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AI literacy in secondary education: framework, assessment, and professional development in the Ukrainian context

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HIGHLIGHTS

- 84% of Ukrainian educators use AI, but only 11% are aware of specialized services beyond ChatGPT.
- A five-level AI literacy framework integrates constructivism, connectivism, and TPACK theories.
- Professional development intervention achieves 24% competence improvement.
- EOSC provides underutilized specialized AI services for secondary education.
- The crisis context accelerates digital adoption while highlighting infrastructure gaps.

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ABSTRACT

The rapid proliferation of artificial intelligence tools in educational settings has created an urgent demand for AI literacy among secondary educators, yet empirical research examining this phenomenon in non-Western and crisis-affected contexts remains limited. This multi-study investigation employs a sequential explanatory mixed-methods design to examine AI literacy among Ukrainian secondary educators through national survey analysis ($n = 2018$), targeted educator surveys ($n = 116$), professional development evaluation ($n = 1130$), and systematic mapping of European Open Science Cloud (EOSC) services. Findings reveal that while 84% of surveyed educators report AI use in professional practice, only 11% can identify specialized services beyond ChatGPT, indicating a pattern of high adoption coupled with limited specialized awareness. The study proposes a five-level AI literacy framework (Awareness, Application, Evaluation, Creation, Ethics) integrated with three paradigms of AI in education (AI-directed, AI-supported, AI-empowered). Professional development intervention demonstrates 24% improvement in AI competence, with the largest gains in practical application (+27%) and critical evaluation (+26%). Systematic analysis identifies 22 EOSC AI services applicable to secondary education, particularly in biology and geography. Results provide preliminary evidence suggesting that targeted professional development can help advance AI literacy beyond surface-level tool familiarity toward sophisticated pedagogical integration. The Ukrainian context, marked by crisis-driven digital transformation, offers insights relevant to educational systems worldwide confronting the imperative to prepare teachers for AI-enhanced instruction.

1. Introduction

The release of ChatGPT in November 2022 marked a watershed moment in the integration of artificial intelligence into educational practice, triggering unprecedented discourse among educators, policymakers, and researchers worldwide (Divya et al., 2025; Tan, 2025). Within months of its public availability, generative AI tools demonstrated remarkable capabilities in content creation, personalized tutoring, and administrative task automation, fundamentally

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challenging established pedagogical paradigms (Jauhiainen & Garagorry Guerra, 2024; Rawat et al., 2024; Zahorodko & Semerikov, 2026). This technological disruption has accelerated calls for systematic approaches to AI literacy development, particularly among educators who must navigate both the opportunities and risks presented by these rapidly evolving tools (Chee et al., 2025; Kim, 2025). As artificial intelligence increasingly permeates educational environments, the capacity of teachers to critically evaluate, effectively deploy, and ethically integrate AI services has emerged as a critical determinant of educational quality in the twenty-first century (Ahmad et al., 2025; Wu et al., 2024).

Despite the transformative potential of AI in education, a significant gap persists between the availability of AI tools and the preparedness of educators to leverage them effectively. International surveys consistently reveal that while teachers express interest and openness toward AI integration, substantial barriers impede widespread adoption (Chen et al., 2025; Granström & Oppi, 2025). These barriers encompass insufficient professional development opportunities, limited access to appropriate technological infrastructure, and inadequate institutional policy frameworks (Eusebio et al., 2025). Research conducted across diverse educational contexts indicates that over 85% of teachers lack formal AI education, relying instead on incidental learning experiences that fail to develop comprehensive AI literacy competencies (Nagae et al., 2025). Furthermore, studies examining teacher perceptions reveal persistent concerns regarding data privacy, algorithmic bias, academic integrity, and the potential displacement of essential cognitive skills among students (Ramos et al., 2024; Somabut et al., 2025). The Technology Acceptance Model and related frameworks suggest that perceived usefulness and ease of use significantly influence adoption intentions, yet these factors alone prove insufficient without systematic competency development (Eusebio et al., 2025; Tan, 2025).

The dominance of general-purpose large language models, particularly ChatGPT, in educational discourse presents both opportunities and limitations. While these tools offer accessible entry points for AI exploration, their prominence may obscure awareness of specialized AI services designed for specific educational domains (Nguyen & Pham, 2025; Semerikov et al., 2026). Research from multiple contexts indicates that educators predominantly recommend ChatGPT when asked about AI tools for education, demonstrating limited knowledge of subject-specific alternatives that may better address curricular requirements in science, mathematics, and other disciplines (Kim, 2025; Unal & Unal, 2024). This overreliance on general-purpose tools may constrain the pedagogical potential of AI integration, as specialized services often provide domain-specific functionalities, validated datasets, and educational affordances that generic language models cannot replicate (Calatrava et al., 2023). The European Open Science Cloud (EOSC), for instance, hosts numerous AI-powered services originally developed for research communities that possess significant yet underexplored educational applications (Wolski et al., 2022).

The Ukrainian educational context presents particularly compelling circumstances for investigating AI literacy development. Since February 2022, the ongoing war has imposed extraordinary challenges on educational institutions, necessitating rapid adaptation to distance and blended learning modalities (Kaplia et al., 2024; Kuzheliev et al., 2023). Ukrainian educators have demonstrated remarkable resilience in maintaining educational continuity, leveraging digital technologies to mitigate disruption despite infrastructure limitations and security concerns (Vorotnykova et al., 2023). This crisis-driven digital transformation has accelerated technology adoption while simultaneously exposing gaps in digital competencies among teaching staff (Ovcharuk et al., 2020; Vovchasta et al., 2024). Against this backdrop, the emergence of generative AI tools presents both opportunity and challenge: opportunity in the potential to enhance instructional efficiency and personalization, and challenge in the additional competency demands placed upon educators already navigating unprecedented circumstances. Understanding how Ukrainian educators engage with AI technologies, their professional development needs, and the barriers they encounter provides insights relevant not only to conflict-affected contexts but to educational systems worldwide undergoing digital transformation.

Despite growing scholarly attention to AI literacy in education, several research gaps warrant investigation. First, while numerous frameworks have been proposed for conceptualizing AI literacy competencies, limited empirical research examines their applicability to secondary education teacher development (Chiu et al., 2024). Second, studies examining specialized AI services for education remain scarce, with most research focusing on general-purpose tools without systematic mapping of domain-specific alternatives (Wu et al., 2024). Third, evidence regarding the effectiveness of professional development interventions for improving teacher AI literacy remains limited, particularly in non-Western and resource-constrained contexts (Nagae et al., 2025; Termenzhy et al., 2025). Fourth, the relationship between AI literacy and broader digital competence frameworks, such as the European DigCompEdu, requires further theoretical elaboration (Bahari & Liu, 2025). These gaps collectively limit the capacity of educational institutions and policymakers to design evidence-based approaches to AI integration in secondary education.

This study addresses these gaps through a multi-study investigation of AI literacy among Ukrainian secondary educators. The research pursues five interrelated questions:

RQ1: What is the current state of AI awareness and adoption among Ukrainian secondary educators?
RQ2: What competency levels characterize effective AI literacy for secondary education contexts?
RQ3: How can specialized AI services from the European Open Science Cloud be mapped to specific school subjects?
RQ4: What professional development approaches effectively improve teachers' AI literacy?
RQ5: What ethical considerations should guide AI integration into secondary education?

To address these questions, the study employs a sequential explanatory mixed-methods design integrating four complementary investigations. Study 1 analyzes national survey data examining public awareness and attitudes toward AI. Study 2 surveys practicing educators regarding AI service usage patterns and professional development needs. Study 3 evaluates a professional development intervention through pre-post competence assessment. Study 4 systematically maps specialized AI services to secondary school subjects. This multi-study approach enables triangulation of findings across data sources while capturing both breadth (through large-scale surveys) and depth (through intervention evaluation) in understanding AI literacy development among secondary educators.

