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AI Literacy for Skills Formation under Conditions of Accelerating Artificial Intelligence

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Abstract

Progress in artificial intelligence between 2020 and 2025 driven by the generative models such as ChatGPT, Claude, Gemini, Copilot and DeepSeek impact labour markets, educational systems, and skills requirements. The notion of AI literacy as a critical competence is becoming increasingly prominent in academic and professional discourse, with a growing body of research underscoring its significance in various aspects of life. This particular literacy is especially pertinent to individuals' professional lives, as it pertains to the ability to navigate, interpret, and apply AI-related concepts and technologies in one's chosen field. The paper introduces discussion on extended frameworks of AI literacy, analyses its connection to 21st-century skills, and presents approaches for studying and cultivating AI literacy in education and the workforce. The findings demonstrate that AI literacy functions as a meta-competency underlying cognitive, creative, and socio-emotional skills, and is important for developing an innovative workforce in the AI-augmented economy.

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Introduction

The accelerating development of artificial intelligence (AI) is becoming one of the most important factors transforming contemporary economies, institutions and labour markets. It is increasingly evident from both economic literature and analyses by international institutions that the ability of entities – both individuals and organisations – to acquire and update skills is a determining factor in their adaptability within an increasingly complex technological environment. World organizations such as UNESCO, OECD, and the World Bank emphasize that AI literacy is becoming a key factor in sustainable development, which is understood not only as a technical understanding of algorithms, but primarily as the ability to think critically, ethically apply AI, assess risks, manage data, interact with algorithms, formulate queries, and interpret results. The OECD has highlighted that machine learning-based technologies are evolving into 'general-purpose technologies', whose impact extends not only to routine tasks but also to a growing array of activities that demand sophisticated forms of knowledge and cognitive abilities (OECD 2023). However, in contrast to previous automation waves, the impact of AI is not confined to the replacement of labour; it also encompasses the transformation of learning methodologies, information processing capabilities, and decision-making processes.

In this context, the concept of AI literacy, which refers to the competencies that enable individuals to function effectively in an environment saturated with artificial intelligence systems, is becoming increasingly important. A mounting body of research in the social sciences, education and management has demonstrated that AI literacy is not confined to the capacity to utilise IT tools. The dynamic nature of change signifies that the challenges associated with AI skills are not confined to technologically advanced sectors but are permeating almost all areas of professional activity. As the World Economic Forum's Future of Jobs Report 2025 emphasises, over the 2025-2030 period, AI and big data are expected to be among the fastest-growing skills (World Economic Forum 2025). This encompasses both knowledge workers and those performing operational tasks. This signifies that AI literacy is evolving into a novel component of human capital, concurrently serving as an instrumental factor in determining productivity, creativity, and the capacity to engage in public life in the context of mounting automation of communication and decision-making processes.

The primary objective of this article is to provide a comprehensive conceptual synthesis of the extant approaches to defining AI literacy, with a focus on identifying its structural components, cognitive dimensions, and pedagogical foundations. The article's objective is to elucidate the theoretical and practical linkage between the development of AI literacy and the formation of key 21st-century competencies, including critical thinking, problem-solving, digital fluency, ethical reasoning, and collaborative learning. The objective of the present study is to address conceptual inconsistencies by undertaking a comparative analysis of educational and policy frameworks. This analysis is expected to contribute to the design of informed strategies for skill development in AI-driven socio-economic environments.

Conceptual foundations of AI literacy

The definition of 'AI literacy' is a matter of some confusion and the subject of much debate. The concept of AI literacy has emerged relatively recently at the intersection of education, information science, technology and labour economics, which complicates attempts to define it precisely from the outset. The absence of a singular, recognised signification is not attributable to the insufficiency of the concept; rather, it is a consequence of technological evolution, which compels a re-evaluation of the competencies demanded to operate within a milieu characterised by machine learning systems and generative language models. The extant literature on this subject emphasises that the concept is hybrid in nature, encompassing declarative knowledge, procedural skills, critical attitudes and socio-ethical competences that are necessary for the conscious use of and interaction with AI technologies.

Notwithstanding the increasing significance of this concept, its definitions and scope continue to be the subject of controversy and disagreement in the literature. Researchers attribute this discrepancy to the absence of widely accepted terminology, as well as the partial overlap of AI literacy with other areas of expertise, including data literacy, digital literacy and computational thinking.

The most frequently cited definition originates from Long and Magerko (2020), who define AI literacy as a set of skills that enable individuals to 'understand, use, evaluate and critically interact with' artificial intelligence systems. From their perspective, the subject under discussion consists of three complementary components. Firstly, the possession of technical competencies requires an understanding of the fundamentals of machine learning models (including the generation of results, the nature of statistical predictions, and the significance of training data). Secondly, there is a necessity for critical competences, including the ability to analyse risks, errors and biases in algorithms, as well as the ability to assess the reliability of AI system results. Thirdly, the application competencies are defined as the ability to design and solve problems using AI tools in a manner appropriate to the user's objectives.

