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Rethinking artificial-intelligence literacy through the lens of teacher educators: The adaptive AI model

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ABSTRACT

As artificial intelligence becomes increasingly integrated into educational settings, models for measuring related literacy among both teachers and students are rapidly emerging. Yet despite their strengths and benefits, many impose fixed competency levels or overlook contextual factors. Using design-based research, and with the participation of 22 higher-education teacher educators, this study critiques existing models and introduces the novel Adaptive Artificial-Intelligence-Literacy Model (AALM), grounded in case-study analysis. This evaluation framework highlights the dynamic, multi-dimensional nature of artificial-intelligence literacy, organized around three inter-related core axes: contextual fitness, professional needs, and dynamic development. A reflective self-assessment tool is also presented, enabling teachers to evaluate their own artificial-intelligence literacy. This framework offers practical guidance for educational policy and teacher development, advocating for assessment approaches that consider social and cultural contexts, professional needs, and the evolving nature of skills amid rapid technological change. Finally, the case studies illustrate the model's relevance across diverse educational settings.

Introduction

The integration of artificial intelligence (AI) into education has introduced new opportunities for teaching and learning, and AI-literacy assessments have evolved beyond the simplistic binary framework of "has – yes/no" to more sophisticated evaluation models [1]. Assessment frameworks examine technical, pedagogical, and ethical competencies (e.g., [2]), advocating for a holistic perspective that encompasses cognitive, disciplinary, cultural, and technological aspects [3]. However, existing models present notable limitations. First, they adopt a linear approach, assuming that AI literacy develops sequentially through predetermined stages (e.g., [4]). Moreover, they prioritize cognitive aspects over contextual ones (e.g., [5]). Finally, they tend to assess static situations instead of evaluating dynamic, long-term skill development, despite AI literacy being a continuum rather than a binary state [6].

The need for non-linear, contextual, and dynamic tools for assessing AI literacy in education is rooted in theories such as Vygotsky's [7] social-constructivist approach, Lave and Wenger's [8] situated learning, Bronfenbrenner's [9] ecological theory, and the dynamic systems theory [10,11]. These frameworks emphasize the importance of context, adaptability, and complexity in learning and assessment processes.

Linear models for assessing AI literacy

These models assume a gradual learning process, from basic to complex concepts. In their conceptual framework, Long and Magerko [1] present three main axes: "What is AI?" "What can AI do?", and "How does AI Work?". They also outline 15 pedagogical design-considerations for AI literacy, emphasizing transparency, structured interactions, and data contexts. These researchers highlight critical thinking regarding AI limitations and ethical concerns, such as biases, privacy, and responsibility. Yet Druga et al. [12] found cultural gaps when implementing the framework across international contexts. As such, the need for a more adaptable assessment tool emerged – one that would account for cultural and educational diversity.

In their comprehensive review of studies on AI literacy in education, Ng et al. [4] noted that most definitions draw from existing literacies in other fields. They therefore proposed a new framework based on Bloom's [13] taxonomy, offering a hierarchical model that progresses from basic understanding to creation. This framework includes specific indicators for evaluating student progress, while explicitly addressing social responsibility and ethical awareness. For AI-literacy assessments in educator-training settings, the researchers recommend updating AI knowledge, integrating advanced technologies, refining pedagogical

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strategies, and tailoring curricula to student age. However, this theoretical review predates the widespread adoption of generative AI and presents a generic universal framework, while overlooking cultural and social factors that may impact literacy implementation. Moreover, its reliance on Bloom's taxonomy renders continuous adaptation and revision challenging.

Pedagogical integrative models for AI literacy

Such models view learning as an experiential process that combines technological, pedagogical, and content knowledge, while emphasizing ability, motivation, and ethical responsibility – as per the learners' developmental stage. They integrate technical, social, and ethical dimensions of AI learning, fostering research and higher-order thinking skills through active learning. Rather than introducing AI as a standalone subject, it is embedded within existing disciplines [14]. Grounded in the self-determination theory [15], these models also promote learner autonomy, belonging, and competence, enhancing both technical expertise and socio-cognitive skills [16]. Building on Koehler and Mishra's [17] technological, pedagogical, and content knowledge (TPACK) framework, Celik [18] proposes the Intelligent-TPACK framework, adding the ethical dimension to the four previously existing ones. Hava & Babayiğit [19] found positive associations between teachers' digital proficiency and AI-TPACK competencies, including AI integration in teaching. Using structural equation modeling, they also demonstrate that digital proficiency significantly predicts teachers' AI-TPACK competencies.

Importance of the socio-cultural context

In an era where AI increasingly permeates education and society, understanding socio-cultural contexts is essential for effective, ethical, and meaningful application in education. In her critical examination of 17 frameworks for assessing AI literacy in elementary schools, Yim [5] found that these tools tend to focus on constructivist and technical perspectives, while neglecting ethical and social aspects. To bridge this gap, she proposes an intelligence-based framework, viewing AI thinking as a novel cognitive process that emerges from human-AI interactions. This model combines cognitive, creative, and critical thinking, while addressing social, ethical, and environmental concerns. Grounded in Vygotsky's [7] socio-cultural theory, it also introduces an inter-disciplinary approach, designed to empower young learners.

In their AI-skills model, Miao & Shiohira [20] outline 18 core skills for teachers across five domains: AI fundamentals, pedagogical strategies and integration, ethical considerations, practical application, and ongoing professional development. They also outline four core skills for students: technical knowledge, practical application, ethical awareness, and critical evaluation. However, as noted by the authors, these frameworks were not developed in collaboration with practicing teachers.

