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Cultivating Students' Digital-Intelligent Literacy in the Era of Generative Artificial Intelligence

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Abstract: Generative artificial intelligence (GenAI) is changing how students search for information, construct knowledge, revise language, and produce creative work. In basic education, the central question is therefore no longer whether students can access intelligent tools, but whether they can use them in ways that are questioning, evidence-based, ethically responsible, and creatively transferable. This article conceptualizes students' digital-intelligent literacy as a four-dimensional construct: intelligent-tool application, data and algorithm understanding, critical verification and evidential reasoning, and ethical responsibility with innovative transfer. Building on international digital competence frameworks and recent policy guidance on GenAI in education, the article argues that many students already have a practical foundation of tool contact and application willingness, yet their literacy profile remains weighted toward low-threshold generation and result adoption. The main problems are not simply "risks" to be prohibited; they are developmental gaps in goal design, learning process, assessment evidence, ethical governance, teacher guidance, and equity support. The article proposes a countermeasure system that links objectives, tasks, assessment, rules, and teacher collaboration: reconstruct literacy goals around credible human–AI collaboration; redesign assignments so that GenAI can assist but cannot replace thinking; rebuild process assessment through an evidence chain and use declaration; move ethical governance from after-the-fact punishment to before-the-task design; strengthen teacher capacity through collaborative lesson research; and reduce inequality through public scaffolds rather than restriction alone. The purpose is to shift students from "being able to generate" toward "being able to judge, justify, take responsibility, and create.

Keywords: generative artificial intelligence; digital-intelligent literacy; basic education; human–AI collaboration; process assessment; educational equity.

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1. Introduction

The educational significance of generative artificial intelligence lies not only in its technical capacity to produce fluent text, images, code, summaries, and solutions. More importantly, it changes the starting conditions of learning. Students increasingly begin tasks not from a blank page but from a generated draft; not from a limited set of teacher-provided materials but from an apparently endless stream of plausible content; not from a slow search for sources but from immediate synthesis. This shift is sometimes described as a threat to learning, and sometimes as a shortcut to productivity. For basic education, neither description is sufficient. The real issue is developmental: when intelligent generation becomes normal, the formation of judgment, evidence awareness, responsibility, and originality must be deliberately designed rather than assumed.

International frameworks have long established that digital competence is broader than operational skill[1]. DigComp 2.2 defines digital competence through interconnected areas such as information and data literacy, communication and collaboration, digital content creation, safety, and problem solving, emphasizing knowledge, skills, and attitudes rather than button-clicking alone. The global reference framework developed for digital literacy measurement similarly treats literacy as the ability to access, manage, understand, integrate, communicate, evaluate, and create information through digital technologies in ways appropriate to life, work, and learning. These frameworks remain relevant, but GenAI adds a new pressure: the production of polished outputs is becoming cheap, while the verification of outputs is becoming more consequential. A student can obtain a well-formed answer before forming a well-formed question. Education therefore has to move the center of gravity from access and operation toward warranted use.

Policy guidance has begun to recognize this shift. UNESCO's guidance on generative AI in education and research calls for a human-centered approach, attention to inclusion and equity, protection of human agency, validation of systems for ethical and pedagogical appropriateness, development of AI competencies for learners, and capacity building for teachers[2]. The direction is clear: schools should neither romanticize GenAI as an automatic tutor nor treat it merely as a cheating machine. They should cultivate the conditions under which students can use powerful tools without surrendering the obligations of inquiry. For basic education, this means that digital-intelligent literacy must be embedded in ordinary tasks, ordinary feedback, and ordinary classroom rules—not confined to a one-time "AI awareness" lecture.

This article uses the term digital-intelligent literacy to describe the integrated quality that students need when digital environments are increasingly mediated by generative systems. The term is intentionally narrower than "digital competence" in one respect and broader in another. It is narrower because it focuses on learning situations in which students interact with data-driven, probabilistic, generative tools. It is broader because it connects tool use with evidential reasoning and ethical responsibility. In this article, students' digital-intelligent literacy is defined as the capacity to (a) select and apply intelligent tools for meaningful tasks, (b) understand enough about data and algorithms to interpret generated content critically, (c) verify claims and construct evidence-based explanations, and (d) act responsibly—protecting privacy, acknowledging contributions, respecting intellectual boundaries, and transferring what is learned into new creation. Table 1 is four dimensions of digital-intelligent literacy at a glance.