To embed AI literacy in the conceptual system of digital competences with precision, it is necessary to examine its relationship to three key constructs: data literacy, digital literacy and computational thinking. The interpenetration of these concepts forms the foundation of contemporary competence frameworks, both within educational settings and in the context of the labour economy. However, it should be noted that AI literacy cannot be considered as the mere sum of these components, given that it possesses its own specific characteristics resulting from the properties of artificial intelligence systems.

Data literacy, defined as the capacity to acquire, interpret, analyse and evaluate data, is recognised as one of the most fundamental components of AI literacy. The extant literature operates under the assumption that an absence of competence in data management and analysis constitutes a significant obstacle to the discussion of AI system comprehension. Since the functionality of these systems is contingent upon the calibre and configuration of the training data. Data literacy focuses on the analysis of data, whereas AI literacy focuses on human-AI interaction and understanding the nature of models. It can thus be concluded that data literacy is a necessary condition for achieving full AI literacy, but not a sufficient one.

Digital literacy can be defined as the ability to function in a digital environment, including technical, communication and information skills. This concept is one of the oldest and most widespread in educational and information literature. The term is frequently interpreted as 'digital literacy', the ability to utilise digital technologies in an effective and critical manner. Digital literacy is a term used to describe the ability to use information technologies in general. In contrast, the term AI literacy refers to the ability to use technologies that not only process information but also generate new representations, inferences and predictions. This suggests that AI literacy can be interpreted as a form of post-digital literacy, defined as a competence that operates in an environment where digital technologies become active participants in the cognitive process.

The term 'Computational thinking' (CT) refers to a method of problem-solving that is based on algorithmic logic, decomposition, abstraction and design (Wing J. 2006). The concept of CT has a long-standing tradition, firmly embedded in the domain of computer science education. The objective of CT is to cultivate a mode of thinking that is analogous to computational thinking. The distinction between these two concepts lies in the requirement for programming skills and advanced algorithmic thinking in the former, although these skills can be enhanced by the latter. Computational thinking focuses on the design of algorithmic solutions, while AI literacy involves the comprehension of the functionality of pre-existing machine learning systems.

Despite the prevalence of this definition, recent studies have called its validity into question, particularly considering the rapid advancements in generative models. Chiu and co-authors (2024) posit the argument that generative systems require the definition to be expanded to include a component of metacognitive competence. This refers to the ability to monitor and calibrate one's own trust in AI results (AI self-efficacy), as well as an understanding of the nature of the fluid knowledge generated by models. From this view, AI literacy encompasses not only knowledge of how the system works, but above all an awareness of its epistemic limitations — the impenetrable mechanisms of representation creation, the ephemeral nature of training data, and the internal opacity of models.

Furthermore, the evolution of multimodal and agent-based models necessitates the continual refinement of the concept of AI literacy. These systems have evolved beyond their original function as mere analytical tools; they are now becoming active participants in cognitive tasks, thereby altering the traditional relationship between the user and the technology. The prevailing view in the literature is that AI literacy also includes the ability to delegate, i.e. to design tasks that maximise the synergy between user and system actions while minimising the risk of losing control over the decision-making process.

The significance of issues pertaining to artificial intelligence competencies has been particularly emphasised in recent years as part of Stanford University's research project 'One Hundred Year Study on Artificial Intelligence' (AI100). The inaugural report of this initiative, which was published in 2016 and then in 2021 (each five years) under the title Artificial Intelligence and Life in 2030, represented a significant turning point in analyses of the impact of AI on society, institutions and education systems. This document, prepared by an interdisciplinary team of experts and updated every five years, is noteworthy for its attempt to view AI not as a set of technologies with narrow applications, but as a global transformative factor affecting almost every area of life. The report indicated that the primary challenge of the forthcoming decades would not be the availability of technology itself, but rather the capacity of societies to comprehend its functionality, the social ramifications, and the mechanisms of interdependence between technology and organisational practices. AI100 contributed to introduce into public and academic debates the need to develop citizens' critical thinking skills about AI, which in subsequent years became the conceptual basis for developing the concept of AI literacy. The report indicated that the primary challenge that societies will face in the forthcoming decades will not be the availability of technology itself, but rather the capacity to comprehend its functionality, the social ramifications, and the mechanisms through which it operates (Littman et al. 2021).

The present study explores the interdependence between technology and organisational practices. Subsequent editions of the report (2016, 2021) have further investigated these observations, emphasising the increasing disparity between the pace of technological advancement in AI systems and the capacity of public institutions, organisations, and individual users to effectively utilise these systems. It has been demonstrated that the accelerated development of generative models and deep learning-based applications has led to a notable enhancement in the significance of analytical competencies, data interpretation, the reliability of algorithmic outputs, and the capacity for critical evaluation of machine-generated recommendations. In the contemporary era, reports AI100 have emerged as a pivotal source that validates the necessity for the cultivation of AI literacy, encompassing not solely technical competencies but also its role as a prerequisite for thriving in societal, economic, and educational contexts, particularly in the context of rapid advancements in the field of artificial intelligence. In the context of research conducted on the development of skills, these documents indicate that the capacity to learn from AI and to use AI is becoming a fundamental element in ensuring the competitiveness and adaptability of individuals and organisations in the 21st-century economy.