The study makes several contributions to the field of AI in education. Theoretically, it proposes and empirically examines a five-level AI literacy framework progressing from awareness through application, evaluation, and creation to ethical considerations, extending existing conceptualizations to address the specific needs of secondary education. Methodologically, it demonstrates a multi-study approach to AI literacy research that integrates survey, intervention, and systematic analysis methods. Practically, it provides evidence-based guidance for professional development design and identifies specialized AI services applicable to diverse subject areas. The Ukrainian context, while presenting unique characteristics related to wartime education, offers insights transferable to educational systems worldwide confronting the imperative to develop AI literacy among teaching professionals.

Fig. 1 presents the overall research framework connecting the Ukrainian educational context, research questions, and the multi-study methodology employed in this investigation.

The remainder of this article proceeds as follows. Section 2 reviews relevant literature on AI literacy frameworks, teacher professional development, and AI tools in education. Section 3 presents the theoretical framework integrating the five-level AI literacy model with

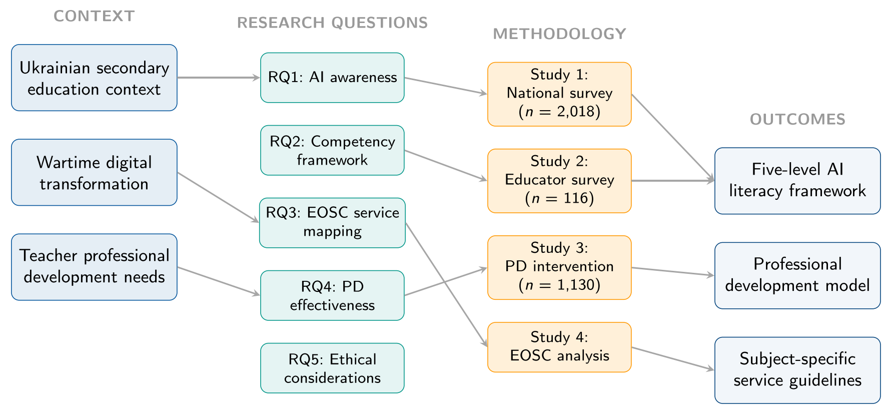

Fig. 1. Research framework illustrating the connections between the Ukrainian educational context, research questions, multi-study methodology, and anticipated outcomes. The sequential design enables the progressive building of evidence across studies.

paradigms of AI in education. Section 4 describes the research design, participants, instruments, and analytical procedures. Section 5 reports findings from each study component and integrated analysis. Section 6 interprets results in relation to research questions and existing literature, addresses limitations, and identifies implications. Section 7 summarizes contributions and suggests future research directions.

2. Literature review

2.1. Defining AI literacy in educational contexts

The concept of AI literacy has evolved substantially since its initial articulation, reflecting both the rapid advancement of AI technologies and the growing recognition of the need for systematic competency frameworks. Long and Magerko (2020) provided a foundational definition identifying AI literacy as “a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace”. This conceptualization emphasizes functional capabilities alongside critical evaluation, establishing AI literacy as distinct from mere technical proficiency.

Building upon this foundation, Ng et al. (2021) proposed a four-component framework encompassing: (1) knowing and understanding AI, (2) using and applying AI, (3) evaluating and creating AI, and (4) AI ethics. This framework has been influential in subsequent research, providing a structured approach to competency identification that balances technical, practical, and ethical dimensions. The framework’s emphasis on evaluation and creation distinguishes AI literacy from passive technology consumption, positioning learners as active participants capable of critically assessing and potentially contributing to AI development.

Recent scholarship has elaborated on the distinction between AI literacy and AI competency. Chiu et al. (2024) argue that while literacy emphasizes foundational knowledge and critical awareness, competency encompasses the practical abilities to deploy AI effectively in professional contexts. Their comprehensive framework identifies five interconnected components: knowledge of AI technology, awareness of AI’s societal impact, ethical reasoning about AI applications, skills for human-AI collaboration, and capacity for ongoing self-reflection regarding AI use. This expanded conceptualization recognizes that effective AI integration requires not only understanding what AI can do but also developing sophisticated judgment about when and how to employ AI tools appropriately.

Chee et al. (2025) extend these frameworks to address developmental progression from K-12 through higher education and into the workforce. Their learner competency framework identifies eight core competencies and eighteen sub-competencies organized across cognitive, affective, and behavioral domains. Importantly, they articulate age-appropriate expectations at different educational stages, providing guidance for curriculum developers seeking to implement AI literacy education across the lifespan. This developmental perspective proves particularly relevant for secondary education, where students are transitioning between foundational learning and preparation for post-secondary education or employment.

The relationship between AI literacy and broader digital competence frameworks requires attention. The European Digital Competence Framework for Educators (DigCompEdu) provides a comprehensive model for educator digital competence that predates the current AI revolution but offers structural guidance for AI literacy integration (Bahari & Liu, 2025). Recent work on the Intelligent-TPACK framework extends the established Technological Pedagogical Content Knowledge model to encompass AI-specific competencies, positioning AI literacy within the broader context of technology-enhanced pedagogy. This integration suggests that AI literacy should not be conceptualized as entirely separate from existing digital competencies but rather as an extension and deepening of them.

The emergence of generative AI tools, particularly large language models, has prompted reconsideration of AI literacy frameworks. Yue Yim (2024) argues that existing frameworks inadequately address the novel affordances and risks presented by generative AI, calling for updated conceptualizations that emphasize prompt engineering, output evaluation, and the distinctive ethical considerations raised by content-generating systems. This critique highlights the dynamic nature of AI literacy as a construct that must evolve alongside technological capabilities.

Table 1 summarizes major AI literacy frameworks relevant to K-12 education, highlighting their core components, target audiences, and assessment approaches.

2.2. Theoretical frameworks for AI in education

Beyond competency frameworks for individuals, theoretical perspectives on AI’s role in educational processes provide essential context for understanding AI literacy development. Ouyang and Jiao (2021) propose three paradigms characterizing AI integration in education: AI-directed, AI-supported, and AI-empowered learning. In the AI-directed paradigm, AI systems function as primary instructional agents, directing learning processes while human teachers adopt facilitative roles. The AI-supported paradigm positions AI as a collaborative tool that augments human capabilities without displacing human agency. The AI-empowered paradigm envisions AI as enabling transformative learning experiences that would be impossible without AI assistance, with learners exercising agency over AI systems to pursue self-directed goals.

Table 1
Comparison of AI literacy frameworks in K-12 education.

Framework	Core components	Target audience	Assessment focus	Source
Five Big Ideas (AAAI/CSTA)	Perception, Representation, Learning, Interaction, Impact	K-12 students	Conceptual understanding	AI4K12 (2023)
AI Literacy Framework	Know/Understand, Use/Apply, Evaluate/Create, Ethics	General learners	Competency progression	Ng et al. (2021)
AI Competency Framework	Technology, Impact, Ethics, Collaboration, Self-reflection	Educators & Students	Professional practice	Chiu et al. (2024)
Learner Competency Framework	8 competencies, 18 sub-competencies	K-12 to workforce	Developmental stages	Chee et al. (2025)
AIware Model	98 competencies across domains	K-12 curriculum	Standards alignment	Sattelmaier and Pawlowski (2025)
UNESCO AI CFT	Foundation, Application, Creation	Teachers	Professional development	Miao and Cukurova (2024)
Intelligent-TPACK	AI-enhanced TPACK dimensions	Pre-service teachers	Pedagogical integration	Bahari and Liu (2025)

These paradigms carry implications for AI literacy development. Teachers operating within AI-directed contexts require competencies for evaluating AI instructional systems and monitoring their effects on students. AI-supported contexts demand collaboration skills and judgment about when AI assistance enhances versus undermines learning goals. AI-empowered contexts necessitate creative and innovative capacities to leverage AI for novel pedagogical approaches. The paradigmatic perspective suggests that AI literacy is not monolithic but context-dependent, with different competency emphases appropriate for different integration approaches.

