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AI Literacy as a Core 21st Century Competency in Secondary Education: A Systematic Review and Conceptual Framework

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Abstract- Adolescents have become routine users of artificial intelligence (AI) systems faster than school systems have become teachers of them. This paper asks whether AI literacy has the standing of a core twenty-first century competency for secondary education, and what a defensible framework for it would look like. Adopting a structured integrative review, we analysed a purposive corpus of 29 sources across four strands: nine influential competency frameworks, eight review syntheses, six instrument-validation studies and seven system-level survey datasets. Cross-framework mapping shows strong convergence on five constructs understanding AI, using AI, evaluating AI, creating with AI, and positioning oneself toward AI but persistent divergence on whether creation belongs in general education, whether the affective dimension is a competency or a mediator, and how progression should be indexed. Measurement lags conceptualisation: of sixteen validated scales identified in the field, thirteen are self-report and only two are purpose-built and large-sample validated for secondary students, so the higher-order strands are largely evidenced by learners' claims about themselves. System-level data reveal a widening gap: reported use by students rose from 13% to 54% in two survey years, while provision of student training, policy and explicit instruction all remain below 45%. We propose the AILSE framework, which organises the five convergent strands across three progression levels indexed to autonomy, abstraction and accountability, and specifies four enabling conditions teacher capacity, curricular host, assessment validity and equitable access without which the competencies are not attainable. The contribution is a framework that treats implementation not as an afterthought but as part of the construct.

Keywords- AI literacy; twenty-first century skills; secondary education; competency framework; curriculum integration; assessment validity

I. Introduction

The twenty-first century skills movement endowed education systems with a durable lexicon (critical thinking, communication, collaboration and creativity) but that lexicon was established long before machines could even reasonably process any of the four. Those skills now describe processes that are mediated by generative AI. The student who asks a chatbot to summarise a source, produce an argument against it or draft some conclusions is not evading thinking faces; rather the critical work transfers from creating a claim to testing an existing one. The extent to which that move actually improves or destroys the core function rests almost entirely on what the student understands about the system they are using.

As early as October 2023, two observations lead me to treat AI literacy not as a subset of the larger topic digital literacy. The first is empirical. According to Survey evidence in the US [19], chatting bots are used for schoolwork by 13% of teenagers, increasing to 26% and 54% in 2024 and 2025 respectively [20],[21]; approximately one in ten reports using chatbots for all or most of their school work [21]. That's the rate of adoption a future that never happens to plan for; it is the present condition to be taught into. The second observation is conceptual. Digital literacy frameworks were constructed for tools that manage to follow instructions deterministically. AI systems have generated probabilistically plausible content, can respond interactively, but provide no direct textual warrant for their outputs. Epistemic habits provenance checking and calibrated trust as well as a tolerance for uncertainty, that was absent in earlier frameworks needed to be specified.

Responsiveness at the institutional level has been at best uneven, and at worse a travesty. A bibliometric analysis shown in Figure 1 indicates that, while literacy research was exploratory from 2014-2023, the timeline shows exponential growth with 335 empirical articles published between 2014 and 2024 and 156 of which were written in only this last year (exponential fit: R^2 =0.9871 [29]). Given increasing scale, frameworks have proliferated and now cover instruments from research teams, subject associations and since 2024 intergovernmental bodies [10], [11], [17]. Still, a global mapping by UNESCO discovered that only 11 member states had developed and approved K–12 AI curricula (four were in development [26]), thus national curricula are the exception rather than the norm.

This widespread expansion gives rise to a particular challenge for secondary schools. There are family resemblances among frameworks, but they use different names for overlapping constructs, disagree on the membership of constructs in general education, and have inconsistent ideas about progression. Measurement is even weaker: the measures available are dominated by self-report, which cannot provide evidence of the higher-order constructs most of what these frameworks want to argue for. Almost none of the competencies in any state’s framework outlines what a school must already have in place for those competencies to be teachable at all. This paper addresses four questions.

