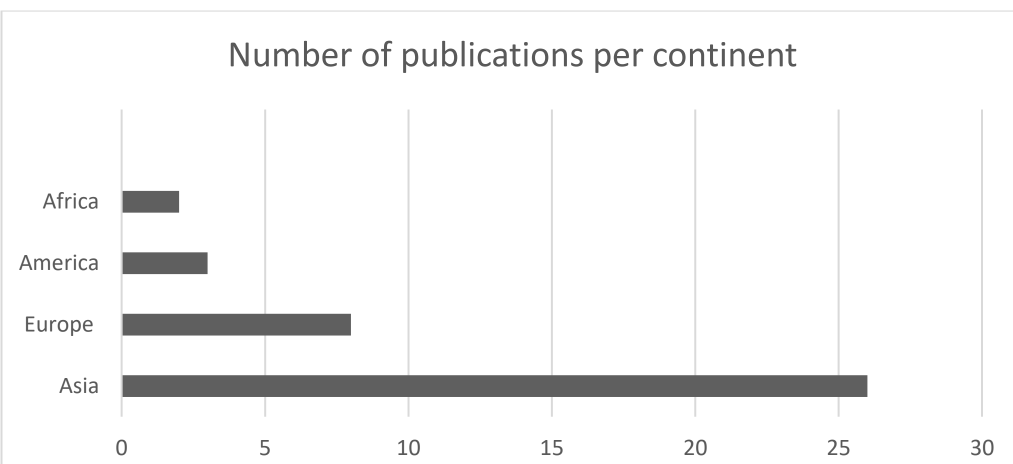

Figure 3

Number of Publications per continent

Approximately 87% (n=34) of the total publications were from Asia and Europe reflecting a strong scholarly engagement in AI literacy across countries such as China, South Korea, India, Turkey and UK. The rest of the regions, including Africa, had few publications suggesting that research in AI literacy is still at an early stage in those regions.

Features of Scales

A review of 39 AI literacy scales reveal the number of items range from as few as 4 items (Møgelvang & Grassini, 2025) to as many as 41 items (Chai et al., 2024). This variation indicates differing conceptualizations of what constitutes AI literacy. Short scales (n=9) that are fewer than 10 items prioritize brevity. In contrast, long instruments (n=10) aim to capture the multi-dimensional nature of AI literacy. 51% of the scales (n=20) fall in the medium category (11-25 items), suggesting researchers' aim to capture multiple dimensions of AI literacy while remaining concise enough to encourage participants to complete them. Across the reviewed scales, ChatGPT emerged as the most frequently cited generative AI tool, reflecting its rapid integration in educational institutions.

Mapping AI Literacy Constructs Within a Socio-Technical Framework

RQ2- To what extent do existing AI literacy scales in the higher education context capture AI competencies when evaluated through the socio-technical theoretical framework?

An in-depth analysis of the 39 AI literacy scales was conducted based on the four major dimensions of the socio-technical framework namely: 1) Technology-oriented 2) Task- oriented 3) User-oriented 4) Structure-oriented (Bostrom & Heinen, 1977). The theory was adopted to examine whether the items in existing AI literacy scales capture the competencies required in higher education. Each scale was independently reviewed to determine the dominant category it represented, and the number of items in each of the four categories was recorded.