Methodology

Research design and approach

This study is designed as a conceptual and comparative policy review that synthesizes how AI literacy is currently defined and operational zed across educational and workforce-related settings. The approach differs from a systematic literature review or meta-analysis. Rather than aggregating empirical findings, it offers an interpretive, framework-oriented reading of how selected countries and international organisations conceptualise, structure, and institutionalise AI-related competency models through official policy documents, educational guidelines, and institutional reports.

The methodological choice follows from the present state of the field. AI literacy has emerged as a distinct policy and educational domain only recently, with most widely circulated frameworks developed after 2019. The area is also characterised by rapid revision cycles—often annual—and by substantial conceptual heterogeneity, where definitions and competency architectures vary more than they converge. Under such conditions, a systematic quantitative synthesis would risk premature closure and limited explanatory value. Accordingly, the article adopts a perspective close to comparative institutional analysis, treating AI literacy frameworks as policy objects that are constructed, negotiated, and stabilised within particular national and supranational contexts.

The analysis is guided by three research questions:

1. How do major international organisations and selected national systems define and structure AI literacy?
2. Along which dimensions do AI literacy frameworks differ (e.g., competency structure, pedagogical orientation, degree of integration into formal education, target populations)?
3. How is the discourse shifting from general "AI literacy" toward more context-specific "AI skills" and "AI competence" approaches, and what institutional implications follow from this shift?

Case selection and analytical scope

Cases were selected according to four criteria, intended to balance breadth with analytical depth.

(1) Institutional authority and policy influence. Priority was given to frameworks developed or endorsed by institutions with standard-setting capacity and demonstrable policy reach, including supranational organisations (e.g., UNESCO, OECD, European Commission/JRC) and national governments that articulate explicit AI education or AI skills strategies.

(2) Framework maturity and documentation. Inclusion required publicly available and sufficiently detailed materials, not merely aspirational strategy statements.

(3) Diversity of institutional and governance contexts. To capture variation in how AI literacy is institutionalised, the corpus intentionally reflects different educational philosophies and governance arrangements: school-based models (including K–12-oriented approaches), adult and citizen education initiatives, teacher professional development frameworks, and public-sector capacity-building models. Similarly, the selection seeks variation across policy coordination logics (federal and decentralised systems, centralised national strategies, and supranational coordination).

(4) Recency and relevance (2019–2025). Given the pace of technological and policy change, the primary focus is on frameworks published or substantially revised between 2019 and 2025, with particular attention to documents updated in 2024–2025.

On this basis, the final corpus combines: (a) international and supranational competency frameworks, (b) selected national initiatives and widely adopted educational programmes, and (c) foundational academic contributions that function as reference points for subsequent institutional documents.

The core comparative corpus consists of publicly available AI literacy/AI competence frameworks published or substantially revised between 2019 and 2025, including AI4K12 (USA), Elements of AI (Finland), DigComp 3.0 (European Commission/JRC), UNESCO's AI Competency Frameworks for Students and Teachers (2024), the OECD Framework for Digital Talent and Skills in the Public Sector (2021), the Alan Turing Institute's AI Skills for Business Competency Framework (UK 2024), and the Australian Framework for Generative AI in Schools (2025). Additional national policy texts were used for contextualisation of the "AI skills" shift in workforce and public-sector settings (e.g., UK skills initiatives and Canada's AI Strategy for the Federal Public Service 2025–2027).

Data sources and collection procedure

Tlaborhe empirical material is documentary in nature and consists of official frameworks, strategies, guidance notes, reports, and—where available—implementation materials (e.g., curriculum resources, training outlines, assessment instruments). Sources were identified through three complementary strategies.

(1) Institutional document retrieval. Official websites and publication repositories of key organisations and public institutions were systematically reviewed (international organisations; EU-level bodies; national ministries or agencies responsible for education, digitalisation, innovation, and public sector reform). This strategy

yielded primary framework documents as well as supporting guidance and contextual policy texts.

(2) Citation tracking and "snowball" sampling. Starting from recognised foundational works and widely referenced reports, cross-references within policy documents were traced to identify related frameworks and programmatic linkages. This approach was particularly useful for reconstructing diffusion pathways—how certain competency categories, "big ideas," or educational rationales travel between initiatives and become embedded in institutional templates.

(3) Targeted retrieval of high-uptake programmes. For educational initiatives known to have broad adoption or strong visibility, additional documentation was collected, including technical reports, curriculum packages, implementation notes, and evaluation summaries where publicly available.

All included sources were required to be publicly accessible and available in English. This introduces a potential Anglophone bias. However, the constraint is partially mitigated by the fact that major international frameworks are routinely published in English, and a substantial share of national initiatives provide English versions of strategic documents or executive summaries.