Collaborating with teachers, Filo et al. [21] developed a rubric comprised of four key areas: identifying AI mechanisms, conscious AI use, agency through proactive value-driven application, and ethical consideration. However, this rubric is designed for teachers and students alike, making it more generalized than models like Falloon's [22] teacher digital competence framework. In contrast, Ding et al. [23] employed a context-based approach to AI literacy for pre-service teachers through case-based learning. This method places complex tasks in real-world scenarios, enabling teachers to apply AI knowledge to enhance their learning and professional development.

Towards more holistic models

Heung and Yim [24] offer guidelines for policymakers and curriculum designers to implement holistic AI-literacy education for young learners, equipping them for future challenges. Stolpe & Hallström [25] stress context-sensitivity in technological education, offering a framework that integrates technical skills, scientific-technological knowledge, and socio-ethical awareness of their impact on individuals and society. Their work expands technological literacy to encompass sub-literacies, such as media and design.

Wang and Lester [26] and Ng et al. [27] further explore teacher-specific AI competencies by identifying three core domains: technical, pedagogical, and ethical. Their main contribution is a framework that positions teachers as designers of AI-integrated learning, emphasizing the monitoring and interpreting of student data. Finally, Chan [28] introduces the dynamic AI-literacy model – a more holistic assessment tool comprised of five AI components – concepts, applications, emotional impact, safety and security, and responsible use – each mapped by literacy levels (low, medium, and high). This model focuses on emotional and ethical aspects, while acknowledging diverse individual literacy levels amid rapid technological advancements. However, empirical validation is lacking.

The current review highlights shifts in AI-literacy assessment models in education. These changes reflect growing attention to cultural and social contexts, and the need for adaptable tools suited to complex, rapidly evolving technological environments. It also underscores the lack of teacher-focused models that support non-linear skill development and cultural adaptation. Moreover, existing models often omit technical, pedagogical, ethical, and emotional components, and lack mechanisms for ongoing updates.

Research aims and questions

This study, conducted in collaboration with academic educators with broad digital-learning knowhow, presents a dynamic, context-sensitive framework for assessing AI literacy among teachers. The paper reviews existing models, introduces the proposed framework with case studies – including a reflective assessment model – and offers both theoretical insights and practical tools tailored to diverse educational needs.

The study is guided by the three research questions:

1. What are the principles, strengths, and limitations of existing AI-literacy assessment models in various educational settings?
2. What are the components of an innovative, context-sensitive model that meets the evolving needs of pre-service and in-service teachers? How do its principles support renewed analysis of diverse educational contexts?
3. What are the key indicators for a teacher's self-evaluation tool across different educational settings, based on the proposed model?

Methodology

Research-methodology rationale

Design-based research was selected for this study as it bridges between theory and practice in assessing AI competencies in education. It enables the generating of evidence-based solutions through an iterative cycle of design, implementation, and evaluation (citation omitted; [29]). This approach integrates the grounded theory, which offers insights into emerging needs [30,31], with a systematic design aimed at creating practical outcomes. Its cyclical structure allows continuous refinement, based on feedback from the field, while generating new theoretical understanding [32]. The ongoing shift between design and implementation supports a model that is rooted in both theory and practice, and enhances research-design efficacy when creating models that merge conceptual depth with real-world applicability.

Participants

The research was conducted as part of a year-long course titled

Table 1
Participants' demographics.

Pseudonym	Gender	Degree	Experience in teacher education (yrs.)	Discipline
Janet	Female	Ph.D.	15	Science
Guy	Male	Ph.D.	20	Education
Michaela	Female	M.A.	12	Psychology
Irina	Female	Ph.D.	18	Computer sciences
Karen	Female	M.A.	10	Social sciences
Israa	Female	M.A.	8	English
Mulu	Male	M.A.	5	Multicultural education
Nura	Female	Ph.D.	16	Science
Hasi	Female	M.A.	14	Educational counseling
Rachel1	Female	Ph.D.	22	Speech therapy
Rachel2	Female	M.A.	10	Education
Suli	Female	M.A.	18	Educational Assessment
Merry	Female	Ph.D.	20	Neuro-pedagogy
Nicole	Female	Ph.D.	15	Science
Tzafi	Male	Ph.D.	25	Education
Eric	Male	Ph.D.	22	Environmental studies
Jadir	Male	Ph.D.	19	English
Iyad	Male	M.A.	12	Education
Osnat	Female	Ph.D.	14	Philosophy
Hadil	Female	M.A.	9	Curriculum development
Hanan	Female	M.A.	12	Mathematics
Hella	Female	Ph.D.	20	History
Zelda	Female	Ph.D.	15	Arts

Innovation and digital-learning design in academia (180 h), aimed at training teacher educators to integrate pedagogical innovation and advanced technologies into teacher-training institutions. Twenty-two teacher-education experts (82 % females) were selected through a rigorous process based on three criteria: substantial experience in teacher education and technology integration, a graduate degree (64 % held a Ph.D.), and strong digital and pedagogical skills. The participants represented diverse regions and sectors across Israel, from Arab, Jewish-state, and Jewish-religious academic institutions. Table 1 presents their demographic backgrounds. Participation rate was 100 % across all study stages. Such a complete response, particularly within a well-defined, cohesive group, enhances the functional validity of the sample, contributes to data completeness, and minimizes the risk of attrition bias. This high response rate thus strengthens the credibility and robustness of the findings [33,34]

Procedure

Data was collected in four distinct iterations (Table 2, Fig. 1).

A detailed methodological journal was maintained by the author throughout the study, documenting each stage of the process, including discussions, decisions, analyses, interpretations, and reflections. The journal tracked model revisions and their rationale, field insights, and participant feedback, ensuring transparency and monitoring while preserving the link between theory and practice.