- RQ1. How is AI literacy conceptualised across the frameworks most relevant to secondary education?
- RQ2. Which constructs converge across frameworks, and which remain contested?
- RQ3. How adequately do available instruments measure those constructs for secondary students?
- RQ4. What framework would integrate the convergent constructs with a defensible progression logic and the conditions its enactment requires?

The contribution is threefold: a cross-framework convergence analysis for the secondary phase; an appraisal of measurement coverage against the construct’s frameworks assert; and the AILSE framework, which pairs five competency strands and three progression levels with four named enabling conditions.

II. Positioning AI Literacy Within the Skills Tradition

Therefore, the canonical definition defines AI literacy as a spectrum of ability needed to critically analyse and evaluate these technologies as well as communicate and collaborate with them at home, online and at work [9]. I want to emphasize two features of this definition. It is intentionally non-technical: there is nothing in it that requires a learner to build a model. And it is relational: a collaboration with a system not just an operation of one.

The reviews invariably conclude that AI literacy has a significant overlap with data, information, digital and algorithmic literacies [1, 16], and is ultimately built on top of them rather than besides them [29]. That discovery goes against the grain of any temptation to regard AI literacy as a fifth C simply added on like a new shoe. Perhaps more accurately, AI literacy is a re-specification of a number of existing competencies under the condition that critical thinking must occur under conditions of fluent, unattributed content generated by probabilistic modelling. So, there is an actual, practical consequence to framing it this way. If AI literacy is actually new, it needs its own slot in the curriculum. This requires teacher capacity, not curriculum design: if it is a re-specification, it can and should be spread across subjects.

III. Method

Importantly, this is a structured integrative review not a systematic review. This means that the most policy relevant AI literacy frameworks are published as institutional or grey literature which bibliographic databases index unreliably, therefore a database-only protocol would systematically omit the documents with the greatest potential for influencing policy. Moreover, exhaustive database sampling from the empirical literature has already been performed here on: a systematic review of 179 K–12 studies [1], a bibliometric analysis of 335 articles [29] and a scoping review of 31 school-based cases [18]; these works are treated as secondary evidence rather than replication. Thus, our sampling was purposefully across 4 strands of source, illustrated in Figure 1.

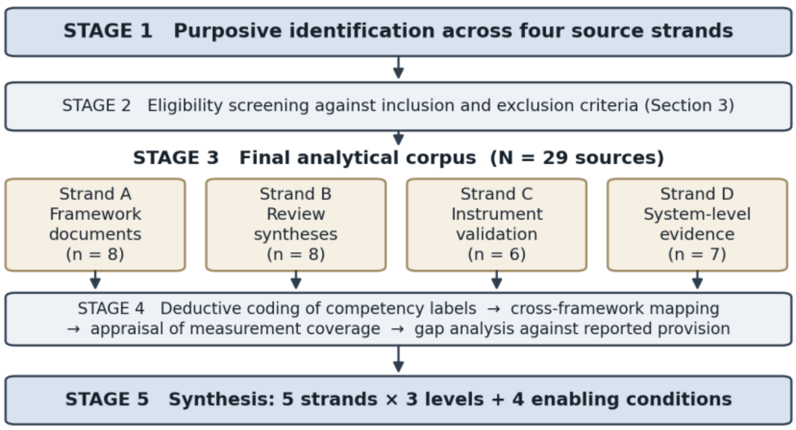

Figure 1. Source selection and synthesis workflow. Counts refer to sources retained in the final analytical corpus.

Inclusion criteria were: a source that defined or measured AI literacy as a learner competency, targeted learners aged approximately 11–18 or included cross-sector explicitly, and published in English from 2020 to 2026. We ensured that we excluded vendor training material, studies of AI as an instructional tool with no literacy construct, and commentary without a declared framework. Frameworks that were designed only for post-secondary education were ruled out because level of expectation on a competency is not appropriately aligned with school-age learners.

