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AI Literacy Does Not Eliminate Challenges: Evolving Complexity among English Education Students in AI Integrated ELT Classrooms

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Abstract

The increasing integration of artificial intelligence (AI) in education has generated a widespread assumption that higher AI literacy reduces the challenges students face. This study challenges that assumption by examining how challenges persist and evolve alongside students' developing AI literacy. Focusing on 47 English Education students enrolled in an AI-integrated ELT classroom at an Islamic State University in Java, Indonesia, this research investigates: (1) the level and distribution of AI literacy, and (2) how challenges shift across different levels of competence. A sequential explanatory mixed-method design was employed, combining questionnaire data from 47 respondents, adapted from the Meta AI Literacy Scale (MAILS), with semi-structured interviews involving three purposively selected participants representing contrasting literacy levels. Grounded in socio-technical systems theory and critical AI literacy frameworks, the findings reveal that students demonstrate a generally high level of AI literacy ($M = 2.97$), with the strongest performance in operational use ($M = 3.07$) and the weakest in generative competence ($M = 2.53$). More importantly, challenges do not diminish as literacy increases; instead, they become more complex. Lower-level students struggle with basic operational issues such as prompt formulation and output interpretation, while intermediate-level students encounter cognitive difficulties in refining and aligning AI responses. Higher-level students face critical challenges related to accuracy evaluation, bias detection, and uncertainty management. These findings suggest that AI literacy development is not a linear progression toward reduced difficulty, but a layered socio-technical process in which higher competence exposes deeper limitations. This study contributes to AI literacy research by reframing challenges as evolving rather than diminishing and highlights the need for instructional approaches that emphasize critical, reflective, and ethical engagement with AI in educational contexts.

1. Introduction

The rapid advancement of digital technology has led to the emergence of transformative innovations, among which Artificial Intelligence (AI) has become one of the most influential. AI refers to computational systems capable of performing tasks that typically require human intelligence, including reasoning, learning, and problem-solving (Russell & Norvig, 2020; Nilsson, 2010). In educational contexts, the integration of AI is not merely a technological enhancement but represents a fundamental shift toward more complex, data-driven, and interactive learning ecosystems (Holmes et al., 2019; Luckin et al., 2016). Within higher education, AI tools are increasingly embedded in students' academic practices, particularly in activities such as writing, information retrieval, and problem-solving (Zawacki-Richter et al., 2019).

AI offers substantial opportunities to enhance learning. AI-powered systems provide immediate feedback, personalized support, and expanded access to learning resources, thereby improving efficiency and inclusivity (Holmes et al., 2019; Chen et al., 2020). Additionally, AI facilitates academic work by accelerating data processing and supporting knowledge construction, enabling students to engage with information at unprecedented speed (Jordan & Mitchell, 2015; Roll & Wylie, 2016). As a result, AI has become deeply integrated into students' learning processes, functioning not only as a tool but also as an active mediator in how knowledge is accessed and produced (Selwyn, 2019).

However, the increasing reliance on AI introduces challenges that extend beyond technical usage. Concerns such as academic dishonesty, overreliance, and reduced cognitive engagement have been widely discussed (Ateeq et al., 2024; Kasneci et al., 2023). Furthermore, AI-generated outputs are often characterized by issues of inaccuracy, hallucination, and lack of source transparency, raising critical concerns regarding their reliability in academic contexts (Zhou et al., 2019; Bender et al., 2021). Bias embedded in training data further complicates AI use, potentially reinforcing inequalities and misrepresentation (Mehrabi et al., 2022; Crawford, 2021). These challenges indicate that interacting with AI involves complex cognitive, evaluative, and ethical processes that go far beyond tool operation.

Despite these concerns, much of the existing discourse implicitly assumes that challenges can be mitigated through improved AI literacy. AI literacy is commonly defined as a multidimensional competence encompassing knowledge, skills, and attitudes required to effectively and responsibly engage with AI technologies (Long & Magerko, 2020; Carolus et al., 2023). From this perspective, increasing literacy is expected to reduce difficulties and improve user outcomes. However, this assumption oversimplifies the nature of human–AI interaction.