Data collection

Data collection occurred across four iterations within eight (8) sessions (= 64 academic hours) of a 180-hour course, conducted primarily online with one face-to-face session dedicated to team presentations and final discussion. Research instruments included: (a) Audio Recordings and Transcripts**:** Group discussions addressing each iteration's activities (Table 2) were recorded and transcribed through Zoom. (b) Written Responses: Participants provided individual responses to key questions via shared documents and forms. (c) Collaborative Documentation: Participants created intermediate products (Table 2) including model drafts, frameworks, and the final questionnaire, serving as both process outcomes and data sources.

Between sessions, the researcher analyzed products and prepared subsequent tasks based on emerging insights, following design-based research methodology [29].

Data analysis

An integrated qualitative approach was applied, combining content and thematic analysis [40,41]. The analysis process was tailored to address each research question using specific data sources and analytical procedures.

Research Question 1 was addressed through systematic content analysis of literature review materials and case study discussions from the first iteration. Participants' critical examinations of existing models identified key content categories based on thematic similarities to establish strengths and limitations of current frameworks.

Research Question 2 employed iterative thematic analysis across the second and third iterations. Participants' proposed alternatives and consensus-building discussions were analyzed to identify recurring patterns and core themes that informed the development of the model. Each iteration's findings informed subsequent analysis stages, following design-based research principles [37].

Research Question 3 utilized collaborative analysis of the fourth iteration's questionnaire development process. Participants' collective creation of assessment indicators and their rationales were analyzed to establish the self-evaluation tool's components and structure.

Triangulation across data sources and peer debriefing through participant validation ensured analytical rigor [36]. The analysis process concluded when broad consensus was reached regarding the proposed model and its key components, aligning with the iterative, consensus-building nature of the research design.

Trustworthiness

Trustworthiness was ensured through several qualitative-research strategies [37]. In addition to the journal detailed above, which systematically documented major decisions and provided an audit trail, data analysis was conducted collaboratively with participants to verify interpretations. This included cross-referencing data across iterations, to enhance trustworthiness and depth of findings. Following the analysis, the theoretical model was presented to the participants for validation (i.e., member check), ensuring consistency with their intent. These strategies conform with established principles for ensuring rigor in qualitative design-based research [37,36].

Validation

The AI literacy model developed through this research process and its accompanying self-assessment questionnaire (presented in the findings section) underwent qualitative validation through multiple mechanisms. Content validity was established through systematic evaluation by the 22 participating teacher educators, who assessed each model component and questionnaire item for relevance, clarity, comprehensiveness, theoretical soundness, and practical applicability during the third iteration, reaching consensus on all elements. Construct validity was demonstrated through the successful application of the emerging

Table 2
Data collection iterations.

Iteration	Activity	Key Questions	Theoretical Rationale	Main Outcomes
First Iteration	Critical examination of existing models for assessing AI literacy/ competencies through structured team dialogue.	1. What are the principles of existing models for assessing AI literacy? 2. Present a case study of a pre-service teacher and explain how the models address the assessment of AI literacy/competencies in teacher training. 3. What are the main strengths and limitations of existing models?	Grounded in systematic literature review methodology [30] and design-based research principles requiring initial exploration of existing knowledge before developing new frameworks [29]. Case-based analysis aligns with situated learning theory [8] for contextual understanding.	Advantages, challenges, critiques, and insights on existing models that served as the basis for the following round.
Second Iteration	Organized synthesis of critiques and insights from the previous round. Participants were asked to propose concrete alternatives for measuring literacy and respond to their colleagues' proposals.	1. What concrete alternatives would you suggest for assessing AI literacy/competency? 2. What is your position regarding the alternatives proposed by your colleagues for measuring AI competencies? 3. How do you think the proposals made by other participants can be improved or adapted? 4. What advantages and disadvantages do you see in each proposed alternative?	Based on collaborative knowledge construction theory [35] and the iterative design process fundamental to design-based research [32]. Peer dialogue supports socio-constructivist approaches to knowledge building [7].	Alternative proposals for aspects of literacy assessments and formulating characteristics for each aspect based on dialogue and critique.
Third Iteration	Presentation of the emerging model from the previous two rounds. Participants were asked to express their agreement with the model components and suggest final corrections.	1. To what extent do you agree with each component of the proposed model? 2. What corrections or adaptations do you suggest for each component of the model? 3. Do you think essential components are missing from the model? If so, what are they? 4. Do the connections and relationships between model components correctly reflect the reality in the field? 5. How do you assess the applicability of the proposed model? Apply it to the case study presented in the first stage and examine its suitability.	Aligns with member checking procedures for ensuring validity in qualitative research [36] and consensus-building approaches in Delphi methodology [37]. Model validation through practical application supports design-based research validation principles.	A consolidated final model for assessing teachers' AI competencies, agreed upon by all participants. This iteration served as the primary validation phase, where participants confirmed the model's theoretical coherence and practical utility.
Fourth Iteration	Development of a self-assessment tool for pre-service or in-service teachers based on the developed model.	1. How can the model's components be translated into measurable indicators? 2. What format would be most effective for self-assessment?	Grounded in self-determination theory supporting autonomous learning [15] and reflective practice principles [38]. Questionnaire development follows established instrument development procedures in educational research [39]	A self-assessment questionnaire in the context of the developed model, allowing teachers to evaluate their AI competencies, in line with the framework.