Table 1. Four dimensions of digital-intelligent literacy at a glance

Dimension	Core student question	Observable evidence in schoolwork
Intelligent-tool application	What should be delegated, iterated, or done directly?	Delegation plan; constraints in prompts; comparison of outputs; decision not to use a tool
Data and algorithm understanding	Why might this output be fluent but wrong?	Explanation of model limits; identification of bias, hallucination, or missing context
Critical verification and evidential reasoning	How do I know this claim deserves acceptance?	Source map; cross-checking; uncertainty notes; explicit adoption/rejection criteria
Ethical responsibility and innovative transfer	Can I defend this as mine and safe to share?	Use declaration; privacy confirmation; attribution; original transformation beyond the generated draft

The article follows a problem-oriented structure. It first analyzes the current situation: policy and infrastructure conditions are improving, student application scenarios are expanding, and the practical foundation for literacy cultivation is stronger than before. It then identifies five interrelated problems: the narrowing of literacy goals to tool operation; the thinning of learning processes through cognitive offloading; the opacity of assessment when final products hide process evidence; the under-specification of ethics, privacy, and academic integrity; and the unevenness of teacher guidance, family support, and institutional resources. Finally, it proposes countermeasures that are designed as a system rather than a list. The core argument is that GenAI does not automatically produce higher literacy; it amplifies the quality of the learning design into which it is placed[3]. If tasks reward only speed and polish, GenAI will train students to accept fluent outputs. If tasks require

questioning, sourcing, comparison, revision, and public explanation, GenAI can become a powerful environment for cultivating judgment.

Three boundary choices should be stated. First, the article focuses on basic education rather than higher education or workforce training. This matters because students in basic education are still forming epistemic habits: what counts as a good answer, what counts as evidence, and what counts as one's own work. Second, the article is conceptual and design-oriented. It does not report a new empirical dataset; instead, it synthesizes established frameworks and policy guidance into a teachable and assessable structure for schools. Third, the article avoids a deficit narrative. The problem is not that students are "unqualified" for the GenAI era. On the contrary, many students show strong curiosity, rapid tool adoption, and flexible use across scenarios. The educational task is to convert this existing energy into durable literacy by raising the level of demand embedded in tasks and assessments.

2. Current Situation

2.1 Policy and infrastructure conditions are creating a real cultivation basis

The conditions for cultivating digital-intelligent literacy are no longer purely hypothetical. Over the past decade, digital competence has been institutionalized through frameworks, action plans, teacher standards, and measurement initiatives. The European Union's digital education agenda has framed high-quality digital education as a system-level priority rather than a local experiment. DigCompEdu has articulated what educators need in order to promote learners' digital competence, including professional engagement, digital resources, teaching and learning design, assessment, empowerment of learners, and facilitation of learners' digital competence. UNESCO's ICT Competency Framework for Teachers similarly links teacher development with the wider goal of preparing learners for knowledge societies[4]. These documents differ in scope and governance context, but they converge on one point: digital learning is not an accessory; it is part of the basic structure of contemporary schooling.

GenAI guidance has added urgency without replacing earlier foundations. UNESCO (2023) explicitly warns against treating GenAI as a neutral plug-in and urges governments and institutions to consider age appropriateness, privacy, transparency, validation, and the long-term implications for knowledge and assessment. For basic education, the significance is practical. Schools are being asked to make decisions before all evidence is settled: what students may use, what they must disclose, what teachers should model, what data should never be uploaded, and how assessment should change when polished output can be produced quickly. This is a difficult position, but it is also an opportunity. Precisely because GenAI exposes weaknesses in task design and assessment, it can push schools to clarify what student learning is supposed to look like.

The policy environment should therefore be read as enabling, not merely restrictive. When policy emphasizes human agency, inclusion, and competence development, it gives schools permission to move beyond the false choice between "ban" and "laissez-faire." A ban may reduce some visible risks while driving use underground and widening the gap between students who receive guidance and those who do not. Laissez-faire adoption may increase short-term productivity while leaving students without criteria for trust. The more productive reading is that schools now have a mandate to design guided use: clear boundaries, explicit learning goals, visible reasoning, and accountable output.