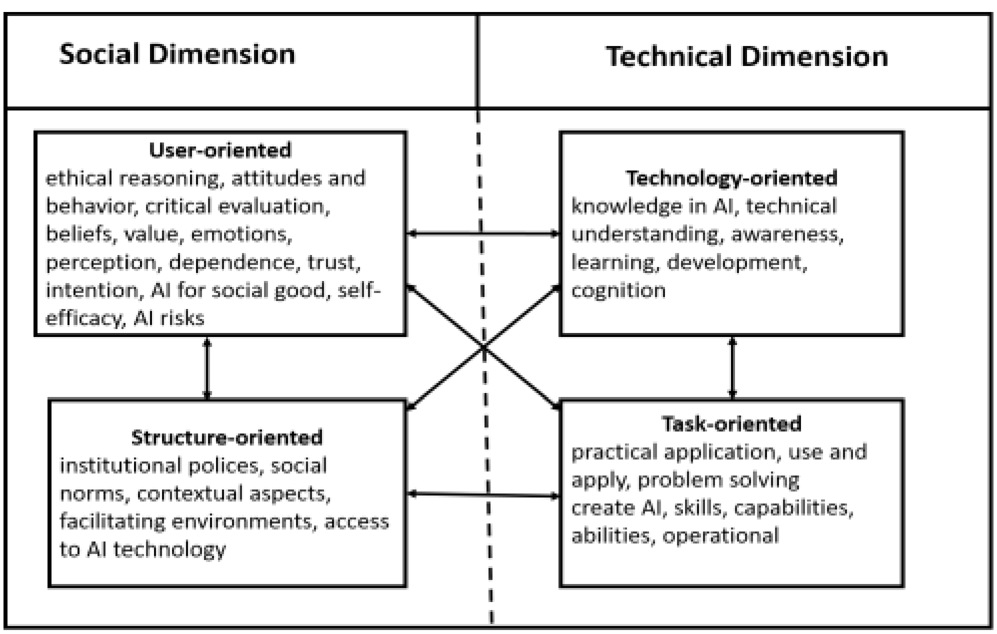

Figure 4

Joint optimization of AI literacy scale items based on socio-technical theory (Emery, 1993; Trist & Bamforth, 1951a)

To determine the category for each scale, key terminology and factors were examined. For instance, as shown in figure 4, terms such as knowledge, technical understanding of AI, machine learning steps were placed under the technical dimension; practical application and use were grouped under task-oriented; ethics, critical evaluation, privacy and responsibility were classified within user-oriented; and facilitating environments was placed under structure-oriented. Table 2 presents the distribution of publications by their primary socio-technical focus and provides examples of scale items for each competency assessed within each category.

Table 2

Number of Publications per Socio-Technical Focus

Socio-technical dimension	No of publications	Sub-theme	Name of Scales	Sample scale items
Technology-oriented scales	7	Technical understanding	GLAT; AILIT-S; AICHE; AILIT; MAIRS-MS; MAICF; AIKQ	"I can explain how AI systems are trained" (Karaca et al., 2021) "I can understand the basic logical structure of the program" (Chai et al., 202 4)
Task-oriented scales	6	Practical application	CUS; CULL; MAILS; EUAIPS; CKUA; GUS	"I use AI tools to complete school tasks efficiently" (Barcelona et al., 2025), "I can operate AI application in everyday life" (Koch et al., 2024), "I use ChatGPT to paraphrase complex academic concepts for better understanding" (Nemt-allah et al., 2024), "I use ChatGPT to learn communication skills" (Çobanoğullari & Özbek, 2025)
User-oriented scales	26	Ethical aspects Dependency on AI Academic Integrity Self-efficacy Negative perception	EVT; AIAS-4; MDAILS; AIERS; AIGI; GAIDMCS; AILS; AIEAS;AILS-CCS; LRCEL; ICAP; FtAIS; EAI-T; SNAIL-T; AIAS; GAS; AILIS; DLAI; DAI; GSE-6AI; AIAI; AI-EAAI; BIDC; ABT; CAILS; CAIDS	"We should prevent AI systems from harming humans." (Kong & Zhu, 2025), "I think AI technology is positive for humanity" (Köse et al., 2025), "I have profound fear that one day, AI will rule the world" (Albikawi, 2025), "I feel guilty when I use AI tools to complete my assignments" (Chan, 2025). "I do not believe that what is presented by AI is always true" (Hwang et al., 2023).
Structure-oriented scales	0			

Technology-oriented scales

Approximately 18% of the AI literacy scales primarily focused on the technical knowledge of AI tools. Consistent with the findings of Ng et al. (2021), our analysis revealed that most early publications considered AI literacy in terms of knowledge and understanding.

Task-oriented scales

Approximately 15% of articles used most of the items to assess students' ability to apply AI tools to their educational tasks. These scales focus on the practical application in problem-solving and decision-making. Task-focused scales usually go beyond just measuring students' knowledge to assessing their ability to perform tasks using AI tools. For example, they evaluate students' capability to use AI tools for research and communication (Barcelona et al., 2025), academic writing support (Nemt-allah et al., 2024) and solving everyday problems (Koch et al., 2024; Kong et al., 2025). These scales indicate a move toward action-oriented literacy, emphasizing practical use. However, most reviewed scales relied on self-report data, which may not fully capture students' true abilities. Incorporating performance-based items might provide a more authentic assessment.