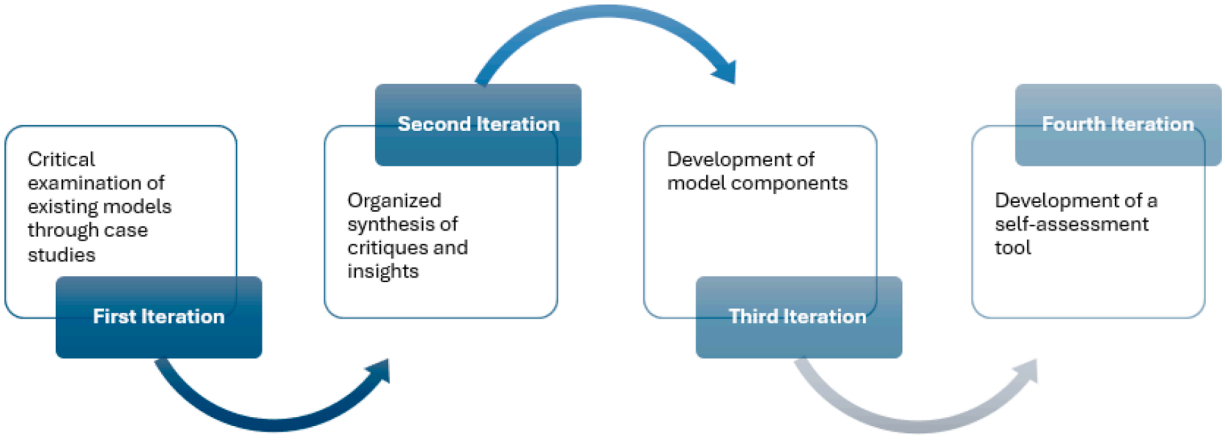

Fig. 1. Iterations of the model's development.

Table 3
AI-Literacy assessment models in educational settings.

Authors (publication year)	Framework / model name	Key components	Target audiences	Main strengths	Main limitations	Illustrative quotes
1. Filo et al. [21]	AI-Competency Framework	Four main skills: identifying AI mechanisms, efficient and informed use of AI, AI agency (proactive and value-creating use of AI), and ethical use of AI.	Teachers and students.	Based on collaborations between researchers and teachers. Offers an implementation model for schools.	Too comprehensive in relation to the need for assessing teachers' literacy.	"The model offers a practical division into four implementable domains, but when working with pre-service teachers, I think it lacks specific tools for assessing their progress. It's an excellent model for course planning, but not for assessment."
2. Hava & Babayiğit [19]	AI-TPACK (Technology, pedagogy, and content knowledge)	Enables assessments of teachers' professional knowledge for ethically integrating AI tools into their teaching.	Teachers, curriculum developers, and educators.	Relies on a well-established model and includes a scale for assessing teachers' ability to integrate AI applications in the teaching process.	Lacks contextual considerations.	"The significant advantage of the AI-TPACK model is the pre-service teachers' prior familiarity with the basic model. This makes it easier for them to understand the complexity of integrating AI into teaching. However, in my courses, I encountered difficulties when trying to adapt it to different disciplinary contexts. For example, how to apply it when teaching science versus teaching language."
3. Touretzky et al. [42]	Five Big Ideas in AI	Conceptual foundation for understanding AI core concepts in technical, ethical, and social contexts.	Students, teachers, and curriculum developers.	Addresses both the technical and the social impact of AI.	Does not directly focus on teachers and requires practical translations for classroom teaching.	"The Five Big Ideas provide an excellent theoretical foundation. When I presented them in a seminar for teacher educators, they understood for the first time the depth of AI beyond the tools that they know. But the question always remains 'Okay, I understand in principle, but what do I do with this in class tomorrow?' It requires significant translation work."
4. Ng et al. [27]	ABCE Approach (affective, behavioral, cognitive, and ethical)	AI literacy in 4 key dimensions: affective, behavioral, cognitive, and ethical.	Researchers, educators, teachers, and students.	Holistic framework, including a questionnaire for assessing AI literacy.	Lacks reference to technological aspects of AI literacy and lacks considerations of social and cultural contexts.	"The questionnaire developed within the ABCE model is an excellent diagnostic tool. I used it at the beginning and end of a course that I taught, and it enabled me to see the precise changes in the students. But there was a gap in the technical aspect. My students improved their ethical and emotional knowledge regarding AI, but still lacked significant technological knowledge."
5. Mott et al. [43]	Use-Modify-Create Framework	Graduated framework for learning AI in elementary school through use, modification, and creation.	Elementary-school teachers.	Supports gradual transition from passive consumption to active creation of AI products.	Tested on a relatively small sample; linear framework that focuses on computational tasks; lacks consideration of social and ethical aspects.	"The Use-Modify-Create model is an excellent pedagogical tool to teach pre-service teachers how to progress with their students in a gradual manner. It became a common language in our course. But when we tried to apply it to complex topics like AI ethics or algorithmic biases, the model didn't provide enough tools for dealing with the difficult questions that arose."

model to three diverse case studies, where the framework effectively captured distinct AI literacy profiles and differentiated between various contextual and professional scenarios. The questionnaire's face validity was confirmed through participants' ability to complete it meaningfully and provide concrete examples for each item. However, this study did not include quantitative reliability testing or large-scale empirical validationEthical considerations

The research adhered to strict ethical standards and was approved by the author's affiliated institutional ethics committee [name removed for blind review]. The participants submitted their informed consent, after

being assured full confidentiality. They were also given the option to withdraw at any stage without consequences. Pseudonyms are used throughout the article, to preserve anonymity.

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Findings

Research question 1

To examine the first research question – What are the principles, strengths, and limitations of existing AI-literacy assessment models in various educational settings? – the participants were asked to identify and analyze relevant frameworks (First Iteration - critical examination and case study analysis). The included articles were recently published (since 2022), empirical, and related to models that were explicitly designed for educational use. These five frameworks represent the most comprehensive and diverse approaches available in the limited literature on AI literacy assessment in education, selected to capture varied theoretical foundations, target audiences, and assessment methodologies. A comparative analysis of the five identified articles is presented in Table 3, accompanied by illustrative citations from the group discussions, and three case studies.