In reality, AI use operates within a socio-technical system where user

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cognition, system behavior, and contextual demands interact dynamically (Baxter & Sommerville, 2011; Shneiderman, 2022). Within this framework, challenges associated with AI do not simply disappear as literacy increases; instead, they evolve. Less experienced users encounter operational challenges, such as formulating prompts and interpreting outputs. As users become more proficient, the nature of challenges shifts toward higher-order concerns, including evaluating output credibility, aligning AI responses with complex intentions, and managing ambiguity. This shift reflects changing cognitive demands consistent with cognitive load theory, where increased expertise introduces more complex decision-making rather than eliminating effort (Sweller, 2011; Paas & van Merriënboer, 2020).

This perspective also aligns with emerging discussions on critical AI literacy, which emphasize reflective, ethical, and epistemic engagement beyond functional use (Ng et al., 2021; Pangrazio & Selwyn, 2023). Together, these frameworks socio-technical systems theory, cognitive load theory, and critical AI literacy form the conceptual foundation of this study, which proposes that AI literacy development is not a reductive process of difficulty elimination but a transformative one of increasing complexity.

Existing research has largely focused on measuring AI literacy levels or identifying general user challenges (Pinski & Benlian, 2023; Syauqi Harsyah et al., 2024). What distinguishes the present study is its attention to how challenges transform not merely exist as literacy develops. Previous studies treat challenges as static barriers that competence should resolve; this study treats challenges as dynamic phenomena that are reshaped by competence. This reframing constitutes the theoretical novelty of the study.

This gap is particularly pronounced in English Language Teaching (ELT), where AI tools are used for tasks that are central to learning itself writing, text generation, grammar correction, and language exploration (Godwin-Jones, 2022). Unlike in STEM or business contexts where AI may support supplementary tasks, in ELT, AI can directly perform the core activities students are meant to develop. This creates a heightened risk of overreliance, surface-level engagement, and the replacement of cognitive effort with AI-generated output. For English Education students, who are future language teachers, this concern is compounded: their inability to critically evaluate AI use will shape how future generations engage with AI in educational settings.

Based on these considerations, this study aims to: (1) assess the level of AI literacy among English Education students in an AI-integrated ELT context, and (2) analyze how the challenges they encounter evolve across different levels of literacy, particularly in relation to operational, cognitive, and critical dimensions. By reframing challenges as dynamic and evolving rather than static obstacles, this study seeks to provide a more nuanced and contextually grounded understanding of AI literacy development.

2. Method

This study employed a sequential explanatory mixed-method design, in which quantitative findings guided the purposive selection of qualitative participants and provided the structural basis for deeper interpretation (Ivankova et al., 2006). This design was chosen because neither quantitative data alone nor qualitative data alone could adequately capture both the scope and the texture of AI literacy challenges: survey data provided breadth across participants, while interview data provided depth of explanation for how challenges are experienced and articulated.

The study was conducted at an Islamic State University in Java, Indonesia, where an "AI for Education" course is integrated into the English Education curriculum. A total of 47 students who had completed the course participated in the quantitative phase. The sample consisted of undergraduate students in their third and fourth years of study, with 38 female and 9 male participants. All participants had prior exposure to AI tools through the course and were actively using AI in academic tasks at the time of data collection. Purposive sampling was employed to ensure that all participants had relevant experience with AI use in ELT contexts.

Quantitative data were collected using a questionnaire adapted from the Meta AI Literacy Scale (MAILS) (Carolus et al., 2023), which measures AI literacy across multiple dimensions including Use and Apply AI, Know and Understand AI, Detect AI, AI Ethics, Create AI, AI Self-Efficacy, and AI Self-Competency. The instrument employed a four-point Likert scale (1 = strongly disagree to 4 = strongly agree). The forced-choice format was used to enhance response discrimination and reduce neutral-response bias (Chyung et al., 2017). The adapted instrument was reviewed by two experts in educational technology and AI literacy for content validity. Reliability was assessed using Cronbach's Alpha, yielding a coefficient of $\alpha = .84$, indicating good internal consistency. Data were analyzed using descriptive statistics and classified into four levels Very Low, Low, High, and Very High based on interval ranges adapted from Alkharusi (2022).

Based on the quantitative results, three participants representing distinct levels of AI literacy (low, medium, and high) were selected using maximum variation purposive sampling to capture the widest range of challenge experiences. Qualitative data were collected through semi-structured interviews conducted individually via video call, each lasting approximately 30 to 45 minutes. The interview protocol was developed based on the quantitative findings and focused on students' experiences using AI in academic tasks, including challenges related to prompt use, output reliability, bias, ethical use, and critical evaluation. Interviews were audio-recorded with participants' consent and subsequently transcribed verbatim. Transcripts were analyzed using thematic analysis following Braun and Clarke's (2006) six-phase framework, involving familiarization, initial coding, theme development, review, definition, and reporting. The analysis focused

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on identifying patterns of challenges across literacy levels and categorizing them into operational, cognitive, and critical dimensions.