Analysis proceeded in four steps. Step one Each competency label was extracted as is and coded deductively across all frameworks. Secondly, labels were mapped across frameworks to find constructs that are recurrently named and constructs that appear in only some. Third, each instrument listed within strand C was evaluated relative to the resultant construct set, and measurement coverage of those constructs was determined. Fourth, the construct set was compared against system-level provision as a way of estimating the gap between what is expected on paper and what schools are actually delivering. Coding was performed by a single analyst, which is a limitation discussed in Section 7.

IV. Findings

1. The framework landscape (RQ1)

The nine frameworks that remained in strand A are summarised in Table 1, and we see the emergence of three generations. The first, represented by Long and Magerko [9] and the Five Big Ideas of AI4K12 [25], defined an AI-literate person. The second, mostly from Hong Kong and mainland Chinese research groups [5], [12], [14], [31] offered affective and moral dimensions of content along with the first calibrations tools for secondary learners. The third, written for adoption into national curricula rather than research use, is intergovernmental [10], [11], [17] and from 2024 onward.

Table 1. Nine AI literacy frameworks relevant to secondary education, 2019–2026.

Framework (source)	Origin and scope	Organising structure	Progression model	Fit to secondary schooling
Long & Magerko (2020) [9]	HCI research; general public	17 competencies plus four design considerations; definition centred on evaluating, communicating with and using AI	None	Indirect: informs design, not curriculum sequencing
Five Big Ideas, AI4K12 (Touretzky et al., 2019) [25]	United States; K–12 subject association	Perception; representation and reasoning; learning; natural interaction; societal impact	Grade-band progression charts	High; strongest technical scaffolding
Ng, Leung, Chu & Qiao (2021) [12]	Exploratory review of 30 studies	Know and understand AI; use and apply AI; evaluate and create AI; AI ethics	First three dimensions ordered by Bloom's taxonomy	Moderate; sector-neutral

Framework (source)	Origin and scope	Organising structure	Progression model	Fit to secondary schooling
Kong, Cheung & Tsang (2023) [5]	Hong Kong; senior secondary programme	Cognitive; affective; sociocultural	Not specified	High; derived from a school programme
ABCE framework (Ng et al., 2024) [14]	Hong Kong; junior secondary	Affective; behavioural; cognitive; ethical	Not specified	High; paired with a validated instrument
KAT framework (Zhong & Liu, 2025) [31]	China; secondary	AI knowledge; AI affectivity; AI thinking (engineering design and computational thinking)	Informed by Bloom's taxonomy and Piagetian stages	High; explicitly targets higher-order thinking
UNESCO AI competency framework for students (2024) [11]	Global policy instrument	12 competencies across four aspects: human-centred mindset; ethics of AI; AI techniques and applications; AI system design	Three levels: Understand, Apply, Create	High; designed for national curriculum adoption
UNESCO AI competency framework for teachers (2024) [10]	Global policy instrument	Five aspects, adding AI pedagogy and AI for professional development	Three levels: Acquire, Deepen, Create	Teacher-facing complement
AILit framework (OECD & European Commission, 2026) [17]	Global; primary and secondary; feeds PISA 2029	Four sequential domains: Engage with AI; Create with AI; Manage AI; Shape AI, each combining knowledge, skills and attitudes	Sequential domains, differentiated for primary and secondary	High; the most curriculum-ready to date

The trajectory matters for practice. The early frameworks, however, addressed the question of what is AI literacy? and left curriculum designers to guess the order. The generation 2024–26 tells answers at the question of: “what should a learner know to be able to do, when? The UNESCO student’s framework has established1512 competencies across four domains at three progression levels [11]; while the Alit framework organises competences into four sequential strands Engage with AI, create with AI, Manage AI and Shape AI each combing knowledge, skills and attitudes that within its scope will feed into the PISA 2029 assessment cycle [17]. The fact that we have an international assessment programme about to test AI literacy is, per se, strong evidence that the construct has gained core competency status.