2.2 Student application scenarios are expanding across everyday learning

Students' encounters with GenAI are not limited to formal computer science or information technology classes. They appear in language learning, writing, reading comprehension, mathematics explanation, science inquiry, history source interpretation, art and design, presentation production, coding, and project-based learning. Even when a school does not formally introduce GenAI, students may meet it through search engines, office software, translation tools, mobile applications, social platforms, and peer recommendations. The boundary between "using AI" and "using digital tools" is becoming blurred. A student may not say "I used generative AI"; the student may say "I checked a summary," "I polished a paragraph," "I generated a picture," or "I asked why my code was wrong."

This expansion has three features. First, it is low-threshold. Natural-language interaction reduces the need for specialized commands. Students can obtain outputs through everyday language, which makes the tool feel intuitive and friendly. Second, it is cross-scenario[5]. The same tool can support brainstorming, outlining, translation, explanation, summarization, style revision, visual generation, and feedback simulation. Third, it is socially contagious. Students learn prompts and workflows from peers, short videos, online communities, and family members, not only from teachers. As a result, classroom practice often lags behind the informal learning ecology surrounding students.

These features provide a genuine starting point for literacy cultivation. Students are not beginning from indifference. Many are curious, fast to experiment, and willing to compare different outputs. They can often describe what a tool is "good for" in practical terms: making language smoother, giving examples, generating ideas, or explaining a concept in another way. The problem is not the

absence of contact; it is that contact does not automatically become competence. A student who can obtain five answers is not necessarily able to judge which answer is relevant, accurate, appropriately sourced, ethically usable, or worth transforming into original work.

2.3 The emerging capability profile: broad access, uneven depth

The current situation can be summarized as a literacy profile with broad access but uneven depth. At the surface level, students show growing familiarity with generation, revision, and multimodal production. At a deeper level, the capabilities that determine educational value are less evenly developed: asking well-specified questions, setting constraints, recognizing hallucination, checking sources, distinguishing correlation from explanation, identifying bias, protecting personal information, acknowledging machine contribution, and defending one's own reasoning.

This unevenness is visible in common task chains. A weak chain looks like this: receive assignment → paste prompt → accept first plausible output → make cosmetic edits → submit. A stronger chain looks different: interpret the task → decompose it into sub-questions → decide what may be delegated to the tool → generate alternatives → compare claims against sources → identify uncertainty → revise for purpose and audience → explain what was accepted, rejected, and changed. The second chain is not defined by "less AI." It may use AI extensively. What distinguishes it is the location of human judgment. In the weak chain, judgment is outsourced to fluency. In the strong chain, judgment is exercised before, during, and after generation[6].

The gap between these chains explains why simple frequency statistics can be misleading. If we ask only whether students use GenAI, we may find rapid adoption and conclude that literacy is rising. If we ask how students validate outputs, disclose use, or preserve authorship, the picture becomes more complex. DigComp 2.2's emphasis on attitudes is useful here: literacy includes dispositions such as criticality, responsibility, and willingness to update one's understanding. In the GenAI context, these attitudes must become observable behaviors. "Being critical" cannot remain a slogan; it must appear as source comparison, uncertainty annotation, and revision history.

It is therefore inaccurate to describe the present moment only as a crisis. It is better described as a transition from access-driven digitalization to judgment-driven digitalization. Students already have a foothold in tool use. Schools already have policy language and frameworks to build upon. The next step is to align tasks, assessment, and teacher guidance with a higher standard of use. That alignment is the focus of the problems and countermeasures below.

2.4 What is genuinely new: five shifts in the literacy demand

It is tempting to say that GenAI is simply one more technology in a long line of educational tools. This is partly true and partly misleading[7]. The continuity is real: students still need to read, reason, calculate, cite, create, and collaborate. The discontinuity is also real: GenAI changes the economics of production. When the cost of producing a plausible artifact approaches zero, the scarce educational resources become attention, discrimination, warrant, and responsibility. Five shifts clarify what is new.