This study followed ethical procedures consistent with institutional guidelines. All participants provided written informed consent prior to participation. Anonymity was maintained through the use of participant codes (P1, P2, P3). Data were stored securely and used solely for research purposes. No institutional ethics committee approval was required under the applicable regulations; however, the study adhered to ethical norms regarding voluntary participation, confidentiality, and the right to withdraw at any time.

3. Result

Students' AI Literacy Level

The first finding examines the level and distribution of students' AI literacy as a foundation for understanding how challenges emerge and evolve across different levels of competence. As presented in Table 1, students demonstrate an overall high level of AI literacy (M = 2.97), indicating that they are generally able to use AI tools effectively in academic contexts. However, this competence is not uniformly developed across dimensions, revealing a structurally uneven literacy profile.

Table 1. Mean Scores, Classification, and Interpretative Patterns of AI Literacy

Dimension	**Aspect**	**Mean (M)**	**Level**	**Dimension Mean (M)**	**Key Evidence**	**Interpretation**
AI Literacy	Use and Apply AI	3.07	High	2.97	Task simplification (M = 3.34); daily AI use (M = 3.26)	Strong operational proficiency
	Know and Understand AI	2.92	High		Limited evaluation of constraints (M = 2.79)	Surface-level conceptual understanding
	Detect AI	2.87	High		Strong in visible AI (M = 3.13); weak in embedded AI (M = 2.69)	Limited metacognitive awareness
	AI Ethics	3.00	High		Cross-checking and filtering practices	Procedural ethical awareness
Create AI	Create AI	2.53	High	2.53	Programming (M = 2.19); tool selection (M = 2.44)	Weak generative competence
AI Self-Efficacy	Problem Solving	2.87	High	2.87	Confidence in solving tasks with	Practice-based confidence

					AI	
	Learning	2.87	High		Confidence in AI-supported learning	Practice-based confidence
AI Self-Competency	AI Persuasion Literacy	3.21	High	3.13	Awareness of AI influence	Emerging critical awareness
	Emotion Regulation	3.05	High		Managing responses to AI output	Emerging critical awareness

As shown in Table 1, students' strongest performance is concentrated in the operational dimension, particularly in the Use and Apply AI aspect (M = 3.07). Several indicators reach very high levels, including the use of AI to simplify tasks (M = 3.34) and to support daily academic activities (M = 3.26). This pattern indicates that students are highly proficient in the functional use of AI, largely driven by frequent interaction and practical experience.

In contrast, other aspects within the AI Literacy dimension Know and Understand AI (M = 2.92) and Detect AI (M = 2.87) although categorized as high, reflect comparatively weaker performance. Students demonstrate basic conceptual knowledge but show limited ability to evaluate system constraints (M = 2.79) and to recognize less visible forms of AI (M = 2.69). This suggests that their understanding remains largely surface-level and lacks deeper metacognitive awareness.

A similar imbalance is evident in the Create AI dimension (M = 2.53), which represents the lowest-performing dimension in the entire profile. Lower scores in programming ability (M = 2.19) and tool selection (M = 2.44) indicate that students primarily function as consumers rather than creators of AI, with limited capacity to construct or adapt AI-driven outputs.

In terms of self-related dimensions, both AI Self-Efficacy (M = 2.87) and AI Self-Competency (M = 3.13) fall within the high category, indicating strong confidence and emerging awareness in interacting with AI. Relatively high scores in AI Persuasion Literacy (M = 3.21) and Emotion Regulation (M = 3.05) indicate an emerging awareness of AI influence and the ability to manage interactions contextually. However, these competencies remain largely situational rather than deeply reflective.

Overall, the findings demonstrate that students' AI literacy is high but unevenly structured, with a clear dominance of operational proficiency over conceptual, generative, and critical dimensions. This imbalance provides an important basis for understanding how challenges are not eliminated but instead shift in nature as literacy develops.

Evolving Challenges Across AI Literacy Levels

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Building on the uneven AI literacy profile identified in RQ1, this section examines how the nature of challenges shifts across different levels of competence. Qualitative data from semi-structured interviews with three participants representing low, medium, and high AI literacy levels respectively were analyzed through thematic analysis (Braun & Clarke, 2006).