Pedagogical frameworks for AI education have also received scholarly attention. Constructionist approaches emphasize learning through creating AI systems, positioning students as designers rather than consumers of AI (Tedre et al., 2021). Project-based learning frameworks engage students in authentic AI applications, developing competencies through meaningful problem-solving. Inquiry-based approaches foster critical questioning about AI capabilities, limitations, and implications.

Digital storytelling has emerged as a particularly promising pedagogical approach for AI literacy development. Ng et al. (2022) demonstrate how narrative-based learning experiences can make abstract AI concepts accessible while engaging affective dimensions often neglected in technical instruction. Storytelling approaches enable exploration of ethical considerations through scenario-based reasoning, developing moral imagination alongside technical understanding. The integration of AI tools into digital storytelling projects provides authentic contexts for competency development while producing meaningful artifacts that demonstrate learning.

2.3. Teacher professional development for AI integration

Research on teacher professional development reveals significant gaps in AI-related training. Nagae et al. (2025) found that among Swedish teachers, over 85% lacked formal AI education prior to targeted intervention, with most acquiring whatever AI knowledge they possessed through informal channels. Similar patterns emerge across international contexts, suggesting that AI literacy development among educators has proceeded largely through self-directed exploration rather than systematic preparation.

Survey research examining teacher perceptions and practices provides insight into current states of AI integration. Chen et al. (2025) surveyed 1454 teachers in an urban U.S. school district, finding widespread interest in AI tools alongside significant variation in usage patterns across grade levels and subject areas. Teachers reported using AI primarily for administrative tasks and lesson planning, with direct instructional applications less common. Barriers to adoption included concerns about academic integrity, uncertainty about appropriate uses, and insufficient professional development.

Studies of AI adoption barriers identify multiple factors impeding effective integration. Technical barriers include inadequate infrastructure, limited access to devices, and unreliable internet connectivity – factors particularly salient in under-resourced contexts (Nguyen & Pham, 2025). Pedagogical barriers encompass uncertainty about effective integration strategies, concerns about displacing essential learning processes, and lack of curricular guidance (Eusebio et al., 2025). Institutional barriers include policy ambiguity, insufficient administrative support, and the absence of professional development structures (Tan, 2025).

Effective professional development for AI integration shares characteristics with broader principles of effective teacher learning while requiring attention to domain-specific considerations. Unal and Unal (2024) emphasize the importance of hands-on experience with AI tools, collaborative learning among educators, and ongoing support extending beyond initial training. The AIPACK model proposed by Balta (2024) integrates AI-specific competencies with established TPACK dimensions, providing a framework for professional development design that connects AI literacy to pedagogical practice. Studies employing pre-post designs demonstrate that targeted interventions can significantly improve teacher AI literacy, though sustained implementation requires ongoing support structures.

2.4. AI tools and services for education

The landscape of AI tools applicable to education has expanded dramatically, yet research suggests educator awareness remains concentrated on a narrow range of highly visible tools. Kim (2025) found that when asked to identify AI tools for education, K-12 educators predominantly named ChatGPT, with limited awareness of alternatives despite the availability of numerous subject-specific services. This pattern of concentrated awareness poses risks of over-reliance on general-purpose tools whose capabilities and limitations may not align with specific educational needs.

General-purpose large language models offer accessibility and versatility but present limitations for specialized educational applications. While ChatGPT and similar tools can assist with content explanation, question generation, and feedback provision, they lack domain-specific training data, validated pedagogical approaches, and subject-matter expertise that specialized tools may provide (Hmoud et al., 2024). Furthermore, general-purpose tools raise concerns about accuracy, particularly in technical domains where model hallucinations could propagate misconceptions.

The European Open Science Cloud represents an underexplored resource for specialized AI services in education. Originally developed to support research communities, EOSC hosts AI-powered services across scientific domains including biodiversity analysis, geographic information systems, molecular modeling, and data visualization (Calatrava et al., 2023). Marienko et al. (2023) and Shyshkina et al. (2024) have begun exploring educational applications of these services, demonstrating their potential for secondary science education while noting the need for pedagogical adaptation. The EOSC context proves particularly relevant for Ukrainian educators, as European research infrastructure provides accessible alternatives to commercial services that may face restrictions or accessibility challenges in conflict-affected contexts.

Beyond EOSC, subject-specific AI tools offer educational applications often overlooked in discussions dominated by general-purpose chatbots. AI-powered tutoring systems provide adaptive instruction in mathematics and science. Intelligent writing assistants offer feedback beyond what general LLMs provide. Simulation and visualization tools leverage AI for interactive exploration of complex phenomena. Cataloging and mapping these tools to curricular areas represent a significant gap in the literature that limits educator awareness and adoption.

2.5. Research gaps and study rationale

The literature review reveals several gaps motivating the present investigation. First, while conceptual frameworks for AI literacy proliferate, empirical research examining their applicability to secondary education teachers remains limited. Studies tend to focus on either K-12 students or higher education contexts, with secondary teacher competencies receiving less attention. Second, research on specialized AI services for education is scarce, with the literature dominated by studies of general-purpose tools. Third, evidence regarding professional development effectiveness for AI literacy, particularly in non-Western contexts, requires strengthening. Fourth, the Ukrainian educational context, despite its relevance for understanding technology adoption under crisis conditions, remains underrepresented in international research.

This study addresses these gaps through a multi-study investigation combining survey research, intervention evaluation, and systematic service analysis. The Ukrainian context provides both a case of intrinsic interest and insights potentially transferable to other settings confronting rapid digital transformation.

3. Theoretical framework

Building upon the reviewed literature, this section presents the theoretical framework guiding the investigation. The framework proposes a conceptual five-level AI literacy competency model integrated with the three paradigms of AI in education, providing a structured approach to understanding and developing educator AI literacy. As a conceptual framework, it synthesizes existing literature and empirical observations; future research should subject it to psychometric validation through confirmatory factor analysis.

3.1. Five-level AI literacy competency model

The proposed framework identifies five hierarchically organized levels of AI literacy competency, each building upon preceding levels while adding distinctive capabilities. The levels progress from foundational awareness through sophisticated ethical reasoning, reflecting developmental trajectories observed in related domains of professional competence.

Level 1: Awareness. At the foundational level, educators develop recognition of AI technologies and their presence in everyday contexts. Competencies include identifying AI applications in common tools and services, understanding basic AI concepts (machine learning, algorithms, data), and recognizing the distinction between AI and non-AI technologies. Teachers at this level can explain to students what AI is and identify its uses in their daily lives.

Level 2: Application. Building upon awareness, the application level involves the functional use of AI tools for educational purposes. Competencies include operating AI-powered educational services, integrating AI tools into lesson planning and instruction, and managing AI-assisted workflows. Teachers at this level effectively employ AI services to enhance their practice while students use AI tools under teacher guidance for learning activities.

Level 3: Evaluation. The evaluation level develops critical assessment capabilities regarding AI outputs and implications. Competencies include assessing AI-generated content for accuracy and appropriateness, identifying AI limitations and potential biases, comparing AI tools to select appropriate options for specific needs, and evaluating claims about AI capabilities. Teachers at this level model critical evaluation for students and design activities requiring evaluative reasoning about AI.

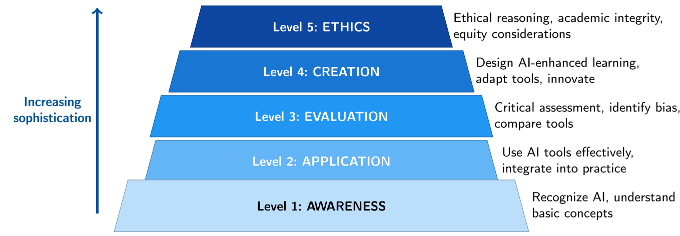

Fig. 2. Five-level AI literacy framework visualized as a developmental pyramid. Each level builds upon preceding competencies, with ethical reasoning positioned as the most sophisticated capability requiring a foundation in awareness, application, evaluation, and creation.