2. Convergence and divergence (RQ2)

Mapping the nine frameworks against one another (Table 2) yields five constructs that recur across almost all of them, though rarely under the same name. We label them S1 understanding AI, S2 using AI, S3 evaluating AI, S4 creating with AI, and S5 positioning oneself toward AI.

Table 2. Cross-framework convergence matrix. ● = construct named explicitly as a dimension or domain; ◐ = present but subsumed within a broader dimension; ○ = not addressed. Framework abbreviations follow Table 1.

Construct in the synthesis	L&M 2020	AI4K12 2019	Ng 2021	Kong 2023	ABCE 2024	KAT 2025	UNESCO 2024	AILit 2026
S1 Understanding AI	●	●	●	●	●	●	●	●
S2 Using AI	●	◐	●	◐	●	◐	●	●
S3 Evaluating AI	●	◐	●	◐	◐	◐	●	●
S4 Creating with AI	○	◐	●	○	○	◐	●	●
S5 Positioning toward AI	◐	●	●	●	●	●	●	●
Explicit progression levels	○	●	◐	○	○	◐	●	●
Named preconditions for enactment	○	◐	○	◐	○	○	◐	◐

S1 and S5 are near-universal: every framework in the corpus names both a knowledge dimension and a values or ethics dimension. The pattern for S5 is notable because it contradicts a common assumption that ethics is a later addition to technically framed models; the AI4K12 Big Ideas included societal impact from the outset [25], and the Hong Kong frameworks made the affective dimension constitutive rather than supplementary [5], [14].

There are still three real issues to make. Its REALLY important to ask the question: S4 in gen ed? Creation (Long and Magerko do not include) Kong et al and the ABCE framework considers it outside of the core; while the 2024-26 intergovernmental frameworks consider it central [11], [17]. The conceptual version of this question is really a politics-curriculum one: if S4 involves lab-and-tooling and specialists, few secondary systems can manage it. Secondly, the status of the affective dimension. In contrast to other frameworks (e.g., [20], [26], [35]), ABCE and KAT treat affect as part of literacy [14], [31], while most others treat attitude as a mediator of competence. This distinction has implications for measurement, because attitudinal items are easy to write, and raise reported literacy; Thirdly, how progression should be indexed. Adjacent concepts for AI4K12 indexed to grade band, Ng et al. based on cognitive taxonomy: [12], [31]; and KAT to depth of engagement: UNESCO, AILit [11], [17]. None indexes to learner autonomy, which we suggest in Section 5 is the better choice because it survives change in the tools themselves.

Finally, the last row of Table 2 records the most consistent absence. Only the intergovernmental frameworks offer implementation guidance at all, and even these frame it as advice on curriculum design and pedagogy rather than as preconditions. No framework in the corpus states that its competencies are unattainable where teacher capacity, timetabled time, valid assessment or device access are missing despite this being precisely what the system-level evidence in Section 4.4 shows.

3. Measurement coverage (RQ3)

A systematic quality appraisal of AI literacy scales using COSMIN criteria identified 22 validation studies covering 16 scales, of which 13 are self-report and only three are performance-based; scales generally showed good structural validity and internal consistency, but few had been tested for content validity, construct validity or responsiveness, and none for cross-cultural validity or measurement error [8]. Table 3 summarises the instruments in our corpus and the strands each address.

Table 3. Instruments available for measuring AI literacy, and their coverage of the five convergent strands.