The analysis revealed that students' challenges are not uniform but can be organized into three interrelated themes operational, cognitive, and critical challenges which correspond to increasing levels of AI literacy. Rather than representing separate categories, these themes form a progressive structure of difficulty, where each level reflects a qualitatively different type of engagement with AI. Table 2 summarizes the relationship between themes, representative codes, and their alignment with literacy levels.

Table 2. Evolving Challenges Across AI Literacy Levels

Theme	**Codes (Examples)**	**Description**	**Literacy Level**	**Representative Quote**
Operational Challenges	Prompt confusion; misunderstanding outputs; trial-and-error use	Difficulty in basic interaction with AI tools	Low	"Sometimes I don't know how to ask the question properly, so the answer is not what I expect." (P1)
Cognitive Challenges	Inefficient prompting; difficulty refining outputs; mismatch with task	Difficulty optimizing and adapting AI responses	Medium	"I can use AI, but sometimes the result is too general, so I need to adjust it again." (P2)
Critical Challenges	Evaluating accuracy; detecting bias; verifying information	Difficulty in judgment, evaluation, and alignment	High	"Sometimes the AI sounds convincing, but I'm not sure if it is actually correct." (P3)

Operational Challenges: Limited Procedural Control

At the lowest level of AI literacy, challenges are primarily operational, centering on basic interaction with AI systems. Students struggle to formulate effective prompts and to interpret outputs accurately, often relying on trial-and-error strategies. This pattern indicates limited procedural control over AI use.

"Sometimes I don't know how to ask the question properly, so the answer is not what I expect." (P1)

"I just try different prompts until it works, but I'm not sure why it works." (P1)

Cognitive Challenges: Transitional and Unstable Use

At the intermediate level, the nature of challenges shifts toward cognitive processing. As indicated in Table Y, students are able to use AI tools but encounter difficulties in refining prompts, selecting relevant outputs, and aligning responses with specific academic needs.

"I can use AI, but sometimes the result is too general, so I need to adjust it again." (P2)

"I know the answer is not wrong, but it doesn't really fit what I need." (P2)

This stage reflects a transitional form of competence, where students move beyond basic use but lack stable strategies for optimizing AI performance.

Critical Challenges: Reflective but Demanding Engagement

At higher levels of AI literacy, challenges become critical and evaluative. As summarized in Table Y, students demonstrate awareness of issues such as accuracy, bias, and reliability. However, this awareness introduces new complexities, including uncertainty and the need for verification.

"I don't always trust the answer, so I need to check it again from other sources." (P3)

"Sometimes the AI sounds convincing, but I'm not sure if it is actually correct." (P3)

These findings indicate that increased literacy leads to deeper engagement, where students must actively evaluate and justify AI-generated outputs rather than simply use them. The challenge at this level is not procedural but epistemic: students must decide how much and under what conditions to trust an AI system whose reasoning is opaque.

Taken together, the patterns identified in Table 2 and elaborated in the narrative analysis reveal a consistent trajectory in the nature of AI-related challenges. As students' AI literacy develops, the type of difficulty they encounter shifts from procedural interaction to cognitive processing and ultimately to critical evaluation. This progression suggests that AI literacy development is not associated with a reduction in challenges, but with a reconfiguration of their complexity and nature. To synthesize this pattern, Table 3 presents a refined conceptual model illustrating how challenges evolve across different levels of AI literacy.

Table 3 Presents A Conceptual Model

AI Literacy Level	**Level Type of Challenges**	**Nature of Difficulty**
LOW	Operational	How to use AI prompting, interpretation, basic use
MEDIUM	Cognitive	How to optimize AI refinement, selection, adaptation

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HIGH	Critical	How to evaluate AI refinement, selection, adaptation

To further strengthen the integration of quantitative and qualitative findings, Table 4 presents a joint display connecting survey-based indicators of AI literacy with the qualitative themes identified through interview analysis. This joint display illustrates how the uneven distribution of AI literacy dimensions (RQ1) directly shapes the type and nature of challenges experienced at each level (RQ2).