Comparative analysis of the five models presented above reveals several insights (**(based on First Iteration)**. First, they offer varied perspectives of AI literacy, ranging from technical and pedagogical skills [21,19] to holistic frameworks that include emotional and ethical dimensions [27]. Moreover, despite their comprehensive theoretical foundation, the participants addressed the models' gaps between theoretical and practical teacher-training applications. The models also lack specific assessment tools, socio-cultural attention, and practical classroom-implementation guidelines. Synthesis of their strengths and weaknesses underscores the need for a more integrative model that blends theoretical principles with practical tools, and that can be tailored to the evolving needs of teacher education.

To further explore this issue, the current article presents three representative case studies selected from 22 cases shared by participating teacher-educators (emerging from First Iteration dialogues). Based on real dilemmas conveyed by their pre-service and in-service students, these cases illustrate diverse contextual challenges: resource-limited peripheral settings (Case A), varied pedagogical approaches and subject matters (Case B), and educational leadership contexts (Case C). They serve as the foundation for evaluating existing models and exemplify the broad spectrum of situations encountered in contemporary teacher education.

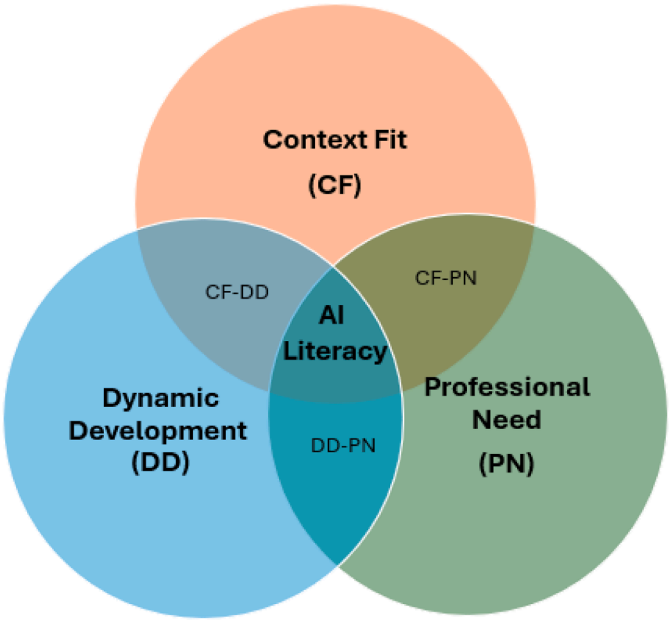

Fig. 2. The Adaptive AI-Literacy Model (AALM).

Case-study A

Mai, a third-year pre-service high-school teacher, works with the Bedouin population in a resource-limited region in the periphery of Israel, where even basic infrastructure is lacking. Classrooms often have no computers or internet access, electricity is unreliable, and not all students have mobile telephones – factors that greatly diminishes her motivation to explore AI tools. Instead, she focuses on developing instructional materials for her students, which are ultimately printed and distributed by hand. She was deliberating whether to learn to create AI bots – a skill that would likely be redundant for her students – or focus on different competencies.

In such settings, traditional AI-literacy assessment tools in education reveal fundamental flaws. They assume a direct link between technology usage and AI literacy, overlooking how minimal yet mindful use may reflect advanced pedagogical insights. Due to their technological bias, these tools place undue emphasis on the use of advanced technologies, while neglecting important pedagogical approaches and cultural contexts. Furthermore, they often prioritize technical proficiency, while disregarding socio-cultural relevance and educational context. By ignoring social disparities and digital gaps, they risk misjudging teacher capabilities. Their rigid focus on specific skills fails to recognize creative adaptation within constraints. Moreover, their underlying assumption of uniform progress neglects the principle that at times, less is more. True AI literacy lies in meaningful, context-aware application, grounded in a deep understanding of student and community needs.

Based on the adaptive AI-Literacy approach, strategic recommendations for Mai's dilemma include prioritizing competencies suited to current conditions – such as using AI to create culturally relevant materials, developing print-deliverable content, and planning for gradual technology integration. As such, skills that are not immediately applicable, such as bot building, should be deferred until infrastructure improves. This approach ensures that AI integration is responsive to both context and resources.

Case-study B

Ruth is an experienced high-school math teacher who specializes in exam preparation. Danny is a novice social-science teacher at an alternative high school, who teaches through discussion and inquiry, fostering critical thinking about social issues. Ruth needs AI literacy that supports precision, structured problem-solving, and abstract concepts visualization, while Danny needs skills for conducting text analysis, identifying social bias, and navigating ethical concerns. Ruth could benefit from mastering tools like WolframAlpha and Microsoft Math Solver, while Danny should focus on platforms such as NotebookLM and article summarizers.

Current AI-literacy assessment models overlook such differences in teachers' needs. While they measure usage, understanding, and ethics, the skills that they measure are generic rather than being tailored to specific subject areas or pedagogical approaches. Since AI textual fields evolve faster than mathematical ones, teachers may not need to achieve the same AI-literacy levels. Yet existing models impose uniform requirements that may be irrelevant to certain roles. A dynamic contextual assessment, on the other hand, would recognize that Ruth must identify mathematical errors in AI outputs while using AI tools for visual demonstrations, while Danny needs to analyze social trends, synthesize diverse sources, and address socio-ethical concerns regarding AI.

Case-study C

Roni, a high-school principal in a medium-sized city, oversees about 800 students and 70 teachers. She leads efforts to implement

Table 4
Comparison of AALM with Existing AI Literacy Models.