Instrument (source)	Target population	Structure and type	Strands addressed	Reported validation status
AILQ (Ng et al., 2024) [14]	Junior secondary; pilot n = 363, Hong Kong	32 items, four factors (affective, behavioural, cognitive, ethical); self-report	S1, S2, S5; S3 partial	Four-factor structure confirmed; good reliability; average variance extracted marginal for intrinsic motivation (.44) and AI ethics (.46)
AILS / KAT (Zhong & Liu, 2025) [31]	Secondary; n = 1,392, China	48 items, three factors; self-report	S1, S3, S4, S5	Rasch analysis plus exploratory and confirmatory factor analysis; satisfactory reliability and validity; gender differences detected
AILS (Wang, Rau & Yuan, 2023) [27]	General adult users	12 items across awareness, use, evaluation and ethics; self-report	S1, S2, S3, S5	Validated by subject-matter experts; not calibrated for adolescents
SNAIL (Laupichler et al., 2023) [32]	Non-expert adults	31 items across technical understanding, critical appraisal and practical application; self-report	S1, S2, S3	Factor analyses plus a Delphi study; validated largely with medical students

Instrument (source)	Target population	Structure and type	Strands addressed	Reported validation status
MAILS (Carolus et al., 2023), as appraised in [8]	Adults	Facets include using and applying, understanding, detecting AI, ethics and creating AI; self-report	S1–S5	Good structural validity and internal consistency; content validity and responsiveness untested
SAIL4ALL (Soto-Sanfiel et al., 2025), as appraised in [8]	General population	56 items across four themes; performance-based	S1, S2, S3, S5	One of only three performance-based instruments identified in the field

Two conclusions follow. Limited instruments exist in the literature: Two of the tools which have been constructed specifically for secondary students and tested on large samples are the AILQ, designed based on ABCE framework (Scale proposed by C. Y.Hau) and pilot tested with 363 Hong Kong students [14], and, AILS which was assessed based KAT framework (Scale developed by L. Guo), hashed broad validation undergone among 1392 Chinese secondary Students utilizing Rasch analysis in concert with exploratory and confirmatory factor analyses [31]. Both were developed in the East Asian context and a serious constraint with respect to their application elsewhere is that they have not published cross-cultural validation

Second and more importantly, the strands that frameworks most want to point toward are often the ones whose internal validity self-report can least back. Asking a fifteen-year-old to rate how much they agree with the statement "I know an AI output when I see one" tests confidence, not skill, and confidence and competence are known to diverge most strongly among novices. S3 and S4 within the Evidence section are performance tasks which involve different qualities of outputs provided to learner or a design brief along with a record of their process. There are three such instruments in the field and none specifically designed for the secondary phase. Assessment not conceptualisation is the bottleneck in the field now.

4. The provision gap

Strand D provides the context in which any framework must operate. Figure 2 places adoption alongside provision. Panel (a) tracks reported use of chatbots for schoolwork by US teenagers across three survey years; panel (b) sets 2025 reported use against reported provision of the training, policy and instruction that would make that use competent.

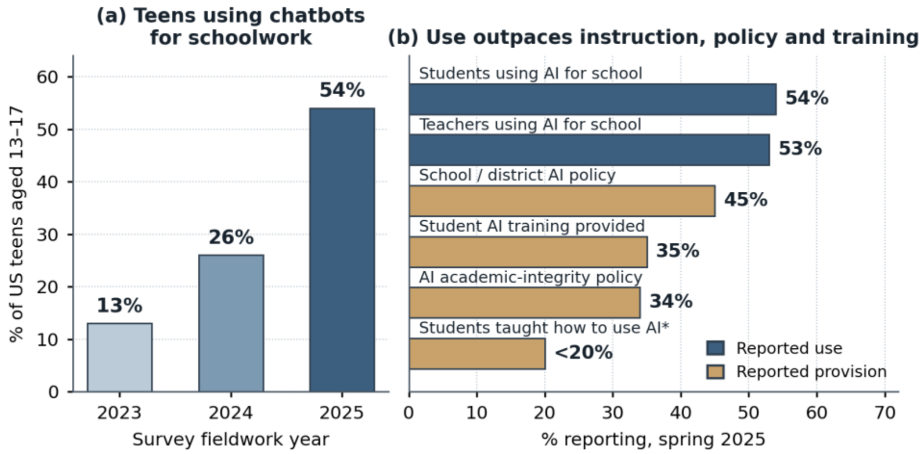

Figure 2. Adoption and provision, United States. Panel (a): Pew Research Centre surveys of teens aged 13–17, fieldwork 2023 (n = 1,453 approx.), 2024 (n = 1,391) and 2025 (n = 1,458) [19], [20], [21]. The 2023 and 2024 items asked specifically about ChatGPT; the 2025 item asked about AI chatbots generally, so the series overstates growth to an unknown degree and should be read as directional. Panel (b): RAND survey panels, spring 2025 [22]. *Derived: over 80% of students reported that teachers did not explicitly teach them how to use AI for schoolwork.