Table 4. Mixed-Method Joint Display: Integrating AI Literacy Indicators and Qualitative Challenges

Literacy Level	**Quantitative Indicators (MAILS)**	**Qualitative Themes (Interview)**	**Integrated Interpretation**
Low AI Literacy	Lower mean scores in Know & Understand (M=2.92) and Detect AI (M=2.87); weak metacognitive awareness	Operational challenges: prompt confusion, trial-and-error, misinterpretation of outputs	Limited conceptual understanding translates into procedural difficulties; students lack strategies for basic interaction
Medium AI Literacy	Moderate performance in Create AI (M=2.53); functional but transitional competence	Cognitive challenges: difficulty refining outputs, output-task mismatch, unstable use strategies	Transitional competence exposes limitations in optimization; students can use AI but struggle to align outputs with specific needs
High AI Literacy	Strong operational skills (Use & Apply: M=3.07); emerging AI Self-Competency (M=3.13), but limited deep critical evaluation	Critical challenges: output credibility evaluation, bias detection, uncertainty management, verification needs	Higher competence introduces more sophisticated evaluative demands; increased awareness generates new cognitive complexity rather than reducing difficulty

4. Discussion

AI Literacy as Uneven and Operationally Dominated

The quantitative findings confirm that students demonstrate a high overall level of AI literacy, yet this competence is structurally skewed toward functional operation. Students show strong performance in using and applying AI tools while exhibiting weaker capabilities in conceptual understanding, generative competence, and critical evaluation. This finding aligns with Long and Magerko's (2020) multidimensional conceptualization of AI literacy but extends it by demonstrating that dimensions do not develop proportionally. Frequent interaction with AI tools primarily reinforces procedural knowledge rather than deeper conceptual or critical competencies.

From a socio-technical perspective, this imbalance is partly attributable to the design of contemporary AI tools, which are engineered for accessibility and ease of use (Shneiderman, 2022). Students can effectively operate AI without understanding its mechanisms a pattern that supports surface-level engagement while simultaneously masking deeper literacy gaps. This finding is consistent with Lérias et al. (2024), who noted that AI tool usability often outpaces users' critical understanding of system behavior.

While some studies have reported similar operational dominance in student AI literacy profiles (Syauqi Harsyah et al., 2024), others have found more balanced development, particularly among students with formal AI training (Pinski & Benlian, 2023). The present study suggests that course completion alone is insufficient to produce balanced AI literacy; instructional design must intentionally target conceptual and critical dimensions to counteract the operational bias introduced by habitual tool use.

From Reducing Difficulty to Transforming Difficulty

The qualitative findings directly challenge the assumption that higher AI literacy leads to fewer difficulties. Instead, challenges evolve across three levels operational, cognitive, and critical corresponding to increasing literacy development. This progression can be interpreted through cognitive load theory (Sweller, 2011; Paas & van Merriënboer, 2020): increased expertise does not eliminate cognitive demand but reconfigures it. At higher literacy levels, students encounter more sophisticated decision-making requirements involving reliability assessment, bias recognition, and the management of epistemic uncertainty.

This finding diverges from the implicit assumptions in much of the AI literacy literature, which frames literacy acquisition as a pathway toward reduced difficulty (Carolus et al., 2023; Long & Magerko, 2020). The present study proposes instead a transformative model, in which competence reshapes the nature of challenges rather than eliminating them. This distinction has important theoretical implications: if challenges evolve alongside competence, then educational assessments based on the presence or absence of difficulties may systematically misrepresent students' actual AI literacy development.

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AI Literacy as a Socio-Technical and Developmental Process

The integration of quantitative and qualitative findings reveals that AI literacy should be understood as a developmental and socio-technical process rather than a static or linear skill set. The uneven distribution of literacy dimensions creates the structural conditions for evolving challenges: as students become more experienced, they become more aware of AI's probabilistic, opaque, and context-dependent nature (Bender et al., 2021; Selwyn, 2019), which in turn introduces new layers of complexity.

This understanding challenges reductionist views of AI literacy that focus solely on skill acquisition. Instead, it positions AI use as an ongoing negotiation between user intention and system behavior one that is never fully resolved, only continually renegotiated as competence develops. This perspective is consistent with socio-technical systems theory (Baxter & Sommerville, 2011), which emphasizes that user-system interactions are always co-constituted by technical affordances, user dispositions, and contextual demands.

Implications for Critical AI Literacy in ELT and Teacher Education

The emergence of critical challenges at higher levels of literacy underscores the importance of moving beyond functional competence toward critical AI literacy in English Language Teaching contexts. In ELT specifically, AI tools are not peripheral aids but potential substitutes for the very activities students must develop: writing, reading, formulating arguments, and constructing meaning through language. This creates a pedagogical environment in which AI can simultaneously support and undermine language learning objectives (Godwin-Jones, 2022).