Aspect	Existing Models (Table 3)	AALM - Key Differences/ Improvements
Assessment Approach	Linear, fixed progression through predetermined stages	Dynamic, non-linear progression based on individual context and needs
Contextual Adaptation	Limited consideration of infrastructure, cultural, and social contexts	Context-fit axis explicitly addresses infrastructure, socio-cultural factors, and local needs
Professional Differentiation	Generic skills applicable to all educators	Professional-needs axis tailored to specific disciplines, pedagogical approaches, and leadership roles
Temporal Perspective	Static assessment at specific timepoints	Dynamic-development axis captures evolution over time and technological advancement
Cultural Sensitivity	Minimal attention to cultural and social diversity	Explicit integration of socio-cultural factors across all three axes
Assessment Flexibility	Standardized rubrics with uniform requirements	Flexible framework allowing different literacy paths for different contexts
Teacher Collaboration	Limited teacher involvement in model development	Co-created with 22 teacher educators through iterative design-based research
Practical Application	Often theoretical with limited classroom implementation guidance	Includes practical case studies and self-assessment tool for immediate use
Validation Method	Mostly theoretical or small-scale testing	Developed and validated through extensive collaboration with diverse teacher educators
Overlap Recognition	Treat dimensions as separate components	Explicitly maps overlapping areas (CF_PN, PN_DD, DD_CF) and central integration zone
Target Specificity	Broad audiences (teachers, students, curriculum developers)	Specifically designed for pre-service and in-service teacher education
Infrastructure Consideration	Assumes adequate technological infrastructure	Explicitly addresses resource-limited and peripheral educational settings
Skill Uniformity	Expects similar competency levels across all users	Recognizes that different educators need different AI literacy levels based on their context
Assessment Tool	Limited practical assessment instruments	Comprehensive self-assessment questionnaire with practical examples and improvement opportunities

Table 5
Adaptive AI-literacy self-assessment questionnaire. "Please rate each of the following items on a scale of 1 (to a limited extent) to 5 (to a great extent)".

Context-fit axis	Rating: 1: to a limited extent. 5: to a great extent.	Example	Improvement opportunities
I adapt my use of AI tools to the technological infrastructure available in my school			
I adapt my use of AI to align with my students' cultural characteristics			
I identify context-specific opportunities for integrating AI into my classroom			
I adapt the level of my AI use to suit my students' abilities			
I account for contextual limitations when selecting AI tools for classroom use			
Professional-need axis			
I use AI to enhance the quality of my teaching			
I identify pedagogical opportunities for integrating AI into my teaching			
I leverage AI to help me achieve my teaching goals			
I select AI tools that suit my subject matter			
I design meaningful learning activities that incorporate AI			
Dynamic-development axis			
I stay up-to-date with AI developments in education			
I experiment new ways of integrating AI into my teaching			
I reflect on my experiences and continually improve my use of AI			
I identify areas for developing my AI practices and selecting appropriate tools			
I feel increasingly confident in my use of AI tools			
Integrative questions between axes			
I align my professional development in AI with the needs of my school and my students			
I develop creative solutions to challenges related to AI use in my specific teaching environment			
I evaluate the effectiveness of AI integration in my specific teaching context			
I adapt my use of AI to changing needs and circumstances			
I share insights with colleagues about adapting AI			

pedagogical innovation while navigating challenges related to integrating AI into teaching, learning, and assessments. This case study highlights the limitations of standardized AI-literacy rubrics, that emphasize principles of AI operations, data interpretations, and others – which overlook leadership and management competencies that are critical to her role.

Roni requires strategic and regulatory literacy to help her shape AI school policies, make informed technology-related investments, and understand their systemic impact on teaching, learning, and assessment processes. Contextual approaches, however, could assess her AI literacy in light of her managerial role, emphasizing skills that are required for effectively creating change, building visions, and managing the school in a rapidly evolving educational landscape.

These case studies, derived from real dilemmas shared by participants, informed the development of the model presented below and demonstrated its relevance across diverse educational contexts.

Research question 2

The second research question asked, What are the components of an innovative, context-sensitive model that meets the evolving needs of pre-service and in-service teachers? How do its principles support renewed analysis of diverse educational contexts?

In light of the inadequacy of existing frameworks for assessing AI literacy in education, a new model was developed (Fig. 2) – in collaboration with the 22 teacher educators who participated in this study (Table 1) (Second and Third Iterations - synthesis and consensus-building) Unlike traditional rubrics with fixed, predefined categories, the proposed model introduces a dynamic, non-linear approach, allowing flexible progression based on individual needs. Its key strength

lies in capturing the complexity of different educational roles and illustrating how AI literacy evolves across contexts and over time.

The model is structured around three inter-related axes. The *context-fit (CF) axis* includes adaptation to available infrastructure, socio-cultural factors, local needs, and the educator's developmental stage in AI-literacy. The *professional-needs (PN) axis* relates to the specific discipline, pedagogical aspects, leadership, and support. Finally, the *dynamic-development (DD) axis* reflects growth in response to technological advancements, evolving roles, changing needs, and expanding capabilities. Together, these axes provide a flexible framework that aligns AI-literacy assessments with the realities of diverse educational settings.

Overlapping areas

The three axes are inter-connected, with several areas of overlap reflecting the complex nature of AI literacy. The *context-professional overlap* (CF_PN) marks the intersection between local conditions and professional demands. The *professional-dynamic overlap* (PN_DD) captures how professional needs evolve over time. Finally, the *dynamic-context overlap* (DD_CF) highlights shifts in the educational environment that influence literacy development. At the core of the model lies the *central AI-literacy area*, where context, professional needs, and dynamic development converge, representing the integrated essence of adaptive, meaningful AI literacy.