The pattern is coherent with what independent sources report. By 2025, the corresponding percentages were 54% of students and 53% of English, mathematics and science teachers reporting that it was used for school, increases of more than 15 percentage points during a one- to-two year period; however in the same year only 35% of district leaders indicated providing students with AI training; while only 45% [22]of principals reported having school or district AI policy; and finally just over a third (34%) [22]of teachers indicated an academic-integrity policy that covered AI. Since autumn 2023, provision of teacher training has increased rapidly from 23% to 48% district-wide (with plans suggesting ~three-quarters by autumn 2025) but the increase is stratified: in autumn 2024, two-thirds of low-poverty districts had been able to train teachers compared with just over one-third of high-poverty districts, and this discrepancy remains [4]. Evidence from surveys of teachers suggests the same: while many teachers use these tools, large majorities report no formal guidance about how to actually use AI for any specific teaching task [33].

Two more discoveries combine to bring a focus to the argument. Students themselves are also reporting this concern that drives AI literacy: Nearly seven in ten middle and high school students report being concerned that using AI for their schoolwork is undermining their critical thinking [22]. The need for AI literacy, however, is not just a systemic one. Second, the international picture is sparser than for the US: as of 20th Oct, only 11 countries have endorsed a K–12 AI curriculum and four further attempted [26], which means that most secondary students experience AI through commercial platforms and peer practice rather than through curriculum. Whatever frame a system takes up, it is taking that on with the understanding that informal learning has long since filled the void

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V. The AILSE Framework

Figure 3 presents the AI Literacy in Secondary Education (AILSE) framework: five competency strands, three progression levels, and four enabling conditions. It is a synthesis, not a rival proposal the strands are the convergent constructs of Table 2, and the level descriptors are compatible with the UNESCO Understand–Apply–Create progression [11] and the AILit domains [17]. Its two departures from existing frameworks are the indexing of progression and the elevation of enabling conditions into the model itself.

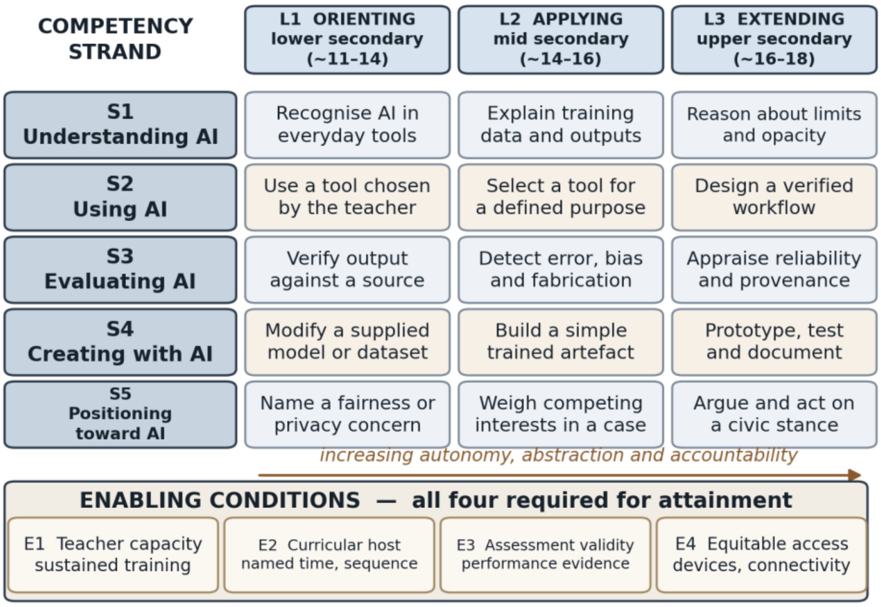

Figure 3. The AILSE framework. Strands synthesise the convergent constructs identified in Table 2; level descriptors are illustrative rather than exhaustive; age **ranges are indicative and should be adjusted to local phase structures.**