Level 4: Creation. At the creation level, educators develop capabilities for generating novel applications of AI in educational contexts. Competencies include designing AI-enhanced learning experiences, adapting AI tools for specific curricular purposes, developing prompts and configurations that optimize AI performance for educational goals, and contributing to resource development for AI integration. Teachers at this level innovate with AI rather than merely consuming existing applications.

Level 5: Ethics. The highest level encompasses sophisticated ethical reasoning about AI in education. Competencies include analyzing ethical implications of AI integration decisions, addressing academic integrity in AI-enhanced contexts, considering equity and access issues, navigating data privacy and consent requirements, and fostering student ethical reasoning about AI. Teachers at this level lead conversations about responsible AI use and model ethical decision-making.

Fig. 2 visualizes the five-level framework as a developmental pyramid, illustrating the progressive building of competencies.

The framework aligns with and extends existing conceptualizations. Levels 1–2 correspond to Ng et al.'s (2021) "knowing/understanding" and "using/applying" categories. Level 3 maps to "evaluating" while Level 4 encompasses "creating". The separation of ethics as a distinct highest level, rather than an embedded dimension, reflects the framework's emphasis on ethical reasoning as a sophisticated capability requiring deliberate development. This positioning aligns with Chiu et al.'s (2024) emphasis on self-reflection and Chee et al.'s (2025) identification of ethical competencies as advanced outcomes.

3.2. Three paradigms of AI integration in education

The five-level competency model connects to Ouyang and Jiao's (2021) three paradigms of AI in education, which characterize different relationships between AI systems, teachers, and learners.

AI-directed learning. In this paradigm, AI systems assume primary instructional roles, directing learning processes while teachers facilitate and monitor. Intelligent tutoring systems, adaptive learning platforms, and AI-driven assessment systems exemplify this paradigm. Teachers require competencies at Levels 1–2 (awareness and application) to effectively deploy and oversee AI-directed systems, along with Level 3 (evaluation) competencies to assess system effectiveness and appropriateness.

AI-supported learning. This paradigm positions AI as a collaborative tool augmenting human capabilities without displacing teacher or student agency. AI writing assistants, research tools, and productivity applications exemplify this paradigm. Effective engagement requires competencies across Levels 2–4, with teachers and students using AI tools (application), critically assessing outputs (evaluation), and adapting tools for specific purposes (creation).

AI-empowered learning. In this paradigm, AI enables transformative learning experiences exceeding what would be possible without AI assistance, with learners exercising agency over AI systems. Creative AI applications, exploratory simulations, and student-directed AI projects

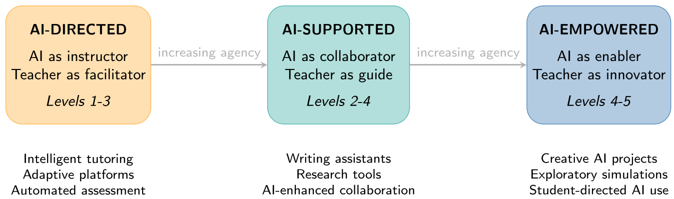

Fig. 3. Three paradigms of AI in education (Ouyang & Jiao, 2021) mapped to the five-level AI literacy framework. Progression across paradigms reflects inArtificial Intelligencecreasing human agency over AI systems, requiring correspondingly advanced competencies.

exemplify this paradigm. Full realization requires competencies at Levels 4-5, with teachers designing innovative AI-enhanced experiences (creation) while attending to ethical implications (ethics).

Fig. 3 illustrates the three paradigms and their relationship to the five-level competency framework.

3.3. Mapping framework to educational practice

The integrated framework provides guidance for curriculum design, teacher development, and assessment. For curriculum designers, the framework suggests a progression from AI-directed applications in early educational stages toward AI-empowered approaches as students develop sophistication. For teachers, the framework identifies differentiated competency expectations based on career stage and integration approach. Novice teachers might initially develop Levels 1–2 competencies, while experienced teachers expand into Levels 3–5. For students, the framework informs age-appropriate AI literacy objectives, with younger learners focusing on awareness and guided application while older students develop evaluative and creative capabilities.

The digital storytelling approach discussed in the literature review illustrates how pedagogical methods can address multiple framework levels simultaneously. Creating AI-enhanced digital stories requires awareness of AI capabilities (Level 1), application of AI tools (Level 2), evaluation of AI-generated content (Level 3), creative adaptation of AI for narrative purposes (Level 4), and consideration of ethical implications such as authorship and authenticity (Level 5). Such integrated approaches may prove more effective than isolated competency instruction.

4. Methodology

4.1. Research design

This study employs a sequential explanatory mixed-methods design (Creswell & Plano Clark, 2018; Fetters et al., 2013) integrating four complementary studies. The multi-study approach enables triangulation across data sources while capturing both breadth and depth in understanding AI literacy among Ukrainian secondary educators. The sequential design allows earlier studies to inform later investigations, with each study addressing specific research questions while contributing to an integrated understanding.

4.2. Study components

The first study analyzes data from a national survey conducted by ZN.UA in June 2023, examining AI awareness and attitudes among the Ukrainian general population ($n = 2018$). The survey employed stratified random sampling to achieve demographic representativeness. Items relevant to this investigation assess familiarity with AI concepts and usage of AI chatbots. This study provides baseline data on the broader context within which educator AI literacy develops. As this constitutes secondary data analysis of a publicly available survey not designed by the present authors, the instrument and sampling decisions were predetermined. Our analysis focuses on items directly relevant to AI awareness and chatbot usage.

The second study administered a targeted survey to educators attending the Artificial Intelligence in Science Education (AISE) 2024 conference and through online distribution ($n = 116$). The survey, conducted in March–April 2024, employed purposive sampling to reach educators with a demonstrated interest in educational technology. The instrument comprised nine items: four open-ended questions examining AI service recommendations and usage examples, and five closed-ended questions assessing frequency, attitudes, and demographics. Open-ended items asked respondents to: (a) recommend AI services they use in education, (b) describe specific examples of AI integration in their practice, (c) identify barriers to AI adoption, and (d) suggest professional development needs. Closed-ended items used 5-point Likert scales (1 = strongly disagree to 5 = strongly agree) to assess the frequency of AI use, perceived usefulness, and attitudes toward AI in education, alongside categorical demographic items (subject area, years of experience, school type).

The third study evaluated a professional development intervention titled “Artificial Intelligence: Enhancing the Digital Toolbox of Modern Educators”, delivered as a masterclass on April 25, 2024, through the Prometheus MOOC platform. The masterclass was structured as a multi-session online program covering four modules: (1) introduction to AI concepts and terminology, (2) practical AI tools for educators (including ChatGPT, specialized services, and EOSC resources), (3) critical evaluation of AI outputs and pedagogical integration strategies, and (4) ethical considerations in AI-enhanced education. Delivery combined synchronous webinar sessions with asynchronous self-paced activities on the Prometheus platform. The attrition from 1130 registrations to 450 active participants to 36 completing both assessments reflects patterns typical of MOOC platforms, where completion rates commonly range from 5% to 15% (Jordan, 2015), compounded by the practical constraints of wartime education in Ukraine. The pre-post assessment design measured four competency dimensions aligned with the theoretical framework.