Unlike existing AI literacy models that adopt linear progression through predetermined stages (e.g., [43,4]), the AALM introduces several key innovations that extend beyond traditional one-dimensional perceptions. First, it employs a dynamic, non-linear approach that recognizes different literacy paths for different contexts - acknowledging that a math teacher in a well-equipped urban school requires different AI competencies than a teacher in a resource-limited peripheral setting (as illustrated in Case Study A). Second, while existing models treat technical, pedagogical, and ethical dimensions as separate components, AALM integrates contextual adaptation, professional differentiation, and temporal development as interconnected axes, emphasizing dynamic interactions between dimensions. Third, the model explicitly addresses infrastructure limitations and socio-cultural factors that previous frameworks largely overlook - a critical gap identified in our analysis of existing models (Table 3). Finally, unlike predominantly theoretical frameworks, AALM was co-created with diverse teacher educators through iterative design-based research, ensuring practical applicability across varied educational contexts. A detailed comparison between the models presented in Table 3 and the AALM framework is provided in Table 4.

Research question 3

Finally, the third research question asked, What are the key indicators for a teacher's self-evaluation tool across different educational settings, based on the proposed model? To address this topic, the researchers and participants jointly created a self-assessment tool for teachers and educators (Table 4). Following systematic review of the case studies and the developed model, participants proposed questionnaire items aligned with each model component. All items emerged through collaborative dialogue, with participants suggesting specific indicators based on their analysis of real-world scenarios. The questionnaire underwent iterative refinement through shared document editing and consensus-building discussions until final agreement was reached (Fourth Iteration - collaborative questionnaire development) (Table 5).

Discussion

The aim of this study was to critically review models for assessing AI literacy in education and propose a more adaptable framework that also accounts for socio-cultural contexts. Some models build on established frameworks for defining learning-complexity levels (Touretzky et al.), while incorporating various literacy elements – from basic knowledge to ethics and critical thinking [21]. Others, like the AI-TPACK, integrate technological, pedagogical, and content knowledge [19].

However, they pose key challenges, including ambiguous definitions of AI literacy that hinder assessment validity [21]. These initial evaluation approaches, which were at the core of the "first wave," (e.g., [4]), tend to overemphasize technical knowledge at the expense of social and ethical considerations, while offering limited adaptability options for addressing diverse educational settings [42]. Additional difficulties stem from the rapid AI evolution, a shift in teachers' competencies, and the need to balance a range of skills while addressing the educator's role, experience, and expectations. This underscores the importance of developing a more dynamic and context-sensitive approach.

The proposed AALM introduces an innovative paradigm for conceptualizing and assessing AI literacy in education, structured around three interrelated axes: (1) context fit (adaptation to available infrastructure, socio-cultural environments, local priorities, and developmental stage); (2) professional needs (subject-specific instructional demands, pedagogical needs, leadership and managerial responsibilities, and support mechanisms); and (3) dynamic development (evolution in response to technological advancements, shifting roles, emerging needs, and developing competencies).

The context-fit / professional-needs axes overlap

The intersection of the context-fit and professional-needs axes reflects a dynamic interaction between environmental-cultural-social factors and demands of the educational profession. It is within this space that educators tailor their AI knowledge to their specific operational context. The above field analysis reveals various expressions of this in practice: Teachers in peripheral regions devise strategies for adapting AI tools to infrastructure limitations, illustrating how the drive for innovation is shaped by contextual constraints. Similarly, educational leaders who serve distinct populations must craft AI usage policies that align with community values, while promoting pedagogical advancement.

The context-fit / professional-needs overlap highlights how AI literacy does not develop in isolation, but is shaped by the educator's specific context. This perspective aligns with socio-cultural perspectives of learning and professional growth [7,35], whereby knowledge and skills are perceived as outcomes of continuous socio-cultural interactions. This overlap also challenges conventional models that emphasize standardization and uniform skill sets, offering a differentiated approach that values the uniqueness of each educational setting. The intersection of context and needs is not just a space for adaptation, but also a platform for pedagogical creativity and innovative use of AI in education. Finally, this overlap underscores the need for a nuanced multi-dimensional approach to assessing AI literacy – one that accounts for the complex environment in which educators work, beyond their technical or pedagogical knowledge [39,44]. This perspective marks an important step towards more targeted professional–development programs.

The professional-needs / dynamic-development axes overlap

The overlap between these two axes illustrates how the AI needs of educators develop over time. This reflects the understanding that AI literacy is a continuous process that is shaped by technological innovation, changing roles, and professional growth. Such progression is evident in the case-study analysis presented above, where the math teacher initially used basic AI tools for checking exercises, yet later adopted more advanced technologies for visual demonstrations that enrich teaching and learning. This shift reflects both increased technical proficiency and a broader perspective on how technology can support subject instruction. Theoretical significance of this overlap lies in

viewing AI literacy as a process of continuous learning and adjustments to a dynamic environment.

This approach draws on professional-development theories [45] and lifelong learning [46] – emphasizing adaptability and skill acquisition as key to effective AI literacy. Moreover, this overlap highlights the need for flexible assessment tools that reflect AI literacy's evolving nature, rather than measures that are linked to specific timepoints. As the case-study analysis shows, educators' AI-literacy developmental varies widely, shaped by factors such as changing role demands, emerging technologies, and both formal and informal learning processes. Finally, this overlap underscores the need for long-term professional-development programs adapted to different developmental stages, enabling gradual growth over time. Such programs should combine practical experiences, ongoing reflection, and professional learning communities that support the continuous development of AI-related skills and knowledge.

The dynamic-development / context-fit axes overlap

This overlap represents a complex space in which social, cultural, technological, and institutional contexts are fluid, posing a dual challenge for educators to grow professionally while continually adapting to changing conditions. The case-study analysis presents several key contextual dynamics that impact AI literacy in education, including variability in technological infrastructure, which impacts the context and limits or expands pedagogical possibilities for teachers. Another additional dimension is the shifting cultural and social perceptions toward AI across communities. One participant described how religiosity permitted the use of AI text-generators, but not visual ones, deeply impacting their AI literacy. This underscores the importance of ongoing awareness of socio-cultural factors in technology integration. A third element involves emerging needs driven by new AI capabilities, such as adaptive learning environments, which introduce new educational demands.