1. The five strands

S1 Understanding AI covers the conceptual foundations a learner needs in order to reason about system behaviour: that outputs are generated from patterns in training data, that models have boundaries, and that fluency is not accuracy. It draws on the AI4K12 Big Ideas [25] and the know-and-understand dimension of Ng et al. [12], but is deliberately non-programming: understanding why a model fabricates a citation requires no code.

S2 Using AI covers purposeful application — selecting an appropriate tool, framing a task, and building verification into the workflow rather than appending it. It corresponds to use-and-apply [12], the behavioural dimension of ABCE [14] and Engage with AI [17]. Its inclusion is uncontroversial; its neglect in practice is not, given that over 80% of students report never being taught it explicitly [22].

S3 Evaluating AI is the strand with the strongest claim to being the twenty-first century skill in question. It covers verification against independent sources, detection of bias and fabrication, and calibrated rather than binary trust. It maps to the critical-evaluation element of the founding definition [9], critical judgement of AI solutions in the UNESCO framework [11], and Manage AI [17].

S4 Creating with AI covers designing, building and testing artefacts. We retain it as a core strand rather than an elective, on the evidence that project-based making produces gains across the other strands: middle-school students' AI literacy improved through summer course design work [7], secondary students developed literacy by building AI-driven recycling bins [16], and project-based ethics curricula deepened both technical understanding and ethical awareness [28], [30]. Creation is, in this literature, the pedagogy through which the other strands are learned.

S5 Positioning toward AI covers ethical reasoning, agency, and civic stance the learner's answer to what AI should be allowed to do, and what they will do about it. It integrates AI ethics [12], the human-centred mindset of the UNESCO framework [11], Shape AI [17] and the affective and sociocultural dimensions of the Hong Kong models [5], [14]. We treat affect as belonging here rather than distributed across strands, which keeps the other four strands assessable by performance.

2. Progression indexed to autonomy, not tooling

Existing frameworks index progression to grade band, cognitive taxonomy or depth of engagement. Each has a weakness. Grade banding hard-codes assumptions about prior exposure that a fast-moving technology invalidates. Cognitive taxonomies imply that evaluation must follow application, whereas in practice students evaluate outputs from their first use. Depth of engagement risks being read as tool sophistication. AILSE instead indexes its three levels to three co-varying dimensions: autonomy (how much of the decision the learner makes rather than the teacher), abstraction (whether reasoning is about this output or about systems of this type), and accountability (whether the learner can justify the choice to someone else). A level-3 student is not one who uses more advanced tools but one who can design a workflow, defend its safeguards, and take responsibility for its outputs. This indexing has the practical advantage of surviving tool churn: the descriptors do not need rewriting when a model generation changes.

3. Enabling conditions

The evidence in Section 4.4 is not context for the framework; it is part of it. AILSE therefore names four conditions and holds that the competencies above are not attainable where any is absent.

E1 Teacher capacity. Training has risen sharply but is typically a single session rather than sustained development, and the majority of teachers report no formal guidance for specific instructional tasks [4], [33]. The UNESCO teacher framework, with its Acquire–Deepen–Create progression [10], is the natural instrument here, and should be sequenced alongside the student framework rather than after it.

E2 Curricular host. A competency distributed across all subjects and owned by none is not taught. Systems must name where each strand is hosted and how the entitlement is sequenced. That only 11 countries hold endorsed K–12 AI curricula [26] indicate how rarely this decision has been made.