Limitations

Several limitations should be considered when interpreting the findings. First, coverage is illustrative rather than exhaustive. AI literacy initiatives proliferate across regions and sectors, and new documents appear frequently. The study therefore concentrates on prominent, well-documented cases with visible policy influence or large-scale uptake. Consequently, significant initiatives in regions outside the main corpus may be underrepresented.

Second, the analysis focuses on framework design and policy discourse, not on implementation outcomes. The study does not evaluate effectiveness, learner experience, teacher practice, or behavioural impacts. It should be read as an analysis of competency architectures and institutional framings rather than as programme evaluation.

Third, the article provides a temporal snapshot of a moving field. Frameworks evolve rapidly in response to technological developments—particularly generative AI—as well as pedagogical experimentation and cross-jurisdictional policy learning. Some documents are newly revised or subject to further updates. The conclusions therefore capture a structured state-of-the-field view as of December 2025.

Fourth, the restriction to English-language materials means that national classroom-level resources (teacher guides, assessment rubrics, local curricula) may be unevenly represented. This may lead to a partial view of implementation instruments in contexts where policy documents exist in English but practical materials remain language-specific.

Despite these constraints, the adopted approach is aligned with the research objectives: it enables a structured comparative overview of how AI literacy is being institutionalised, identifies emerging patterns and divergences in competency design, and provides a grounded basis for future empirical work that can test implementation fidelity, learning outcomes, and distributional effects.

Positioning within economic sociology

From an economic sociology perspective, AI literacy frameworks can be interpreted as institutionalised templates that shape skill formation and the production of human capital in knowledge economies. Three sociological strands are particularly relevant.

First, work on skill formation and institutional change highlights how competency frameworks tend to reflect broader national arrangements that coordinate education, training, and labour market needs. In this view, differences in AI literacy architectures are linked to the ways in which education and training systems evolve within distinct institutional settings and policy traditions (Thelen, 2004). Accordingly, frameworks oriented toward individual initiative and technical specialisation can be read differently from those emphasising universal access, social inclusion, or public-sector capacity-building.

Second, perspectives on cultural capital suggest that AI literacy frameworks operate as symbolic resources that shape legitimacy and distinction. The question of who defines AI literacy—international organisations, states, educational institutions, or technology-sector actors—matters because it influences what counts as "valid" competence and which forms of knowing are privileged (technical understanding, critical evaluation, operational proficiency, ethical judgement). In this sense, frameworks participate in the politics of knowledge and the distribution of recognised competence under conditions of AI diffusion (Bourdieu, 1986).

Third, research on digital divides and inequality draws attention to distributional risks embedded in inclusive literacy agendas. AI literacy initiatives frequently invoke inclusion, yet they may reproduce existing stratification if access to high-quality AI education follows established lines of advantage (institutional capacity, socioeconomic status, geography). The growing differentiation of pathways—from baseline literacy to more specialised role-oriented competences—therefore raises questions about who gains access to advanced forms of AI competence and how such access may map onto occupational hierarchies in AI-saturated labour markets (van Dijk 2020).

Taken together, this positioning frames AI literacy not merely as a pedagogical topic, but as an institutional project that defines normative expectations for participation in AI-augmented economies—and, implicitly, delineates whose interests, capacities, and trajectories are prioritised in that construction.

Comparative analysis of AI literacy frameworks

The term "AI literacy" was first systematically conceptualized by Kandlhofer et al. (2016), who defined it as a set of competencies that enable individuals to know and understand AI and use AI technologies. This conceptualization was significantly expanded by Long and Magerko (2020: 2), who provided one of the most comprehensive and widely cited definitions, describing 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". The authors emphasize that AI literacy goes beyond digital literacy, as it includes working with algorithmic systems, modelling and data processing.

UNESCO (2024) defines AI literacy as a set of knowledge, skills and ethical attitudes necessary for safe, responsible and critical interaction with AI systems in education and society. An important element is the emphasis on ethics and legal aspects. OECD (2025a) emphasizes that AI literacy is a competence of a modern citizen, which includes the ability to understand the decisions of AI systems, interpret models and manage algorithmic risks.

Comparison of AI literacy models is presented at Table 1. Approaches to AI literacy vary considerably by country and organisation. In the US, AI Literacy models, developed by the MIT RAISE and AI4K12 initiatives, provide a framework of at least five domains: perception, representation, learning, natural interaction, and social impact. They focus primarily on technical content and engineering thinking, which makes the American approach the most technologically oriented. The level of integration into formal education is high: there are official recommendations for K-12 students, and schools are piloting projects. In practice, this is manifested through the use of Scratch with AI extensions (for example , the use of ChatGPT (or other generative AI models) in teaching and the development of project activities. Scratch extensions which supports AI learning amongst the youth are for example: Scratch-NB (tools for developing a Naive-Bayes classifier for K-8), Tooee or Face Sensing blocks. Finland uses a model focused on basic understanding of AI, algorithmic thinking, and ethical principles. The "Elements of AI" course has the format of a free mass online course aimed at a wide range of citizens, including students. Unlike the US, where the priority is on the school audience and technical competences, the Finnish approach is aimed at general education. Finland does not want to compete with US or China in developing primary research on generative AI but rather focus on applications of AI, as its Economy Minister Mika Lintilä states: "As the two superpowers vie for technological supremacy, Finland knows it's outclassed on raw resources. There is no point trying to compete with Beijing or Washington in terms of developing the basic technology of AI. So Finland aspires to occupy a niche, as world leader in practical applications of AI" (Delcker 2019)

