Contextualizing Multidimensional AI Literacy for Learning Analytics

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Abstract

AI literacy is critically important for learning in AI-mediated disciplinary contexts; yet, learning analytics currently lacks robust methods to operationalize and measure AI literacy from trace data across these contexts. We address this challenge by applying the ED-AI Lit framework as an analytic lens for AI literacy measurement. The framework defines AI literacy through six interrelated components: Knowledge, Evaluation, Collaboration, Contextualization, Autonomy, and Ethics, which are enacted in combination rather than isolation. We describe how these components manifest differently across two distinct domains, Reading and STEM, due to varying epistemic goals and task structures. These domain-specific manifestations create measurement challenges, as identical surface behaviors may reflect fundamentally different AI literacy configurations. We argue that valid operationalization requires multivariate, context-parameterized models that capture how ED-AI Lit components are jointly expressed rather than treating AI literacy as a unidimensional trait. This positions ED-AI Lit as a generative framework for developing context-sensitive measures of AI literacy in learning analytics.

Keywords

AI literacy, reading, writing, STEM, epistemology

1. Introduction

Generative AI is now routinely used by learners for reading, writing, and STEM problem solving, supporting activities such as summarization, drafting, coding, modeling, and data analysis. In response to its rapid uptake, researchers and educators have increasingly emphasized the importance of AI literacy as a core educational outcome [1]. The learning analytics community has long studied learner interaction in technology- and AI-supported systems, but AI literacy has only recently emerged as an explicit lens for interpreting these data. At present, learning analytics lacks well-established ways to operationalize and measure AI literacy from trace data, particularly across disciplinary contexts. The epistemic goals, task structures, and consequences of error differ sharply across domains such as Reading and STEM [2], suggesting that how AI literacy is enacted, and thus how it might be observed analytically, also varies by domain. This creates an urgent need for context-sensitive foundations for measuring AI literacy in AI-mediated learning environments. To address this measurement challenge, we draw on the ED-AI Lit framework [3] as an analytic lens for conceptualizing what constitutes AI literacy and how it may be enacted and observed across domains.

2. The ED-AI Lit Framework

The ED-AI Lit framework [3] conceptualizes AI literacy as a set of interrelated, multidimensional competencies that extend beyond technical proficiency to include the cognitive, social, and self-regulatory dimensions of learning with AI. The framework emphasizes how learners understand, evaluate, interact with, regulate, and take responsibility for AI use in practice. It specifies six core components or dimensions: Knowledge (understanding how AI systems function and their limits), Evaluation (appraising the

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accuracy, appropriateness, and trustworthiness of AI outputs), Collaboration (productive interaction and coordination with AI systems), Contextualization (situating AI use within disciplinary goals and real-world consequences), Autonomy (regulating reliance, control, and delegation), and Ethics, which operates across these components through considerations of consequence, responsibility, and risk. Crucially, these components are conceptually distinct but enacted in combination within activity, such that AI literacy is expressed as a configuration of situated competencies rather than as a single latent trait.

Overall, these components frame AI literacy as a form of context-sensitive practice with AI, enacted through observable activity rather than possessed as a static trait. However, the framework itself is defined at a domain-general level—i.e., it specifies what competencies matter, but not how they are enacted in particular subject areas or how they should be observed empirically. For learning analytics, this creates a challenge. If the same components are expressed through different disciplinary practices, then the behaviors available in trace data as evidence of AI literacy will also differ. In this sense, ED-AI Lit provides a necessary theoretical lens for interpreting interactions with AI, but it does not resolve the problem of how those interactions should be operationalized and measured across domains.

3. Context-sensitive Manifestations of AI Literacy

To illustrate how AI literacy is enacted through disciplinary practice, we examine Reading and STEM as two contrasting contexts or domains of AI use. Drawing on the ED-AI Lit framework as an analytic lens, we demonstrate how different components of AI literacy become salient in each domain as learners engage with AI for meaning-making, problem solving, and decision-making. Rather than treating each component in isolation, we focus on how multiple dimensions of AI literacy are intertwined in practice and how their observable manifestations depend on the epistemic aims, ideals or standards, and reliable processes [4] and task structures of the domain. Across both contexts, we attend in particular to learners' judgments of AI output, their patterns of interaction with AI systems, and their regulation of reliance on automated support as these features are most visible in learning analytics trace data.