From a theoretical aspect, this overlay is significant for framing AI literacy as an ecological phenomenon, embedded in dynamic systems. This aligns with systemic-ecological theories in education [9,47], emphasizing the interaction between individual growth and broader systemic shifts. This approach challenges linear models for assessing technological literacy, proposing an alternative, complex, and dynamic "literacy landscape" [48].

Finally, this overlap emphasizes the need for "literacy agility" – i.e., the capacity for continuous adaptation to context. Practically, this calls for cultivating educators' meta-cognitive abilities and reflective thinking, to support adaptive responses in shifting operational contexts.

The core AI-literacy zone

At the center of the AALM – where contextual adaptation, professional needs, and dynamic development intersect – lies the core AI literacy dimension. This zone represents optimal AI literacy in educational settings, characterized by full integration and balanced interactions between the model's three central dimensions. Understanding this area offers valuable insights into effective and transformative AI use in educational settings.

One key feature is the seamless integration of context, needs, and development. In this zone, educators align their understanding of their socio-cultural environment with the clear identification of professional needs and awareness of growth processes. Another defining aspect is that AI use becomes authentic and deeply embedded in teaching, with literacy reaching its highest impact and relevance. The case-study analysis reveals that educators in this zone design rich, meaningful pedagogical practices that enhance learning. Strong adaptability is another core trait. Here, educators respond swiftly and efficiently to technological, contextual, and professional change. This flexibility stems from expertise, systemic awareness, and meta-cognitive skills, enabling fluid navigation across the three axes – an essential capability in a fast-changing technological landscape.

This central area also reflects the inherent complexity of AI literacy in education. Unlike binary frameworks (knows: yes/no), it captures the multi-dimensional nature of the phenomenon, and the constant interaction between its components – aligning with complex systemic approaches in education [49]. Another unique characteristic of the proposed model is the ability to shift between dimensions. Educators in this zone flexibly move between contextual aspects, professional needs, and development processes – drawing on each axis to effectively address challenges.

The model also emphasizes the dynamic interplay between dimensions, promoting a holistic understanding that mirrors educational realities. Its strength lies in assessing AI literacy across educational contexts, while addressing specific cultural, social, and pedagogical characteristics. The case-study analysis demonstrates how in peripheral, resource-limited settings, the model is able to identify AI literacy aspects that traditional models overlook, recognizing that no "perfect profile" exists, and that individuals develops skills that are most relevant to their specific situation at a given timepoint.

The AALM self-assessment questionnaire

The reflective diagnostic questionnaire – comprised of self-rating questions and practical examples, and areas for growth – marks significant development in research tools in this field, embodying the AALM's core principles. Its inherent differentiation enables educators to pinpoint their strengths and challenges across each axis of the model, aligning with the multi-dimensional view of AI literacy.

Requiring practical examples bridges between theory and practice, situating self-assessment in real-world contexts. This approach enables teachers to assess their literacy, not as an abstract concept but rather as a practical skill that is manifested in their routine work, following questionnaires presented in earlier research [50,39]. Identifying areas for improvement supports dynamic development, creating tailored growth paths for each educator. The questionnaire's integrative design reflects the model's holistic foundation and encourages connections between the three axes. Reflective assessments of AI literacy fosters self-awareness and lifelong learning, which are both essential for achieving meaningful literacy amid rapid and ongoing technological changes.

Contribution to the educational field

This study offers meaningful multi-dimensional contributions to education across three key domains. First, the AALM model presents an innovative theoretical framework for understanding AI literacy as context-dependent, capturing the complexity of educational settings and their related resources, opportunities, and constraints – a reality that policymakers must consider. Second, the model's integrative perspective has important implications for professional development and teacher training in relation to AI. Rather than narrowly focusing on technical skills, training should foster the ability to integrate multiple dimensions and promote systemic, reflective awareness. The findings suggest that effective professional development requires authentic practice, ongoing reflection, and supportive learning communities – enabling educators to gradually achieve comprehensive and effective AI literacy.

Finally, the proposed self-assessment tool could enable educators to evaluate their own AI literacy, through a dynamic, context-specific lens. It addresses adaptation to local conditions (e.g., infrastructure and cultural alignment), professional needs (such as subject-specific pedagogy), and evolving skill development. Complementing the self-assessment questionnaire – with items such as "I adapt AI use to my students' cultural characteristics" or "I select AI tools that are appropriate for my taught subject " – encourages critical reflection and directly supports the development of the literacy that it measures.

Future directions

Building on this study's foundation, several research directions can advance AI literacy assessment in teacher education. While this study established the AALM model through qualitative validation with 22 teacher educators, future research presents opportunities to expand this foundation and validation through quantitative psychometric testing, longitudinal studies tracking teachers' AI literacy development over time, and cross-cultural validation across diverse educational contexts internationally.

The model's theoretical framework creates a solid base for practical implementation research. Future studies should test AALM-based professional development curricula in real-world teacher education programs, develop institutional assessment protocols integrating the three-axis approach, and investigate policy applications for teacher AI literacy requirements.

Technological advancement presents opportunities for adaptive assessment tools operationalizing AALM principles. Intelligent systems might analyze users' real-time behaviors and needs, adjusting evaluation metrics and offering personalized development paths—detecting when teachers need concept illustration support or ethical guidance.

Long-term research should explore the model's adaptability to rapid technological change, develop objective measures complementing the current self-assessment approach, and investigate relationships between AALM-defined AI literacy and actual teaching effectiveness in AI-enhanced learning environments.

Yet even in such future scenarios, human educators and evaluators will remain essential. Their role in understanding broader human, social, and cultural dimensions – and in shaping assessments and developments to align with educational and ethical goals – will continue to be irreplaceable.

CRediT authorship contribution statement

Liat Eyal: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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