Table 1.Comparison of AI Literacy Models

Country / Organisation	Competency Structure	Approach Features	Level of Educational Integration	Examples
USA (AI4K12)	Five Big Ideas: Perception; Representation and reasoning; Learning; Natural interaction; Societal impact	K-12 oriented national guidelines; framework for standards writers and curriculum developers	High (national guidelines, resource directory, community support; no federal mandate)	Teachable Machine; various state implementations
Finland (Elements of AI)	6 modules covering definition, problem-solving, real-world AI, machine learning, neural networks, and societal implications	Free, mass online course aimed at broad public; supports general AI understanding	Medium (informal/citizen learning; adopted by multiple institutions)	Elements of AI course (University of Helsinki / Reaktor).

Country / Organisation	Competency Structure	Approach Features	Level of Educational Integration	Examples
EU (DigComp 3.0)	21 competences across 5 areas (information and data literacy; communication; content creation; safety; problem solving). AI-relevant aspects integrated across competences (AI treated as traversal skill for all domains)	General digital competence framework used for policy, curricula mapping and training standards (not a dedicated AI-only model)	Varies across countries/sectors	Used for national digital skills strategies and competence mapping.
UNESCO: AI Competency Framework for Students (2024) and AI Competency Framework for Teachers (2024)	STUDENTS: 12 competencies across 4 dimensions: (1) Human-centred mindset; (2) Ethics of AI; (3) AI techniques and applications; (4) AI system design. Three progression levels: Understand, Apply, Create. TEACHERS: 15 competencies across 5 dimensions: (1) Human-centred mindset; (2) Ethics of AI; (3) AI foundations and applications; (4) AI pedagogy; (5) AI for professional development. Three progression levels: Acquire, Deepen, Create.	Human-centred approach prioritizing values (knowledge, skills, values); emphasis on ethics, inclusivity, human agency, and responsible AI use; interdisciplinary integration; focuses on students as AI co-creators and responsible citizens	Advisory/benchmarking level for global education systems; implementation varies by country; guidance for policy-makers, educators, and curriculum developers	Rights-based and inclusive AI guidance; bias awareness; ethical AI design principles; teacher capacity-building programs; integration into national AI education strategies

Country / Organisation	Competency Structure	Approach Features	Level of Educational Integration	Examples
The OECD Framework for Digital Talent and Skills in the Public Sector (2021)	3-pillar model: (1) Digitally-enabling work environment (2) Digital skills (3) Workforce development	Public administration modernisation: skills + work environment + workforce development steps, broader digital framework which includes AI elements	Varies across OECD countries; framework provides guidance for national implementation	UK DDaT Capability Framework; Australian Public Service digital capability monitoring
UK (Alan Turing Institute) AI Skills for Business Competency Framework	Role-based learner personas: AI Citizens, AI Workers, AI Professionals, AI Leaders.	Competence described via Knowledge/Skills/Behaviours across five dimensions: Privacy and stewardship; Data specification/engineering/curation; Problem definition and communication; Problem solving/modelling/visualisation; Evaluation and reflection	Medium (professional/workforce framework for training and progression; not K-12 mandate).	Role-based personas and five dimensions structure skills mapping and progression.
Australia (Australian Framework for Generative AI in Schools)	6 Principles + 25 Guiding Statements. Principles cover: Teaching, Learning; Human and Social Wellbeing; Transparency; Fairness; Accountability; Privacy, Security and Safety.	School-governance guidance for safe, ethical, responsible GenAI use; explicitly multi-stakeholder (systems, schools, teachers, students, parents, providers)..	High (nationally coordinated framework; Education Ministers endorsed the review and the framework is designed to align jurisdictions/sectors; implementation varies).	Principles include academic integrity/assessment guidance, transparency/disclosure, and privacy/data protection expectations.

Source: own elaboration based on (OECD 2021), (UNESCO 2024), (UNESCO 2024a), (Cosgrove & Cachia 2025), (University of Helsinki 2023), (AI4K12 Initiative 2019), (Alan Turing Institute 2024), (Australian Government Department of Education 2025).

The model proposed by UNESCO differs from national models in that it is consultative in nature and focuses on the values, ethics and social impact of AI. It consists of components of knowledge, skills and values that should be formed in teachers, students and citizens.