For writing instruction, these findings suggest that students who uncritically accept AI-generated text may produce outputs that are grammatically coherent but conceptually shallow or contextually inappropriate. Instructors need to design tasks that require students to interrogate AI-generated content rather than simply incorporate it for example, by asking students to compare AI-generated drafts with their own writing, identify discrepancies, and justify editorial decisions.

For language teacher education, the implications are more profound. Future ELT teachers who have not developed critical AI literacy will be ill-equipped to guide their students through the evaluative and ethical dimensions of AI use. Teacher preparation programs should therefore include explicit instruction in AI literacy not merely as a technical competency but as a pedagogical framework one that equips pre-service teachers to model critical AI engagement in their future classrooms.

These findings also suggest that AI literacy instruction should not be delivered as a single course event but integrated across the curriculum in ways that progressively challenge students to engage with AI at higher levels of complexity.

This might include scenario-based tasks requiring accuracy verification, peer discussion of AI-generated outputs, and reflective journaling on experiences of uncertainty with AI tools.

Theoretical Contribution: A Model of Evolving Challenges

This study contributes to AI literacy research by proposing a conceptual shift from a deficit-based view of challenges to an evolutionary perspective. The findings demonstrate that challenges transform across operational, cognitive, and critical dimensions as literacy develops a trajectory that existing AI literacy frameworks do not adequately theorize. This model integrates multidimensional competence (Long & Magerko, 2020; Carolus et al., 2023), socio-technical interaction (Shneiderman, 2022; Baxter & Sommerville, 2011), cognitive complexity (Sweller, 2011), and critical engagement (Ng et al., 2021; Pangrazio & Selwyn, 2023) into a unified developmental framework. By doing so, it provides a more comprehensive account of how learners interact with AI and how their challenges change as competence develops.

Future research should examine how this evolutionary pattern manifests across different disciplines, institutional contexts, and cultural settings. Longitudinal designs tracking individual students over time would enable more precise mapping of the transitions between challenge types. Comparative studies across disciplines for example, contrasting ELT students with STEM or social science students could illuminate how disciplinary AI use shapes the nature and pace of challenge evolution. Additionally, intervention studies testing the effectiveness of critical AI literacy instruction would provide evidence-based guidance for curriculum designers and teacher educators. Expanding the qualitative sample beyond three participants would also strengthen the depth and transferability of findings in future replications of this study.

5. Conclusion

This study demonstrates that students' AI literacy, while generally high, is structurally uneven and predominantly shaped by operational proficiency. While students are able to use AI tools effectively in academic contexts, their conceptual understanding, generative competence, and critical evaluation remain comparatively underdeveloped. This imbalance suggests that current patterns of AI use primarily strengthen functional skills without proportionally supporting deeper dimensions of AI literacy, as conceptualized in multidimensional frameworks (Long & Magerko, 2020; Carolus et al., 2023). More importantly, the findings reveal that AI-related challenges do not diminish as literacy increases.

Instead, they evolve in complexity, shifting from operational difficulties to cognitive processing and ultimately to critical evaluation. This progression indicates that higher levels of AI literacy introduce more sophisticated forms of engagement, requiring learners to manage ambiguity, assess reliability, and make

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informed judgments. In this sense, AI literacy development does not represent a linear reduction of difficulty, but rather a transformation in the nature of challenges, consistent with perspectives on increasing cognitive complexity in learning processes (Sweller, 2011; Paas & van Merriënboer, 2020). These results challenge dominant assumptions that position AI literacy as a pathway toward efficiency and reduced difficulty.

Instead, the study supports a socio-technical understanding of AI use, where competence emerges through ongoing interaction between users, systems, and contexts, and where increased awareness introduces new layers of complexity (Selwyn, 2019; Shneiderman, 2022). From a pedagogical perspective, the findings highlight the need to move beyond functional training toward the development of critical AI literacy, particularly in ELT and teacher education contexts where AI has the potential to displace rather than augment core learning processes.

This study is limited by its context-specific focus and the small qualitative sample of three interview participants, which may restrict the transferability of findings. Future research should replicate this investigation with larger samples and across broader educational contexts to examine how evolving AI literacy challenges manifest across disciplines, cultures, and instructional environments.

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