E3 Assessment validity. Where the only available evidence is self-report, systems will report progress they have not made. Investment in performance and process evidence for S3 and S4 is the highest-value action available to the research community [8].

E4 Equitable access and policy. The training gap between low- and high-poverty districts 67% against 39% [4] means an unadopted framework does not leave provision unchanged; it leaves it to the informal learning that advantaged students access more easily. Equity is a design requirement, not a caveat.

VI. Discussion and Implications

For curriculum. The infusion-versus-subject debate is usually argued on principle and should be argued on capacity. Infusion suits S1, S3 and S5, which are re-specifications of existing disciplinary practices: source evaluation in history, model limitations in science, authorship and voice in language. S4 resists infusion because it needs tooling and specialist support, and is the honest candidate for a named course or elective strand. Systems that infuse everything will find S4 quietly disappears; systems that create a single AI course will find S3 does not transfer.

For pedagogy. The intervention literature converges on project-based and making-oriented designs, with ethics integrated into technical work rather than taught adjacent to it [28], [30]. Interventions of this kind changed not only understanding but attitudes and future orientation [7]. The corollary for practice is that AI literacy is unlikely to be delivered by policy documents and acceptable-use rules, which is currently the dominant institutional response.

For assessment. Two risks deserve naming. The first is measuring attitude and reporting competence, which the dominance of self-report instruments makes easy [8]. The second is treating detection of AI use as assessment of AI literacy; these are opposite activities, and conflating them turns the curriculum into surveillance. A defensible assessment programme for S3 would present students with outputs of varying quality and ask them to identify, justify and correct — a task format the field has barely begun to build for adolescents.

For research. Four priorities follow from the gap analysis: performance-based instruments for S3 and S4 in the secondary phase; cross-cultural validation of the two existing secondary instruments [14], [31]; longitudinal evidence on whether AI literacy instruction protects the critical thinking that students themselves report worrying about [22]; and studies sited outside the North American and East Asian contexts that currently supply most of the evidence base.

Limitations

Four limitations bound these claims. First, data was purposive not comprehensive and only in English; frameworks published in languages other than English and national curriculum documents not identified as part of the UNESCO mapping are expected to be under-represented. Second, coding and cross-framework mapping were performed by one analyst alone therefore the assignments in Table2 particularly an explicit construct versus a subsumed construct requires interpretive judgement that would be assessed through co-coding. Third, most evidence in section 4.4 at the system level is from the USA, and the series of adoptions includes items with different wording across years; whilst these findings are directionally robust, the magnitudes should not be extrapolated to other systems. Fourth, and most importantly AILSE is a synthesis of concepts. The descriptors of progression are proposed and not empirical, and the central claim that competencies cannot be achieved in the absence of enabling conditions is an inference from associative evidence rather than a hypothesis tested. The most obvious next studies are to validate with secondary cohorts the level descriptors and to test if enabling conditions moderate outcomes.

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VII. Conclusion

By those everyday benchmarks, AI literacy has achieved core twenty-first century skill status: intergovernmental frameworks now articulate it, an international assessment programme is poised to measure it, and a majority of the adolescent population already pursue it without being taught. An infrastructure that standing requires, it has not gained. There are five constructs that all frameworks converge on, but they disagree about where creation fits and how progression should be indexed; instruments measure self-reported actions of students to capture theatre classes for learning measures rather than what students can do; and reported provision of training, policy and instruction outstrip reported use by 20 percentage points or more. This is what AILSE responds with by fusing these truths: five strands drawn from the justifiable consensus within the field, three autonomous rather than tool-indexed levels such that they remain relevant through a modelling generation, and four enabling conditions as constraining attainments not aspirational recommendations. The argument of the paper is then basically simple. A competency framework that defines outcomes in concrete terms without reference to what most teachers can do, how much time will be available in the curriculum, which assessment are valid measures, and whether all students will have equal access to content is not a plan; it only describes the void.

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