3.1. AI Literacy in Reading Contexts

In reading contexts, generative AI is commonly used to support sensemaking of texts, positioning Evaluation as a highly salient component of AI literacy. Learners must judge whether AI-generated summaries and explanations accurately represent source material, whether key claims are preserved or distorted, and whether cited sources are reliable and valid. These judgments are not isolated acts—rather, they are tightly coupled with Autonomy, as learners decide when to accept, question, or reject AI output, and with Collaboration, as interaction with the system unfolds through iterative prompting and follow-up questioning. In trace data, this intertwining of components appears in coordinated patterns of prompting, source checking, acceptance, and revision.

At the same time, Knowledge of how generative models produce text and Contextualization of reading goals (e.g., comprehension vs. critical comparison) shape how evaluation and reliance are enacted in practice. Hallucinated references, oversimplified summaries, and superficially coherent but misleading explanations make Ethics relevant through risks of misrepresentation and erosion of epistemic trust [5]. Thus, what appears in trace data as a sequence of prompts and acceptances actually reflects the co-enactment of multiple ED-AI Lit components, whose relative salience is organized around the epistemic demands of text interpretation. For learning analytics, the challenge is not merely detecting evaluation but inferring how these components are coordinated in real time during AI-supported reading, where surface fluency can mask deep misrepresentation.

3.2. AI Literacy in STEM Contexts

In STEM contexts, generative AI is frequently used to support computational and model-based problem solving, rendering Knowledge of system limitations and Contextualization within domain constraints especially salient. Learners must judge whether AI-generated solutions satisfy mathematical, physical, or logical requirements, making Evaluation central but in a fundamentally different form than in reading. These judgments are tightly intertwined with Autonomy, as learners must decide when to delegate computation to AI and when to override its output, and with Collaboration, as problem solving unfolds through human-AI teaming rather than dialogic exchange. In trace data, this co-enactment appears in patterns of code execution, parameter variation, simulation checks, debugging, and acceptance or override.

Hallucinated code, invalid derivations, and superficially plausible outputs that violate domain constraints force learners to continually negotiate authority, responsibility, and control, which makes Ethics salient through issues of safety, bias, and accountability in AI-mediated decisions [5]. Across these activities, what appears in trace data as execution or override behavior reflects the dynamic coordination of ED-AI Lit components shaped by the epistemic structure of STEM problem solving. For learning analytics, this means that inference about any one component (e.g., evaluation or autonomy) is only valid when interpreted in relation to how the others are jointly instantiated in a domain-specific activity, where errors may propagate directly into real-world decisions or systems.

4. Implications for Learning Analytics

For learning analytics, a multidimensional view of AI literacy has methodological consequences. Specifically, trace data from AI-supported environments do not provide direct access to any single component in isolation; instead, observable behaviors reflect the combined expression of multiple ED-AI Lit dimensions within an activity. As a result, the same surface behaviors (e.g., acceptance, revision, override, or prompting) may index fundamentally different configurations of AI literacy depending on how these components are jointly instantiated in context and over time. This creates three core challenges. First, construct validity is threatened when Evaluation is inferred from surface behaviors such as revision or acceptance without accounting for how those behaviors are conditioned by Knowledge and Contextualization. Second, interaction and responsibility modeling are distorted when Collaboration is inferred from generic usage metrics without regard for how autonomy and control are distributed in human-AI activity. Third, agency inference is compromised when Autonomy is operationalized through reliance indicators without considering how ethical constraints and domain consequences shape legitimate delegation. These threats arise because single behavioral indicators collapse distinct ED-AI Lit dimensions into undifferentiated proxies.

Addressing these challenges requires analytic models that can represent how multiple dimensions are jointly expressed and differentiated in learners' activity. Valid operationalizations will therefore depend on multivariate, task-conditioned, and context-parameterized models that allow different ED-AI Lit components to vary independently while remaining jointly interpretable. For example, sequences of prompting, revision, and acceptance behaviors in Reading only become interpretable as evidence of Evaluation when modeled in relation to task demands, validity of outcomes, and concurrent expressions of Autonomy and Knowledge. Likewise, delegation and override behaviors in STEM contexts require models that distinguish changes in control and authority from changes in correctness or reliance alone.

Accordingly, AI literacy cannot be captured through domain-invariant indicators or single-process proxies. Learning analytics must instead develop context-parameterized operationalizations grounded in the multidimensional structure of AI literacy, integrating interaction traces with task metadata, domain constraints, and outcome validity checks, rather than relying on usage frequency or acceptance rates alone. Under this framing, AI literacy is not a latent score inferred from generic interaction intensity, but a patterned multidimensional configuration of competencies inferred relationally from learners' activity. Together, these shifts position ED-AI Lit as a generative framework for rethinking how AI literacy is operationalized and interpreted in learning analytics.

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Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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