The OECD framework is a complex 3-pillar model which focuses on digitally--enabling work environments, digital skills and workforce development, which includes as one of its elements algorithmic literacy and data literacy but goes beyond that. The model is aimed at use in public policy management.

In the 2000s, the concept of digital literacy dominated. The emergence of big data, machine learning and automation requires a transition to algorithmic literacy, which includes an understanding of the logic of models, types of learning, and the principles of recommender and classification systems. The combination of digital, media, information and algorithmic literacy forms the architecture of AI literacy. EU which provides digital competency framework (DigComp 1.0 and further) since 2013 through its European Commission's Joint Research Centre is actively elaborating on the topic of AI competences and its newly released DigComp 3.0 which is the fifth version of European Digital Competence Network treats postulates traversal integration of AI competence into existing 21 digital competences (Cosgrove, Cachia 2025). In this approach AI-related skills, knowledge and attitudes are included inside of each digital competence which is a part of DigComp 3.0. This model is slightly different from previously shown models, as the AI competence is treated as one of existing digital competencies which a person needs to master in order to increase one's digital proficiency.

In addition to the models summarised above, recent policy developments show an emerging second layer of initiatives that are framed less as general AI literacy and more as practical AI skills or AI fluency. In this layer, AI competence is described as a set of abilities that can be operationalised for specific contexts (school, workplace, public administration) and therefore embedded in training standards, organisational processes, and governance instruments. The underlying policy logic is that conceptual AI literacy remains necessary (understanding what AI is and how it can fail), but it is insufficient for safe adoption at scale. As a result, many countries now differentiate between (i) baseline AI skills for all citizens and workers (safe use, critical evaluation, risk awareness), (ii) specialist skills for developers and data professionals (building and deploying AI systems), and (iii) governance skills for managers and leaders (procurement, accountability, and oversight). In comparative terms, this "skills" framing does not replace AI literacy; rather, it complements it by translating literacy into role--specific competence profiles that can be implemented through education and labour market policy (Skills England 2025).

The United Kingdom provides a particularly clear example of how AI skills discourse can coexist with, and partially reshape, AI literacy discourse. In June 2025 the

UK government announced a national skills drive (TechFirst), explicitly connecting school learning, community learning and workforce upskilling within a single programme narrative. TechFirst was framed as a £187 million investment programme designed to bring digital skills and AI learning into classrooms and communities. The same announcement positioned AI competence as a mainstream employability requirement by linking it to large-scale workforce targets through an industry partnership that aims to equip millions of workers with essential AI skills by 2030. Such framing shifts the focus from learning about AI to being able to work and participate in society with AI, while still keeping education as a key delivery channel (school age learning, teacher capacity, and community pathways). (Department for Science, Innovation and Technology and Department for Education 2025). From the perspective of competency architecture, UK initiatives increasingly emphasize role-sensitive frameworks rather than single universal lists. The 2025 Skills England report "AI skills for the UK workforce" is notable because it includes not only an analysis of upskilling needs across growth sectors, but also a practical "AI skills tools package" intended for employers and training providers. The package contains: (i) an AI Skills Framework, mapping AI skills into technical, responsible/ethical and non-technical domains; (ii) an AI Skills Adoption Pathway Model, describing staged organisational adoption and how skill needs evolve; and (iii) an Employer AI Adoption Checklist, designed to help organisations identify readiness and skills gaps, including issues of equity and inclusion. Importantly, the framework aligns AI skills with job levels (entry, mid, managerial), emphasizing that leaders should not only set policy but also possess core competences such as AI literacy, prompt writing and output evaluation. This approach reframes AI competence as distributed across the organisation, rather than confined to technical specialists, and explicitly links skills to responsible adoption (bias awareness, data protection and risk management as practical workplace requirements (Skills England 2025).

A complementary UK effort is the "AI Skills for Business Competency Framework", disseminated as an open resource and developed through multi-stakeholder collaboration. Compared to school-based AI literacy models, this framework is oriented toward capability planning and professional development over the AI lifecycle. It articulates AI competence as a structured combination of knowledge, skills and behaviours needed for responsible and effective workplace engagement, and it is frequently communicated through role archetypes (for example, an AI worker who uses AI in daily tasks, an AI professional who develops and deploys systems, and an AI leader who provides strategic oversight and governance). This role-based structuring has a similar logic to the

Skills England tools (differentiating competence by responsibility and context), and it supports the idea that AI literacy is a baseline that must be extended by operational and governance competences when organisations move from experimentation to scaling (Alan Turing Institute 2023). In this framework co-created with InnovateUK four main groups which will require AI leaders were named: AI Citizens, AI Workers, AI Professionals and AI leaders.