User- oriented scales

The majority of the scales reviewed (67%) fall under this category, underscoring the importance of inculcating ethical values, perceptions, behavior, attitudes, cultural norms, and beliefs in AI literacy. This number mirrors the rise of debates surrounding academic integrity, AI dependence and responsible AI use in higher education following the public release of generative AI (Rasul et al., 2023).

Structure-oriented scales

A critical finding from this review is that no scale had structure as its dominant theme. A few instruments, such as the *AI Learning Intention Scale (AILIS)* (Chai et al., 2024), have incorporated facilitating environments as a sub-dimension to evaluate systemic readiness. From a socio-technical perspective, this absence is consequential. Efforts to enhance AI literacy could face challenges in settings where IT infrastructure and AI policies are limited.

Gaps in AI Literacy scale development

RQ3- What gaps and opportunities can be identified to refine AI literacy scales for higher education?

Findings indicated that multidimensional scales incorporating two or more dimensions (n=22) were more common than unidimensional scales (n=17). This shift towards conceptualizing AI literacy as a multifaceted construct is consistent with the holistic approach advanced by researchers (Biagini, 2024; Ng et al., 2021). However, a critical gap in the under-representation of the structure dimension still persists. Institutional competencies are needed to build AI literacy, enabling students to understand the policies governing the use of AI tools. Another notable gap in AI literacy measurement tools is that most scales (n=36) relied solely on self-report measures, while only 3 scales included some form of open-ended and multiple-choice questions to assess users (Hornberger et al., 2025a; Jin et al., 2025; Santos et al., 2024). The literature shows that most scales are grounded in technology acceptance and motivation models.

Discussion

A systematic review of 39 publications was conducted focusing on AI literacy scales in higher education context. These scales were analyzed to address three research questions: the nature of existing AI literacy scales, item distribution across socio-technical dimensions and gaps and opportunities for improving the scale development process. The socio-technical theory served as an analytical framework to map the scale items. The scales were classified into four categories according to the theory: technology-oriented, task-oriented, user-oriented and structure-oriented.

In response to research question one, we observed that advancements in generative AI have accelerated the development of AI literacy scales, reflecting the growing need to evaluate AI competencies in higher education. Notably, and contrary to common assumptions that AI literacy is predominantly technically oriented, the instruments reviewed contained more items addressing the social dimension than the technical one. According to Makarius et al. (2020), human behavior contributes to the successful integration of new technology into institutions. Failure to account for social factors often leads to lower adoption rates and reduced overall effectiveness (Makarius et al., 2020). However, the items in the social dimensions focused more on the ethical considerations while indicators of critical awareness remained limited. Likewise, the structural dimension was largely underrepresented. These findings were consistent with other reviews on the state of AI in higher education, which suggest that socio-culturally adapted scales that reflect items relevant to students in the global south are largely missing from the literature (Bond et al., 2024; Lintner, 2024). Excluding regions such as Sub-Saharan Africa (SSA) risks creating instruments that fail to capture the influence of diverse cultural norms, informal digital practices, inadequate institutional policies, and connectivity issues. According to Maina and Kuria (2024), successful AI integration in higher education in Africa depends on several factors, including infrastructure readiness, capacity building, collaboration and partnerships, ethics and policy, and active engagement of both educators and students. Furthermore, the limited research on Africa perpetuates inequalities by allowing dominant regions to shape the concept of 'AI literacy'. This regional imbalance of publications means that contextual considerations, such as the role of institutional structures as an enabler, is often missing in AI literacy measurement. As a result, key perspectives such as resource constraints and AI policies are excluded from the global discourse.