First, from finding information to adjudicating synthesis. Search engines return sources; generative systems return synthesis. The older digital literacy challenge was to choose among visible links and evaluate credibility. The new challenge is that the links may be dissolved into a confident paragraph. Students must therefore learn to reopen the black box of synthesis by asking what claims are embedded, which of them require sources, and how the answer would change under different assumptions.

Second, from producing text to managing voice. Writing instruction has always balanced correctness with voice. GenAI can produce correctness without voice, or voice without ownership. Students need criteria for when generated language clarifies their thinking and when it replaces it. This is not only an integrity issue; it is a developmental one. If students never experience the friction of finding words for their own ideas, they may lose the very capacity that revision is meant to strengthen.

Third, from error as visible gap to error as fluent surface. Traditional student errors often signal what a student does not understand. Generated errors can be polished enough to hide. A fabricated reference may look more credible than a real but messy one. A subtly wrong diagram may be more attractive than a rough correct sketch. Literacy must therefore include suspicion toward surface quality: beauty is not evidence, confidence is not accuracy, and coherence is not truth.

Fourth, from individual work to declared collaboration. Students have always collaborated—with peers, books, tutors, family, and tools. GenAI makes collaboration more immediate and more opaque. The important distinction is not "alone" versus "assisted," because almost all academic work is assisted in some way. The distinction is between assistance that is transparent, educationally productive, and owned by the learner, and assistance that is hidden, substitutive, and unexamined. Declared collaboration becomes a literacy practice.

Fifth, from stable rules to evolving norms. Many digital rules could be taught once: cite sources, avoid plagiarism, do not share passwords. GenAI norms are still evolving across disciplines and institutions. Students therefore need

transferable judgment rather than memorized exceptions. They should learn to ask questions that remain useful when tools change: What is the purpose of this task? What evidence does this community respect? What must remain my own? Who could be affected? What must be documented?

These shifts show why "digital literacy" and "AI literacy" should not be treated as separate islands. AI literacy without digital literacy can become tool enthusiasm; digital literacy without GenAI awareness can become outdated. Digital-intelligent literacy names the intersection: students use intelligent tools inside a disciplined culture of evidence and responsibility. Table 2 is what genai changes —and what schooling must protect.

Table 2. What GenAI changes—and what schooling must protect

GenAI shift	Educational opportunity	Risk if left undesigned	Protected learning demand
Synthesis is immediate	Faster access to explanations and alternative framings	Students accept synthesis without reopening its claims	Reconstruct the source base and test consequential claims
Polished production is cheap	More time for drafting, feedback, and multimodal expression	Surface quality hides weak understanding	Require process evidence and live explanation
Assistance is always available	Scaffolding for language, accessibility, and practice	Hidden substitution and uneven home coaching	Normalize declared collaboration and public scaffolds
Errors can look authoritative	Rich material for critique and error analysis	Fluent misinformation gains credibility	Teach suspicion toward confidence, beauty, and coherence
Norms keep evolving	Students can help refine responsible-use rules	Rule memorization fails when tools change	Cultivate transferable judgment: purpose, evidence, ownership, impact

3. Problems

3.1 Goal narrowing: literacy is easily reduced to tool operation

The first problem is a narrowing of educational goals. When schools respond to GenAI, the most immediate response is often operational: which platform to use, how to log in, how to write a prompt, how to format an output, and how to avoid obvious misuse. These are necessary but insufficient. If digital-intelligent literacy is treated as prompt technique, students may learn to obtain better outputs without learning to ask better questions. They may become more efficient users of generated content while remaining uncertain about why one output is credible and another is merely confident.

This narrowing has a hidden consequence: it confuses performance with literacy. A polished paragraph can conceal weak comprehension[8]. A correct-looking solution can conceal a missing model of the problem. A visually attractive poster can conceal an unexamined claim. In traditional tasks, weak understanding often left visible traces—vague explanations, inconsistent logic, missing steps. GenAI can fill those surface gaps. If the goal remains "produce a clean final answer," the tool can simulate achievement. If the goal is "construct and justify an answer," simulation becomes much harder.