The education strand of UK policy further demonstrates how skills language can be translated into classroom governance and professional practice. Department for Education materials on generative AI in education emphasize potential benefits such as reducing administrative burdens and supporting learning tasks (e.g., feedback and tailored support), but they also stress safe exploration and the continuing need for professional judgement. In this framing, teachers and school leaders are positioned as accountable gatekeepers: AI outputs must be checked for accuracy and appropriateness, and responsibility remains with the educator and institution rather than the tool. This policy stance can be interpreted as a practical competence model: teachers need enough AI understanding to assess reliability, manage risks, and design learning activities that use AI as a support rather than a replacement for learning. The UK landscape also shows that devolved systems can foreground ethical and rights-based dimensions more explicitly (Department for Education 2025). For example, Scotland's "Teach AI Literacy" handbook provides a curriculum-linked framework for upper primary and secondary teachers, aimed at teaching both how AI works and how to use AI responsibly to support learning, and was developed with support from Scottish education institutions. This demonstrates how national AI skills discourse can be complemented by rights-centred AI literacy resources that emphasise critical thinking and responsible use norms, rather than simple tool adoption (Robertson 2025). The handbook includes eight important principles on usage and learning generative AI skills in the classroom which include amongst others the right not to use such tools for some reasons such as for example copyrights or environmental concerns and importance of broader ethical and children rights context of AI skills (Robertson 2025: 11).

Both the OECD and European Commission are actively shaping policy discourse through two complementary mechanisms: establishing competence expectations and integrating these into international assessment frameworks. Notably, the OECD announced that PISA 2029 will introduce a new assessment domain called "Media and Artificial Intelligence Literacy (MAIL)", which marks a significant shift—AI competencies are now being formally incorporated into the comparative evaluation framework for 15-year-old students globally. The first results of AI literacy verification by PISA will be available in 2031 and will provide a special environment in which learners will be tested on pro-active and critical testing of generative AI tools and other aspects of AI (OECD 2025a). Simultaneously, the European Commission and OECD initiated the AILit project to develop a comprehensive AI Literacy Framework specifically designed for primary and secondary education contexts. This framework, currently in draft form with stakeholder consultations conducted throughout 2025 and anticipated completion in 2026, provides detailed guidance on competences and practical learning scenarios that can inform curriculum materials, educational standards, responsible AI implementation policies, and assessment methodologies (European Commission, OECD 2025b). From a comparative policy perspective, these developments suggest an interesting feedback mechanism: heightened international visibility through PISA assessments may catalyze national-level curriculum reforms, while a standardized competence framework could enhance cross-national comparability and help address the current fragmentation across different national AI education initiatives—including those that integrate AI literacy within broader digital competence models like DigComp 3.0 (Cosgrove & Cachia 2025).

Australia provides another illustrative case of national-level coordination, especially around the governance of generative AI in schools. The nationally agreed "Australian Framework for Generative AI in Schools" is positioned as guidance for responsible and ethical use of generative AI tools and explicitly targets a wide stakeholder group such as: school leaders, teachers, support staff, students, parents/guardians, service providers and policy makers/ (Australian Government Department of Education 2025). The framework is supported by an ongoing review cycle (review within 12 months and then annually), and Education Ministers endorsed the 2024 Framework Review in June 2025 following consultation across jurisdictions, school sectors and national agencies—suggesting an attempt to coordinate approaches nationally. This schooling--focused governance instrument sits alongside broader national policy narratives about inclusive and trusted AI adoption. (Australian Government Department of Industry, Science and Resources, 2025 For example, Australia's National AI Plan which was recently published in December 2025 frames AI adoption around capturing opportunities, spreading benefits, and keeping Australians safe, explicitly stating that groups at risk of digital exclusion require support. (Australian Government Department of Industry, Science and Resources 2025). More broadly, Australia's risk-and-safety orientation is visible beyond AI policy itself. From 10 December 2025, age-restricted social media platforms are required to take "reasonable steps" to prevent under-16s from holding accounts under the national social mediaminimum age framework—an intervention frequently framed in public debate as a de facto teen social media "ban". This provides a concrete example of Australia's willingness to use statutory platform obligations and compliance mechanisms to govern technology-related harms affecting minors (Australian Government Department of Infrastructure, Transport, Regional Development, Communications, Sport and the Arts 2025).

Canada's recent initiatives show how the AI skills framing can be embedded in public administration modernisation. The Government of Canada's AI Strategy for the Federal Public Service 2025–2027 defines readiness as a combination of data, infrastructure, tools, culture, talent, skills and policy, and identifies "Talent and training" as one of four priority areas. The strategy ties capability directly to implementation capacity: it references government-wide and departmental mechanisms for recruitment, retention and reskilling, and it points to structured learning provision through the Canada School of Public Service (including a data and AI learning pathway, courses, job aids and related resources). In this case, AI competence is explicitly tied to governance: training is part of enabling responsible adoption, ensuring that civil servants can use AI effectively while meeting requirements for transparency, risk management and public trust. Compared to school-oriented AI literacy models, the Canadian approach demonstrates how AI skills can be framed as an organisational capability that supports service delivery and accountability in the public sector (Treasury Board of Canada Secretariat 2025).