The fourth study conducted a systematic analysis of AI services available through the European Open Science Cloud Marketplace. The analysis was performed by the first and third authors, building on prior work mapping EOSC services for educational use (Marienko et al., 2023; Shyshkina et al., 2024). Services were filtered according to inclusion criteria (AI/ML functionality, educational applicability, accessibility) and exclusion criteria (purely research-oriented without educational potential, inaccessible without institutional affiliation). The search employed keyword combinations including “artificial intelligence”, “machine learning”, “deep learning”, “neural network”, and “classification” within the EOSC Marketplace catalog. Each candidate service was independently assessed by two researchers against the inclusion criteria, with disagreements resolved through discussion. Because the task involved binary inclusion/exclusion decisions on a small, enumerable set of candidate services against predefined operationalized criteria – rather than open-ended qualitative coding – a formal inter-rater reliability coefficient (e.g., Cohen’s κ) was not computed. Reliability was instead ensured through three complementary strategies: (a) predefined inclusion and exclusion criteria established before assessment began, (b) independent classification by two researchers, and (c) consensus discussion resolving all disagreements, resulting in full agreement on the final set of 22 included services. Identified services were mapped to secondary school subjects based on domain alignment, producing a curated catalog for educator reference.

Table 2 summarizes the multi-study research design.

The four studies draw upon distinct, non-overlapping populations. Study 1 surveyed the Ukrainian general public through a nationally representative panel. Study 2 targeted practicing educators via the AISE 2024 conference and professional networks. Study 3 recruited participants through the Prometheus MOOC platform, which serves a broader audience than the specialized AISE conference. Study 4 involved no

Table 2
Summary of multi-study research design.

Study	Sample	n	Method	Timing
Study 1	General public	2018	National survey	June 2023
Study 2	Educators	116	Targeted survey	April 2024
Study 3	Masterclass participants	1130 (36 pre-post)	Intervention evaluation	April 2024
Study 4	EOSC services	–	Systematic analysis	2024–2025

human participants, analyzing publicly available EOSC service catalogs. While some overlap between Studies 2 and 3 cannot be definitively excluded, the different recruitment channels and timing minimize this possibility.

4.3. Instruments

Survey instruments were developed in Ukrainian and subjected to iterative pilot testing with practicing educators. The educator survey (Study 2) was designed to capture both quantitative usage patterns and qualitative insights through open-ended responses. The pre-post assessment (Study 3) measured competence across four dimensions: AI service recognition, practical application, critical evaluation, and ethical awareness. Each dimension was assessed through a combination of knowledge-based items (e.g., identifying AI services by name and function) and scenario-based items (e.g., evaluating the appropriateness of AI tool selection for a given pedagogical task). AI service recognition included items requiring participants to name AI services and describe their functions. Practical application items assessed participants' ability to describe concrete integration scenarios. Critical evaluation items presented AI-generated outputs for accuracy and bias assessment. Ethical awareness items posed dilemmas regarding data privacy, academic integrity, and equity in AI-enhanced classrooms. Responses were scored on a rubric from 0 (no competence demonstrated) to 4 (advanced competence), and dimension scores were computed as a percentage of the maximum possible score. Scoring rubrics ensured consistent evaluation, with inter-rater reliability established through dual coding of initial responses. Inter-rater agreement, assessed on 20% of randomly selected responses coded independently by two researchers, yielded Cohen's $\kappa = 0.81$, indicating substantial agreement (Cohen, 1960). Discrepancies were resolved through consensus discussion. Translated excerpts of both instruments are provided in Appendix A.

4.4. Data analysis

Quantitative data were analyzed using descriptive statistics including frequencies, percentages, and measures of central tendency. For Study 1, descriptive statistics (frequencies and percentages) characterized AI awareness and chatbot usage patterns. For Study 2, descriptive statistics summarized closed-ended responses, while open-ended responses underwent qualitative analysis (described below).

For Study 3, pre-post comparisons employed paired-samples t-tests with a significance level of $\alpha = 0.05$. Effect sizes were calculated using Cohen's d, interpreted according to conventional benchmarks: small ($d = 0.2$), medium ($d = 0.5$), and large ($d = 0.8$) (Cohen, 1988). Ninety-five percent confidence intervals were computed for all mean differences. The composite score was calculated as the unweighted mean of the four dimension scores. All statistical analyses were conducted using Python (SciPy 1.11).

Qualitative data from open-ended survey responses underwent thematic analysis following Braun and Clarke's (2006) six-phase approach: (1) familiarization with the data through repeated reading of translated responses, (2) generating initial codes systematically across the dataset, (3) searching for themes by collating codes into potential thematic groups, (4) reviewing themes against coded extracts and the full dataset, (5) defining and naming themes, and (6) producing the final report. Initial coding was conducted independently by the first and third authors, with inter-coder agreement assessed on a random 25% subsample before finalizing the codebook. Integration across studies employed joint display techniques to identify convergent and divergent findings.

Cross-study integration followed the building approach described by Fetters et al. (2013), where Study 1 findings informed the design of Studies 2–3, and Studies 2–3 findings contextualized the Study 4 service mapping. Joint displays were used to compare quantitative patterns (e.g., low specialized service awareness in Study 2) with qualitative themes (e.g., ChatGPT dominance in educator recommendations) to identify convergent and divergent findings across data sources.

4.5. Ethical considerations

All studies received ethical approval from the Institute for Digitalisation of Education, NAES of Ukraine. Participation was voluntary with informed consent obtained. Survey responses were collected anonymously. Data were stored securely according to Ukrainian data protection requirements and GDPR principles for European collaborations.

Fig. 4 presents the research timeline illustrating the sequential relationships among studies.

5. Results

This section presents findings from the four studies comprising the multi-study investigation. Results are organized by study component, with integrative analysis connecting findings across data sources.

5.1. Study 1: National AI awareness

Analysis of the ZN.UA national survey ($n = 2018$) revealed substantial variation in AI awareness among the Ukrainian general population. As shown in Table 3, approximately one-third of respondents (33.9%) indicated they did not know what artificial intelligence is, while 24.0% reported knowing well what AI is, and 42.0% indicated they roughly imagine what it is.

Regarding AI chatbot usage, the majority of respondents (64.1%) reported not using AI chatbots, indicating that while awareness of AI as a concept exists for most Ukrainians, practical engagement with AI tools remains limited among the general population.

5.2. Study 2: Educator AI service usage

The educator survey ($n = 116$) revealed higher levels of AI engagement compared to the general population. A substantial majority (84%)

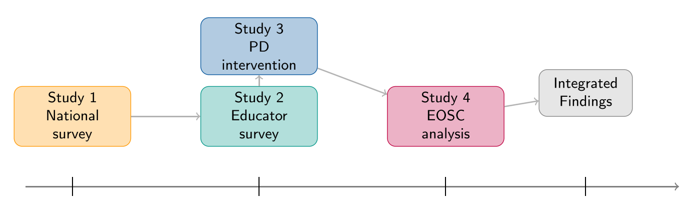

Fig. 4. Research timeline illustrating the sequential relationships among the four studies. Earlier studies inform subsequent investigations, with findings integrated across all components.

Table 3
AI awareness among the Ukrainian general population (Study 1, $n = 2018$).

Level of AI understanding	Percentage	n
Know well what AI is	24.0%	484
Roughly imagine what AI is	42.0%	847
Do not know what AI is	33.9%	684
No response	0.1%	3
Total	**100%**	**2018**

Table 4
AI usage patterns among educators (Study 2, $n = 116$).

AI usage pattern	Percentage	n
Professional development only	34%	39
Both professional development and teaching	35%	41
Teaching/educational process only	13%	15
Do not use AI for educational purposes	16%	19
No response	2%	2
Total	**100%**	**116**

reported using AI in some capacity, with the largest group (35%) using AI for both professional development and classroom instruction. Notably, 16% of respondents indicated they do not use AI for educational purposes at all (Table 4).

Analysis of the open-ended question asking educators to recommend AI services revealed limited awareness of specialized alternatives. Among respondents, 38% (44 of 116) skipped this question entirely, suggesting an inability to identify AI services. Among those who responded ($n = 72$), ChatGPT dominated recommendations at 44%. Only 11% (8 respondents) could recommend specialized AI services, while 7% named non-AI services, indicating conceptual confusion.