The narrowing also affects equity in an unexpected way. Students with stronger language ability may write richer prompts and receive richer outputs. Students with prior knowledge can detect errors that novices cannot. Students with supportive adults may learn rules of disclosure and citation earlier. If schools define literacy narrowly as access plus operation, they may declare success while the deeper gap grows. The goal must therefore include the higher-order capacities that allow students to benefit from GenAI without being governed by it.

3.2 Process thinning: fluent generation encourages cognitive offloading

The second problem is process thinning. Learning depends on desirable difficulty: students need to retrieve, compare, organize, explain, and revise. GenAI can remove friction that is educationally valuable. When a summary is instantly available, students may skip the reading that would have made the summary meaningful. When an essay outline appears fully formed, students may skip the struggle of deciding what they actually think. When a mathematics solution is presented step by step, students may mistake recognition for generation: they can follow the steps but cannot reconstruct them under changed conditions.

Cognitive offloading is not inherently bad. Calculators, spell-checkers, dictionaries, and search engines all offload work. The question is what remains after offloading. If students offload note-taking but still evaluate claims, the tool may free attention for higher-order reasoning. If they offload question formation, evidence selection, and argument construction, little learning remains. GenAI is more seductive than earlier tools because it does not merely retrieve; it composes. It can imitate the external form of reasoning without guaranteeing the internal validity of the reasoning.

Process thinning is especially risky in basic education because students are still learning how knowledge is made. Younger students may treat conversational fluency as authority[9]. Older students may strategically use fluency to reduce effort while appearing engaged. In both cases, the problem is not dishonesty alone; it is an underdeveloped relationship between output and evidence. Students need structured occasions to slow down: to ask "What would count as a good answer?", "What must be true for this claim to hold?", "Which part is factual, which part is interpretive, and which part is stylistic?", and "What would change my mind?"

3.3 Assessment opacity: final products hide process evidence

The third problem is assessment opacity. Many school assessments still rely heavily on final products: essays, reports, presentations, worksheets, posters, and projects. These products remain valuable, but GenAI changes what can be inferred from them. A final text no longer reliably indicates the path by which it was produced. Two students may submit similarly polished work while having very different levels of understanding. One may have used GenAI to test ideas, check counterarguments, and improve expression after drafting. Another may have pasted the prompt, accepted the output, and changed a few words.

When assessment cannot see process, it rewards the wrong signals. It may over-credit linguistic polish and under-credit judgment. It may push students toward concealment because disclosure is perceived as self-incrimination[10]. It may also encourage teachers to rely on detection tools that are unstable, biased against multilingual writers, and unable to distinguish legitimate assistance from substitution. The result is a deteriorating trust environment: students feel suspected, teachers feel deceived, and assessment loses its formative function.

The deeper issue is inferential. Assessment is an argument from evidence to claims about learning. If the evidence no longer supports the claim, the assessment must change. It is not enough to add a rule saying "do not misuse AI." The evidence itself must be redesigned. Students need to submit not only products but traces: prompts, drafts, source checks, rejected outputs, annotations, reflections, and explanations of contribution. These traces are not bureaucratic extras; they are the new evidentiary basis for judging learning in a GenAI-rich environment.

3.4 Ethics and integrity are under-specified at the point of use

The fourth problem is that ethical expectations are often stated globally but under-specified locally. Schools may have policies on academic honesty, plagiarism, data privacy, and acceptable technology use. Students, however, make decisions at the point of use: May I ask the tool to rewrite this sentence? May I upload a classmate's photo? May I use generated code without understanding it? If the rubric says "cite sources," does a generated explanation count as a source? What must be disclosed: the tool name, the prompt, the date, the version, the parts affected, or the human judgment applied?

Under-specification produces two opposite errors. One is permissiveness: students assume that if a tool is available, any use is acceptable. The other is fear: students avoid disclosure, hide legitimate use, or become anxious about ordinary assistance[11]. Both errors damage literacy. Ethics should not be taught as a list of prohibitions detached from tasks. It should be embedded in the task as part of quality. A good GenAI-supported project should make responsibility visible: what was generated, what was verified, what was changed, what was protected, and what remains the student's own claim.

Privacy and safety require particular clarity in basic education. Students may not understand that uploading personal information, images, schoolwork containing names, health details, family circumstances, or location data can create risks. They may also treat generated content as anonymous or ownerless. Yet generated outputs can raise questions of attribution, copyright, misinformation, stereotype, and harm. Ethical literacy means that students can pause before generation and ask: Is this input appropriate? Is this output safe to share? Who could be affected? What must be acknowledged? What should not be automated?