Overall, the comparative picture suggests that AI literacy is increasingly being complemented by skills-to-adoption frameworks. In school contexts, the emphasis remains on conceptual understanding, ethics and critical thinking. The interesting issue is the notion of human-computer interaction and the option of opting-out from the usage of generative AI for these people who have ethical or environmental concerns. In workforce contexts, these concerns are translated into practical competences such as prompting, output evaluation, bias detection and data protection compliance; and in public sector contexts, competence is tied to governance mechanisms (standards, guidance, central capacity, transparency instruments).

Conclusion and future research suggestions

The analysis presented in this article suggests that, in the context of the accelerated development of artificial intelligence, the category of AI literacy is gaining beyond the traditionally understood technological competences. Regarding the research questions guiding the study, the review suggests that **(RQ1)** major international organisations and selected national systems increasingly define AI literacy as a multi-component, hybrid competence that combines foundational understanding of AI with the ability to critically interpret outputs, recognise limitations, and apply AI responsibly in context. Addressing **(RQ2)**, the analysed frameworks differ along recurring dimensions, including competency structure (a stand-alone construct versus integration into broader digital competence models), pedagogical orientation (conceptual understanding versus adoption-focused training), degree of embedding in formal education (binding standards and curricula versus soft guidance), and the intended target groups (students, teachers, citizens, workers, managers, and public servants). Finally, in response to **(RQ3)**, the analysis indicates a gradual shift from general "AI literacy" toward more role – and context-specific "AI skills" and "AI competence" approaches, which carries institutional implications—most importantly the need for differentiated learning pathways, clearer implementation responsibility, and supporting instruments such as teacher preparation, workplace training standards, assessment practices, and governance arrangements. Building on these observations, the following conclusions emphasise the broader consequences of generative AI for work organisation, cognitive processes, and skill formation.

Across the reviewed corpus, AI-related competency architectures cluster into three ideal-type policy models: (i) school-facing AI literacy frameworks prioritising conceptual understanding, ethics and critical judgement; (ii) workplace-oriented AI skills/competence frameworks that operationalise adoption through role-based knowledge–skills–behaviours (e.g., prompting, output evaluation, compliance); and (iii) public-sector capability models that tie AI competence to organisational readiness and governance instruments.

A second cross-cutting divide concerns how AI is positioned relative to digital competence more broadly—either as a stand-alone construct or as a transversal layer embedded across digital competence domains (as in DigComp 3.0).

Taken together, these patterns suggest that the current shift from "AI literacy" to context-specific "AI skills" is less a change of labels than an institutional move toward differentiated learning pathways and clearer responsibility for implementation and assessment.

The advent of artificial intelligence, particularly in the form of generative systems, has precipitated a paradigm shift in the manner in which professional tasks are executed. This technological advancement has also exerted a profound influence on cognitive processes, work organisation and skill acquisition mechanisms. Consequently, competencies that facilitate deliberate and critical interaction with AI systems are becoming imperative for preserving the adaptability of individuals in an environment characterised by rapid technological advancement.

From a theoretical perspective, AI literacy should be interpreted as a cross-cutting competence that not only coexists with other forms of digital literacy, but also organises and conditions them. The utilisation of AI-based tools without a comprehensive grasp of their epistemic limitations, reliance on training data, or the presence of potential sources of bias results in superficial technological adaptation, devoid of enduring competence effects. It is therefore the case that AI literacy plays a stabilising role in skill formation processes. This enables not only the effective use of new technologies, but also the preservation of users' cognitive autonomy.

An analysis of the relationship between AI literacy and skill formation processes indicates that these competencies are conditional rather than merely supportive. In an environment where artificial intelligence is increasingly involved in the processes of analysis, synthesis and content generation, the ability to critically evaluate algorithmic results is becoming an indispensable part of learning. The absence of such competencies can result in the deterioration of higher-order skills, particularly analytical and reflective abilities. In the long term, this can impede the development potential of both individuals and organisations.

A further significant finding of the article is that the notion of AI literacy has not been adequately embedded within national conceptual and institutional frameworks. The dissemination of AI-related issues across a wide spectrum of digital competencies has resulted in the oversight of specific challenges inherent to the autonomous and probabilistic nature of AI systems. Consequently, there is a risk that technological development will outpace the capacity of institutions to prepare users for its implications.

The theoretical issues outlined in the article point to several areas that require further research. Firstly, it appears imperative to elucidate the operationalization of AI literacy in empirical research. The second significant area of research pertains to the analysis of causal relationships between the level of AI literacy and the processes of skill formation over time. Longitudinal studies would be particularly valuable in capturing how AI-related competencies affect learning ability, professional mobility, and adaptation to technological change.

A further significant avenue for future research pertains to the examination of normative and ethical issues. As artificial intelligence systems become integrated into decision-making infrastructure, competences related to understanding algorithmic responsibility, transparency and social risks are gaining civic significance. Consequently, research on AI literacy should encompass not only the instrumental dimension, but also the role of these competences in shaping conscious participation in social and economic life.

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