When asked whether AI services would be useful in education, 72% responded affirmatively without qualification. Importantly, 28% indicated that AI services would be useful but emphasized the need for appropriate methodologies to guide implementation. No respondents indicated that AI services would not be useful.

It should be noted that the Study 2 sample was drawn from the AISE 2024 conference and professional networks, representing technology-engaged educators rather than the broader teaching population. The high AI adoption rate (84%) likely reflects this self-selection and should be interpreted as an aspirational baseline rather than a nationally representative estimate.

5.3. Study 3: Professional development evaluation

The masterclass attracted 1130 registrations with 450 active participants. Pre-post assessment data were available for 36 participants who completed both assessments. The intervention produced a 24% overall increase in AI utilization competence. Table 5 presents changes by competency dimension.

The largest gains occurred in practical application (+27%) and critical evaluation (+26%), dimensions corresponding to Levels 2 and 3 of the theoretical framework. Post-intervention, participants could identify an average of 4.2 distinct AI services, compared to 1.8 at pre-assessment.

Thematic analysis of open-ended responses from Study 2 identified four principal themes through systematic coding. Initial open coding generated 47 codes, which were iteratively consolidated into four themes: (1) *ChatGPT dominance and limited tool awareness* (23 codes; e.g., “I only use ChatGPT – I don’t know what else is available for biology lessons”), (2) *Need for structured methodological guidance* (12 codes; e.g., “AI tools are interesting, but I need a clear methodology for integrating them into my subject curriculum”), (3) *Ethical concerns and academic integrity* (7 codes; e.g., “My biggest worry is that students will use AI to complete assignments without learning the material”), and (4) *Infrastructure and access barriers* (5 codes; e.g., “Many schools in our region have unstable internet, making cloud-based AI tools impractical”).

The small subsample completing both assessments ($n = 36$) precluded meaningful analysis of potential moderating variables such as teaching experience, subject area, or prior technology use. This represents a limitation of the current study; future research with larger samples should examine whether professional development effects vary across educator subgroups.

5.4. Study 4: EOSC service mapping

Systematic analysis identified 22 EOSC AI services applicable to secondary education. The mapping was performed by the first and third authors through systematic searching of the EOSC Marketplace (https://marketplace.eosc-portal.eu) using AI- and ML-related keywords, followed by an independent assessment of each candidate service against educational applicability criteria (Marienko et al., 2023; Shyshkina et al., 2024), achieving full inter-rater consensus on the final included set. Of the 22 identified services, biology and geography accounted for the largest share, reflecting the European research infrastructure’s emphasis on environmental and earth sciences. Services were mapped to school subjects based on domain alignment. Table 6 presents the resulting taxonomy.

5.5. Integrated analysis

Cross-study integration reveals a coherent pattern: high overall AI adoption among educators (84%) coexists with limited awareness of specialized services (11%) and heavy reliance on ChatGPT (44%). The professional development intervention provides preliminary evidence that this situation is amenable to change, with 24% competence improvement following targeted training. The explicit demand for methodological guidance (28% of educators) highlights that technical tool exposure alone is insufficient.

Table 7 summarizes key statistics across all studies.

6. Discussion

The findings of this study address five interconnected research questions that together illuminate the current state of AI literacy among Ukrainian educators.

Regarding the current state of AI awareness and adoption (RQ1), the findings reveal a bifurcated landscape. Among the general population, substantial unfamiliarity persists, with one-third unable to identify what AI is. In contrast, 84% of surveyed educators report AI use. However, high adoption rates mask qualitative limitations: 44% of recommendations consisted solely of ChatGPT, while only 11% could identify specialized alternatives. This pattern of “surface-level” AI literacy has been observed in other contexts (Nagae et al., 2025; Nguyen & Pham, 2025).

Table 5
Pre-post competence changes by dimension with inferential statistics (Study 3, $n = 36$).

Competency dimension	Pre $M(SD)$	Post $M(SD)$	Δ [95% CI]	$t(35)$	p	Cohen’s d
AI service recognition	58(18)	81(14)	+23 [17.5, 28.5]	8.41	<.001	1.40
Practical application	45(20)	72(16)	+27 [20.8, 33.2]	8.85	<.001	1.48
Critical evaluation	42(19)	68(15)	+26 [20.1, 31.9]	8.97	<.001	1.49
Ethical awareness	67(15)	85(11)	+18 [13.4, 22.6]	8.00	<.001	1.33
Overall composite	**53(16)**	**77(12)**	**+24 [19.1, 28.9]**	**10.00**	**<.001**	**1.67**

Note. Scores are expressed as percentages of the maximum rubric score. Effect sizes were computed as Cohen’s $d_z = \bar{D}/s_D$ for paired observations (Cohen, 1988). All effects are large by conventional criteria ($d > 0.80$). 95% CIs are for the mean pre-post difference.

Table 6
EOSC AI services mapped to secondary school subjects (22 services across 6 subject areas).

Subject area	EOSC services	Educational applications
Biology (7)	AI-GeoSpecies, FASTCAT-Cloud, AI4Pheno, LifeWatch ERIC, BioDT, PLANTdataHUB, GBIF hosted portals	Species identification; phenological observation; biodiversity analysis; ecological modeling; plant data exploration
Geography (6)	EOSC EO Pillar, Copernicus Data Space, WEkEO, GEOSS Portal, D4Science spatial services, openEO	Spatial data analysis; climate visualization; land use mapping; Earth observation
Chemistry (3)	OpenBioML, NOMAD, European Chemistry Thesaurus	Structure visualization; reaction prediction; materials data exploration
Physics (3)	Zenodo ML datasets, ESCAPE data lake, Virtual Observatory services	Physical phenomenon modeling; data visualization; astronomical data analysis
Mathematics (3)	EGI Notebooks, AI4EOSC inference, DEEP-Hybrid-DataCloud	Data analysis projects; probability modeling; cloud-based computation

Table 7
Summary of key statistics across all studies.

Metric	Value	Source
General AI awareness gap	33.9%	Don't know what AI is (Study 1)
Chatbot non-usage	64.1%	Not using AI chatbots (Study 1)
Educator AI adoption	84%	Using AI in some capacity (Study 2)
Specialized service awareness	11%	Can name specialized services (Study 2)
ChatGPT dominance	44%	Recommend only ChatGPT (Study 2)
Methodology demand	28%	Request methodological guidance (Study 2)
Training effectiveness	24%	Competence improvement (Study 3)

The five-level competency framework (RQ2) provides a structured lens for interpretation. Survey data suggest most educators operate at Levels 1-2, with limited capacity for critical evaluation (Level 3), creative integration (Level 4), or sophisticated ethical reasoning (Level 5). The professional development intervention suggests that progression through these levels may be achievable through targeted training.

The systematic analysis of EOSC services (RQ3) identified 22 applicable resources, with particular strengths in biology and geography. This finding responds to the need for specialized alternatives, demonstrating that European research infrastructure offers educational resources largely unexploited in secondary education.

Concerning professional development effectiveness (RQ4), the 24% competence improvement provides preliminary, proof-of-concept evidence that targeted interventions can enhance AI literacy. The explicit demand for methodological guidance (28%) carries important implications for professional development design: technical training alone may be insufficient without frameworks for pedagogical integration.

The ethical dimension (RQ5) reveals nuanced patterns. The dominance of ChatGPT raises concerns about over-reliance on a single commercial platform. Notably, self-reported perceived ethical awareness showed the highest baseline scores (67%) and smallest gains (+18%), suggesting educators may already possess ethical awareness even if lacking technical competencies. However, self-report measures of ethical awareness may be subject to social desirability bias, and actual ethical reasoning capacity in practice may differ from perceived competence.