3.5 Support is uneven across teachers, families, and institutions

The fifth problem is uneven support. Teachers differ in technological confidence, subject knowledge, assessment experience, and available time. Younger teachers may be fluent in tools but still developing classroom routines; experienced teachers may have strong pedagogical judgment but less exposure to generative systems. Some teachers see GenAI as a threat to be controlled; others see it as a tutor to be embraced; many are asked to innovate without time to redesign tasks or collaborate with colleagues. DigCompEdu's framework is relevant here because it treats educator competence as multi-dimensional, including assessment and learner empowerment rather than only technical operation[12]. The teacher challenge is therefore not simply "learn the tool," but "redesign learning under new evidentiary conditions."

Families also differ. Some can provide devices, connectivity, paid accounts, language support, and informed discussion. Others cannot. If GenAI use is required but not scaffolded, homework may amplify inequality. If it is banned at home but used informally anyway, students

receive mixed messages. Institutions differ too. Some schools have clear acceptable-use policies, device management, library support, and professional development. Others rely on individual teacher initiative. The result is that students may encounter contradictory expectations across subjects and grade levels: one teacher encourages AI brainstorming, another prohibits all AI, a third ignores the issue. Such inconsistency makes it harder for students to form stable norms.

These five problems interact. Narrow goals make process thinning easier to miss. Thin processes make assessment less interpretable. Opaque assessment makes ethics punitive rather than formative. Under-specified ethics increases inconsistency. Uneven support turns inconsistency into inequality. A serious countermeasure system must therefore address the whole chain rather than adding isolated rules.

4. Countermeasures

4.1 Reconstruct goals: a four-dimensional framework with developmental progression

The first countermeasure is to state clearly what students are expected to become able to do. A four-dimensional framework can guide curriculum design without adding excessive new content.

Dimension 1: Intelligent-tool application. Students should be able to choose an appropriate tool for a purpose, formulate a task with constraints, decompose complex work, iterate outputs, and recognize when a tool is not needed. This dimension includes practical fluency, but it is not limited to prompts. A student who can say "this task needs comparison, not generation" is more advanced than a student who knows twenty prompt templates.

Dimension 2: Data and algorithm understanding. Students do not need to become engineers, but they need a working model of why generated content can be wrong. They should understand that outputs are produced from patterns in data, that training data have scope and limits, that models can reproduce bias, that fluency is not evidence, and that probabilistic generation can produce confident errors. Age-appropriate explanations can use analogies at lower grades and more formal concepts at higher grades.

Dimension 3: Critical verification and evidential reasoning. Students should be able to identify claims that require checking, locate credible sources, compare independent sources, distinguish primary from secondary evidence, mark uncertainty, and explain why a claim is accepted, rejected, or modified. This dimension is the heart of digital-intelligent literacy in the GenAI era because it protects learning from fluency.

Dimension 4: Ethical responsibility and innovative transfer. Students should be able to use GenAI within declared rules, protect privacy, acknowledge assistance, respect intellectual boundaries, avoid harmful outputs, and transform what they learn into new explanations, designs, arguments, or artifacts. The end point is not compliance alone; it is responsible creation.

Figure 1. is A four-dimensional framework for students' digital-intelligent literacy.

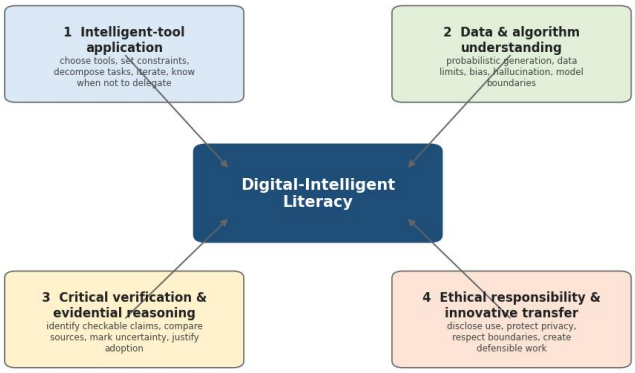


Figure 1. A four-dimensional framework for students' digital-intelligent literacy.