Researchers from SSA, in particular, should work towards localizing scale items to reflect the regional context better and ensure relevance. In this context, scales could be strengthened by framing statements that emphasize the importance of integrating African values like Ubuntu, often summarized as *"I am because we are"* , which reinforce the values of communal relations, collective good and collaboration (Gwagwa et al., 2022). Going forward, researchers could incorporate, for example, statements such as,

> *I collaborate with others to solve problems using AI tools, I consider how my use of AI tools affect others in my community and I use AI tools in ways that benefit my team, I am willing to help others understand how to use AI tools responsibly.*

Furthermore, beyond socio-cultural norms, institutional policies and governance form part of the structure dimension. Future scale development should therefore include items that assess the influence of institutional AI policies on AI literacy development in higher education. As the cornerstone to sustainable AI literacy, institutional policies are enablers of equitable access to AI technology, foster AI readiness, and promote an environment for AI integration in institutions. Example of items could include:

> *My institution has clear policies on the ethical use of AI tools"; "There are institutional programs that support training in AI in my institution";* and *"Institutional policies influence how I use AI responsibly in my studies.*

Based on a review of the various dimensions represented in existing AI literacy scales, most converge on technical proficiency, skills acquisition, critical thinking, and ethical considerations. However, the critical evaluation dimension is underrepresented in the literature. Students' ability to cope with AI-induced disruptions, such as bias and incorrect outputs, is essential yet often an overlooked component (Almatrafi et al., 2024). Such competencies are best evaluated through performance-based tasks, which offer a more reliable and valid method of assessment than self-report (Jin et al., 2025).

Future research should, therefore, incorporate more task-based assessments into AI literacy instruments to capture students' demonstrated critical awareness. Self-report statements such as *"I can evaluate the credibility of AI-generated information"* may capture perceptions but miss actual competence. This discrepancy results in unreliable findings, especially in regions where AI literacy is still in its infancy. Integrating authentic tasks offers a more valid assessment of how students actually engage with AI outputs (Biagini, 2024). Performance-based measures could be delivered through scenario-based questions or error-identification tasks. For instance, adding statements to test logical inconsistency, such as *"Identify if this statement is inaccurate: AI can never make mistakes, but sometimes it produces wrong answers".* Such an inquiry would enhance our understanding of students' critical skills.

It is noteworthy that ChatGPT has emerged as a central reference point for evaluating applied AI literacy. However, incorporating a wider range of AI tools such as Google Gemini, Microsoft Copilot, Grok, Claude and DeepSeek would help minimize platform bias and promote a more balanced assessment. As these tools continue to gain traction within educational institutions, AI literacy scales should likewise evolve to capture other forms of AI engagement, such as multi-modal interactions that extend beyond text generation. An example of such an instrument is the *Generative AI Digital Multimodal Composing Scale (GAIDMCS)* (Liu et al., 2025). Having a strong theoretical backing in scale development is the best practice as theories offer guidance to what constructs are measured, how they are defined, and how the relationships of variables are understood. For instance, the *EVT* scale by Ka et al. (2023) is based on the expectancy value theory, suggesting that it focuses on motivation and attitudinal dimensions. Similarly, scales guided by the socio-technical theory emphasize the interaction between the social and technical dimensions. By grounding scale development in a theory, researchers can produce more holistic and methodologically robust scales.

Conclusion

This systematic review examined 39 AI literacy scales in higher education through the lens of the socio-technical theoretical framework, offering insights into how current instruments capture the multidimensional nature of AI competencies. The findings reveal that while most scales emphasize technical and task-oriented aspects, latent dimensions such as critical awareness and institutional structures remain underrepresented.

The analysis of scale items revealed several notable gaps, including dimensionality, regional representation, assessment method, theoretical grounding, and population diversity. Several recommendations are given to refine the scale development process: 1) Broaden the dimensional scope of AI literacy by designing scales that capture the four dimensions of socio-technical framework, that is, technological, task, user and structure dimensions; 2) Develop more scales grounded in theory; 3) Integrate performance-based assessments; 4) Promote cross-disciplinary population samples; and 5) Develop contextually sensitive scales by localizing scales to cultural and regional contexts.

This study is particularly relevant to researchers, educators, students, and policymakers. It provides insights to advance research on AI literacy scale development in the higher education context. It also provides a socio-technical AI perspective, enabling researchers to categorize the dimensional coverage of emerging instruments.

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