These findings align with broader patterns in the literature. The combination of high general AI awareness with limited specialized knowledge mirrors results from other contexts. Chen et al. (2025), surveying 1454 teachers in the U.S., similarly found widespread engagement alongside significant variation in sophistication. Kim (2025) observed comparable ChatGPT dominance among K-12 educators, suggesting this convergence reflects broader patterns requiring proactive attention in AI literacy education.

6.1. Integration with educational theory

The proposed five-level AI literacy framework can be situated within established educational theories that provide complementary lenses for understanding competency development. From a *constructivist* perspective (Piaget & Inhelder, 2000; Vygotsky, 1978), the framework's hierarchical progression from awareness through creation reflects the active construction of knowledge through increasingly sophisticated engagement with AI technologies. Educators do not passively receive AI literacy; rather, they construct understanding through interaction with tools, reflection on practice, and social negotiation of meaning with colleagues. The zone of proximal development concept (Vygotsky, 1978) suggests that professional development is most effective when it targets competencies just beyond educators' current capabilities – consistent with the observed pattern where the largest gains occurred in practical application and critical evaluation (Levels 2–3), the zones immediately above most participants' baseline.

Connectivism (Siemens, 2005) offers a particularly relevant theoretical lens for AI literacy in the digital age. Siemens argues that learning in networked environments involves the capacity to identify, evaluate, and connect diverse information sources – competencies closely mirrored in the framework's evaluation and creation levels. The finding that educators overwhelmingly converged on ChatGPT as their sole AI recommendation illustrates a failure of connectivist learning: participants had not developed the networked knowledge structures necessary to identify and leverage diverse AI resources. The professional development intervention, by exposing educators to 22 EOSC services alongside general-purpose tools, aimed to foster precisely this networked awareness.

The *Technological Pedagogical Content Knowledge* (TPACK) framework (Mishra & Koehler, 2006) and its AI-specific extension, Intelligent-TPACK (Balta, 2024), provide a lens for understanding how AI competencies intersect with pedagogical and content knowledge. The EOSC service mapping (Study 4) illustrates this intersection: effectively integrating AI-GeoSpecies into a biology lesson requires not only AI tool knowledge (technological) but also an understanding of biodiversity concepts (content) and inquiry-based pedagogy (pedagogical). The five-level framework extends TPACK by articulating the developmental trajectory through which educators build this integrated knowledge.

It is important to note that the proposed framework is *conceptual* rather than empirically validated through psychometric methods. While the framework is grounded in existing literature and consistent with the empirical patterns observed in this study, future research should subject it to confirmatory factor analysis to establish construct validity, examine measurement invariance across educator populations, and investigate the hypothesized hierarchical structure through structural equation modeling.

6.2. Educational innovation and teacher role transformation

The findings illuminate a process of educational innovation that extends beyond simple technology adoption. Drawing on sociotechnical systems theory (Geels, 2004), AI integration in education can be understood as a transition involving simultaneous changes in technology, professional practices, institutional structures, and cultural norms. The gap between high AI adoption (84%) and limited specialized awareness (11%) reflects a system in early transition: the technological artifact (ChatGPT) has been adopted, but the broader sociotechnical reconfiguration – encompassing pedagogical practices, assessment approaches, and institutional policies – remains nascent.

This transition implies a fundamental transformation in the teacher's role. In the AI-directed paradigm, teachers shift from knowledge transmitters to facilitators of AI-mediated learning, requiring new competencies in system evaluation and student monitoring. In the AI-empowered paradigm, teachers become learning designers who orchestrate AI resources to enable experiences otherwise impossible. The professional development intervention's focus on progressing educators beyond awareness toward application and evaluation represents an initial step in supporting this role transformation.

The crisis context adds a distinctive dimension to this innovation process. The concept of "crisis-driven innovation acceleration" describes how external disruptions can compress innovation timelines by removing institutional inertia and creating urgency for change (Kaplia et al., 2024). Ukrainian educators' rapid adoption of AI tools, occurring alongside ongoing adaptation to distance and blended learning during wartime, exemplifies this acceleration. However, crisis-driven adoption may prioritize speed over depth, potentially explaining the observed pattern of widespread but shallow AI engagement.

6.3. Implications for pedagogical data analytics

The competency assessment data generated through the professional development evaluation carries implications for pedagogical data analytics approaches to teacher training. The four-dimensional assessment framework (AI service recognition, practical application, critical evaluation, ethical awareness) provides granular data that could inform personalized professional development pathways. For instance, educators scoring high on ethical awareness but low on practical application – a profile observed in the pre-assessment data – could be directed toward hands-on workshop modules rather than ethics-focused content.

At the institutional level, aggregated competency profiles could guide resource allocation decisions. School districts where educators cluster at Levels 1–2 of the framework might prioritize basic tool training, while those with educators operating at Levels 3–4 could invest in advanced creation and innovation workshops. The EOSC service mapping further supports data-informed decision-making by providing subject-specific AI tool recommendations aligned with curricular needs.

These pedagogical data analytics applications extend the utility of AI literacy assessment beyond summative evaluation toward formative, adaptive professional development design. Future implementations could leverage learning analytics dashboards to track competency development trajectories and identify educators requiring additional support in specific dimensions.

6.4. The Ukrainian context in comparative perspective

The Ukrainian context introduces distinctive considerations that merit extended analysis. Since February 2022, the ongoing war has necessitated rapid digital transformation (Kaplia et al., 2024; Kuzheliev et al., 2023). The high motivation for AI training observed (91% interest in further professional development) may reflect both general enthusiasm and recognition that AI tools could help manage the increased demands of wartime education. The Prometheus platform has played a significant role in supporting educator professional development during the crisis.

Comparing the 84% AI adoption rate among surveyed Ukrainian educators with findings from stable contexts reveals an apparent paradox: adoption rates in a crisis-affected system match or exceed those in well-resourced settings. Chen et al. (2025) reported variable but generally lower rates among U.S. urban educators, while Granström and Oppi (2025) found moderate adoption among Estonian teachers. However, the Ukrainian sample's self-selection bias (AISE conference participants) complicates direct comparison. The high adoption rate likely reflects a combination of sampling bias and genuine crisis-driven acceleration, where wartime disruption lowered barriers to experimentation with new technologies.

The 60% attrition from active participation to pre-post assessment completion (450 to 36) requires contextualization. While this rate appears high, it is consistent with typical MOOC completion patterns: meta-analyses report average MOOC completion rates of 5–15% (Jordan, 2015), and the Ukrainian wartime context introduces additional barriers including power outages, displacement, and competing professional demands. The 36 completers may represent particularly motivated educators, introducing potential survivor bias that inflates estimated intervention effects.

The Ukrainian experience suggests both opportunities and limitations for transferability. The crisis-driven innovation acceleration model may inform educational systems facing other forms of disruption (e.g., pandemic-related transitions, rapid policy changes). However, specific findings – including adoption rates, tool preferences, and professional development effects – are shaped by Ukrainian institutional, cultural, and wartime factors that limit direct generalization to stable educational contexts.

6.5. Limitations

Several limitations warrant detailed acknowledgment.

Self-selection bias. Studies 2 and 3 employed convenience and purposive sampling, recruiting participants through technology-focused venues (AISE conference, Prometheus platform). This self-selection likely inflates estimates of AI adoption, awareness, and training responsiveness relative to the broader Ukrainian educator population. Results should be interpreted as characterizing technology-engaged educators rather than the profession as a whole.

Absence of control group. The pre-post design of Study 3 lacks a comparison group, precluding causal attribution of competence gains solely to the intervention. Maturation effects, testing effects (familiarity with assessment format), and concurrent exposure to AI through other channels represent alternative explanations for observed improvements. Future research should employ randomized controlled or quasi-experimental designs with waitlist control groups.