These dimensions should be translated into a progression. In primary education, the emphasis can be on experience, safety, and simple verification: knowing that generated answers may be wrong, asking where information comes from, and learning not to share personal data. In lower secondary education, the emphasis can shift to method: comparing sources, improving prompts through constraints, documenting changes, and explaining the difference between help and substitution. In upper secondary education, the emphasis can move toward disciplined inquiry: evaluating claims in contested topics, using domain criteria of evidence, managing citation and disclosure, and producing original work under conditions of declared human–AI collaboration. Progression prevents two common mistakes: teaching young students abstract warnings without practice, and teaching older students basic rules without intellectual challenge.

Goal reconstruction also requires school-level alignment[13]. If every subject defines acceptable use separately, students receive mixed signals. A shared framework allows subjects to differ in evidence standards while agreeing on common expectations: do not misrepresent authorship, do not upload sensitive data, verify consequential claims, disclose assistance, and remain responsible for submitted work. Alignment does not mean uniformity. A history class may emphasize source provenance; a science class may emphasize data and reproducibility; a language class may emphasize voice, audience, and citation; an art class may emphasize

originality, consent, and transformation. The common framework keeps these differences coherent.

4.2 Redesign tasks: GenAI can assist, but cannot replace thinking

The second countermeasure is task redesign. If a task can be completed by pasting the assignment into a GenAI tool, the task—not the student—is the first thing to redesign. The aim is not to make assignments artificially difficult or to ban tools. It is to create tasks in which tools are useful but insufficient.

Strong-context tasks. These tasks require local, current, personal, or classroom-specific material that generic generation cannot fully supply. Examples include interviewing a community member and testing the generated summary against the transcript; analyzing data collected by the class; comparing a generated explanation of a local environmental issue with field observations; or revising a school policy proposal after consulting stakeholders. GenAI can help organize questions and language, but the evidential core comes from the student's context.

Strong-evidence tasks. These tasks require visible source work. Students must provide a source map, identify claims that need verification, compare at least two independent sources, and annotate disagreements. For example, in a science task, students may ask GenAI for an explanation of a phenomenon, then test the explanation against a textbook, a dataset, a teacher demonstration, and a reputable public source. The assessment target is not whether the initial explanation was right, but whether the student can build a warranted account.

Strong-performance tasks. These tasks require students to defend or transform their work in real time. Oral defense, peer questioning, live revision, whiteboard reconstruction, studio critique, and reflective memos make hidden understanding visible. A student may use GenAI to prepare, but must explain choices without the tool. Performance does not mean memorization; it means ownership. If a student cannot explain why a claim was included, the claim has not yet become knowledge.

Task redesign should also include explicit delegation decisions. Before using GenAI, students can complete a short "delegation plan": What will I do myself? What may the tool draft? What must be verified? What will not be delegated? This small routine converts ethics from policy into cognition. It also gives teachers a formative window: students reveal whether they understand the task by how they divide labor between human judgment and machine generation.

A common concern is that such tasks take more time. They do, if added to unchanged coverage. The better response is selective depth. Not every worksheet needs an evidence chain. Schools should identify a limited number of high-value tasks per unit where digital-intelligent literacy is deliberately taught and assessed. Other activities can remain ordinary practice. Depth in a few well-designed tasks is more powerful than superficial AI integration everywhere.

4.3 Rebuild process assessment: make learning visible through an evidence chain

The third countermeasure is assessment redesign. In a GenAI-rich environment, assessment should ask for an evidence chain rather than a single artifact. The evidence chain can be lightweight but meaningful: task interpretation; delegation plan; prompt and output excerpts; adoption and rejection decisions; source verification; revision history; final product; and reflective explanation. The point is not surveillance. The point is to restore a valid connection between what is submitted and what is learned.

A practical rubric can include four criteria aligned with the framework. Task understanding asks whether the student interpreted the problem and set appropriate constraints. Evidence quality asks whether claims are checked, sources are compared, uncertainty is marked, and reasoning is transparent. Collaboration strategy asks whether GenAI was used deliberately: Were prompts improved? Were outputs tested? Were weak outputs rejected? Was the tool used to extend rather than replace thinking? Responsibility asks whether disclosure, privacy, citation, safety, and ownership are handled correctly. This rubric shifts credit from polish to judgment.