Social desirability bias. Self-report measures of AI competence, particularly ethical awareness, may be influenced by participants' desire to present themselves favorably. The high baseline ethical awareness scores (67%) and the finding that ethical awareness showed the smallest gains may partly reflect ceiling effects compounded by social desirability rather than genuine advanced ethical reasoning.

Small analytical subsample. The reduction from 1130 registrations to 36 paired observations limits statistical power and generalizability. The small sample precluded analysis of moderating variables and may have introduced survivor bias, as completers likely differ systematically from non-completers in motivation, access, and baseline competence.

Attrition and survivor bias. The 60% attrition from active participation (450) to pre-post completion (36) raises concerns about the representativeness of the analytical sample. Completers may have been more motivated, more digitally skilled, or less affected by wartime disruptions than non-completers, potentially inflating estimated intervention effects.

Wartime context. The ongoing conflict in Ukraine introduces unique contextual factors – including displacement, infrastructure instability, and heightened stress – that shape educator engagement with professional development. While this context is intrinsically valuable for understanding technology adoption during a crisis, it limits the transferability of specific findings to stable educational systems.

Framework validation status. The five-level AI literacy framework is proposed as a conceptual model synthesized from existing literature and consistent with empirical observations. It has not been subjected to formal psychometric validation (e.g., confirmatory factor analysis, measurement invariance testing). The hierarchical structure and level boundaries require empirical verification through future research.

EOSC mapping reliability. The Study 4 service mapping did not employ a formal inter-rater reliability statistic (e.g., Cohen's κ), as the binary classification of a small set of 22 services against predefined criteria differs from open-ended qualitative coding for which such coefficients are most informative. Full consensus was achieved through independent assessment and discussion; however, future mapping exercises covering larger or evolving service catalogs should calculate and report formal inter-rater agreement coefficients.

Additionally, the rapidly evolving AI landscape means that specific tool recommendations may become outdated.

6.6. Implications for practice and policy

These findings carry implications for multiple stakeholders. For professional development providers, results underscore the importance of moving beyond awareness-level training to address application, evaluation, and ethical dimensions. Interventions should expose educators to diverse AI tools rather than reinforcing reliance on single platforms. For policymakers, findings highlight the gap between general AI adoption and the sophistication required for effective integration. Policy frameworks should support sustained professional development and address infrastructure requirements for accessing specialized services. For researchers, the five-level framework offers a structured approach to conceptualizing AI literacy that future studies can adapt and validate, while the Ukrainian context provides insights relevant to educational systems facing disruption.

7. Conclusion

This multi-study investigation examined AI literacy among Ukrainian secondary educators through a sequential explanatory mixed-methods design. The findings illuminate both the current state and developmental potential of AI literacy in secondary education.

The study makes four principal contributions. First, it provides empirical evidence characterizing AI literacy patterns: while 84% of educators use AI, only 11% can identify specialized services, indicating widespread but shallow engagement. Second, it proposes a conceptual five-level AI literacy framework integrated with three paradigms of AI in education. Third, the professional development evaluation provides preliminary, proof-of-concept evidence of 24% competence improvement following targeted training. Fourth, the EOSC service mapping provides practical guidance for educators seeking specialized alternatives.

These findings yield recommendations for multiple stakeholders. Professional development programs should progress beyond tool introduction to address critical evaluation, creative application, and ethical reasoning, while exposing educators to diverse AI services. Educational policymakers should recognize AI literacy as requiring sustained attention, with support for infrastructure enabling specialized service access to expand pedagogical potential. Secondary educators themselves are encouraged to explore specialized AI services beyond ChatGPT, as the EOSC platform offers domain-specific tools that may better serve curricular objectives.

Several directions merit future investigation. Longitudinal research tracking AI literacy development would illuminate developmental trajectories. Comparative studies across educational systems could identify contextual factors shaping AI literacy patterns. Research examining student AI literacy development, particularly how teacher competencies influence student outcomes, would extend understanding beyond the educator focus of this study. Critically, the five-level framework requires formal psychometric validation through confirmatory factor analysis and measurement invariance testing across diverse educator populations. The professional development component should be replicated using randomized controlled trial designs with larger samples and active control conditions to establish causal effects. Future masterclass implementations should prioritize complete data collection to enable moderation analyses examining differential effects by teaching experience, subject area, and prior technology use.

As artificial intelligence increasingly permeates educational environments, the capacity of teachers to navigate this landscape critically and creatively becomes essential. This study reveals that while Ukrainian educators have embraced AI tools, the depth and breadth of their AI literacy require continued development. The Ukrainian experience, marked by both wartime challenges and educator resilience, offers insights relevant to educational systems worldwide confronting the imperative to prepare teachers for an AI-enhanced future.

CRediT authorship contribution statement

Maiia V. Marienko: Writing–review & editing, Writing–original draft, Methodology, Investigation, Conceptualization. **Oksana M. Markova:** Writing–review & editing, Visualization. **Serhiy O. Semerikov:** Writing–review & editing, Supervision, Resources, Project administration, Methodology, Formal analysis, Conceptualization.

Ethical statement

The study was conducted in accordance with the Declaration of Helsinki. The research protocol was approved by the Ethics Committee of the Institute for Digitalisation of Education of the NAES of Ukraine (Protocol No. 04-24, dated March 15, 2024). Informed consent was obtained from all individual participants involved in the study. All participants were informed of the study's purpose, the voluntary nature of their participation, and their right to withdraw at any time. To protect participant privacy, particularly given the sensitive context of wartime education, all survey data were collected anonymously, and personal identifiers were removed prior to analysis.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Claude 4.5 Opus (Anthropic) in order to enhance the readability of the manuscript text. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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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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Appendix A. Survey instrument excerpts

A.1. Study 2: Educator AI service usage survey (translated from Ukrainian)

Open-ended items:

1. What artificial intelligence services can you recommend for use in education? Please list specific tools you have used or are aware of.
2. Describe a specific example of how you have integrated an AI service into your educational practice (lesson planning, instruction, or assessment).

3. What barriers or challenges have you encountered when attempting to use AI services in your professional work?
4. What professional development support would help you more effectively integrate AI into your teaching?

Closed-ended items (5-point Likert scale: 1 = strongly disagree to 5 = strongly agree):

5. I regularly use AI services in my professional educational activities.
6. AI services are useful for improving the quality of education.
7. I feel confident in my ability to evaluate AI-generated content for accuracy and appropriateness.

Demographic items:

8. Primary subject area taught (categorical).
9. Years of teaching experience (categorical: <5, 5–10, 11–20, >20).

A.2. Study 3: Pre-post AI competence assessment (selected items, translated from Ukrainian)

AI service recognition (sample item):

List as many AI services applicable to education as you can identify. For each, briefly describe its primary function (Scored 0–4 based on the number and accuracy of services identified).

Practical application (sample item):

You are preparing a biology lesson on biodiversity in your local ecosystem. Describe how you would use an AI service to enhance student learning in this lesson. Identify the specific AI tool you would use and explain your pedagogical rationale (Scored 0–4 on specificity, pedagogical alignment, and feasibility).

Critical evaluation (sample item):

A colleague shares an AI-generated lesson plan on climate change. Review the following excerpt and identify potential issues with accuracy, bias, or pedagogical appropriateness [Excerpt provided.] (Scored 0–4 on identification of issues and quality of reasoning).

Ethical awareness (sample item):

A student submits an essay that you suspect was partially generated by an AI tool. Describe how you would handle this situation, considering fairness, learning objectives, and school policy (Scored 0–4 on ethical reasoning sophistication and consideration of multiple perspectives).

Data availability

The datasets generated and/or analyzed during the current study are not publicly available due to privacy and ethical restrictions, as they contain information that could compromise the privacy of research participants. However, anonymized extracts of the data supporting the conclusions of this article are available from the corresponding author on reasonable request.Data regarding the EOSC service mapping (Study 4) are publicly available through the European Open Science Cloud Marketplace (https://marketplace.eosc-portal.eu).

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