A student use declaration should be normalized. It can be short: which tool was used; for which stages; what was accepted; what was changed; what was checked; what remains the student's own claim; and whether any sensitive information was excluded[14]. The declaration should be educational rather than punitive. If students disclose use and show strong verification, they should not be penalized simply for using an approved tool. If they conceal use or submit unverified consequential claims, the problem is not only rule-breaking; it is a breakdown in evidential responsibility.

Assessment should also distinguish consequences. Not all errors are equal. A formatting mistake is not the same as a fabricated citation. A weak prompt is not the same as uploading personal data. A response matrix can help teachers respond proportionately: teachable errors receive feedback; verification failures require revision; privacy violations trigger safety procedures; misrepresentation triggers integrity review. Proportionality protects trust. Students are more likely to disclose honestly when disclosure leads to guidance rather than automatic suspicion.

Finally, assessment should create occasions for human explanation. A brief oral check, a live revision, or a

reflective memo can confirm ownership more reliably than unreliable AI-detection scores. This is especially important for multilingual students and students whose writing style changes with support. Process evidence treats assistance as normal when it is transparent and educationally used.

4.4 Move ethics governance from punishment after the fact to design before the task

The fourth countermeasure is to bring ethics into task design. Rules are necessary, but rules alone arrive too late. Ethical governance should shape the assignment before students open a tool. Teachers can specify four zones: Open collaboration zone: brainstorming, alternative phrasing, practice explanations, formative feedback, and accessibility supports are allowed with disclosure. Guided verification zone: GenAI may propose content, but students must verify claims against sources and show the comparison. Human ownership zone: final argument, interpretation, personal reflection, and assessed explanation must be defensible by the student. Restricted zone: sensitive personal data, confidential school information, images of others without consent, and outputs intended to deceive are not permitted. These zones are easier for students to understand than a generic ban. They also make the ethics of use discussable. Students can ask whether a particular use is formative or substitutive, whether it supports access or avoids learning, and whether it respects the people represented in data.

Ethics should be taught through cases. Short classroom cases can present realistic dilemmas: a student uses GenAI to translate their own draft; another asks it to write a "personal" reflection; a group uploads a classmate's interview without consent; a science report includes a generated citation that looks real but cannot be found; an art project imitates a living artist's style[15]. Discussion should move beyond "right or wrong" toward criteria: authorship, consent, evidence, harm, and educational purpose. The aim is not to catch students but to form judgment before high-stakes situations occur.

Schools should also clarify teacher modeling. If teachers use GenAI to prepare materials, they can model disclosure and verification in age-appropriate ways. This does not require revealing every professional workflow; it requires showing students that responsible adults also check outputs, protect data, and remain accountable. Modeling prevents a double standard in which students are asked to be transparent while adults treat tool use as invisible.

4.5 Strengthen teacher capacity through collaborative lesson research

The fifth countermeasure is teacher development, but not as one-off software training. Teachers need opportunities to redesign real tasks and examine real student evidence. Collaborative lesson research is well suited to this. A team can choose one upcoming task, predict how GenAI might change student behavior, redesign the task to preserve thinking, teach it, collect evidence chains, and discuss what the evidence shows. The focus is not "Did students use AI?" but "What did students learn, and how do we know?"

Teacher learning can be organized into three layers. The first layer is tool literacy: understanding basic capabilities, limits, privacy settings, and safe classroom use. The second layer is design literacy: rewriting objectives, tasks, rubrics, and examples so that GenAI cannot substitute for the intended learning. The third layer is interpretive literacy: reading student evidence chains, giving feedback on judgment, and distinguishing productive assistance from dependency. This sequence mirrors DigCompEdu's movement from professional engagement and resources toward assessment and learner empowerment.

Professional development should also use subject-specific examples. Generic AI workshops often fail because teachers cannot see Monday morning[16]. A mathematics department needs examples of solution reconstruction and misconception probing. A language department needs examples of voice preservation, translation boundaries, and evidence for interpretation. A science department needs examples of data explanation and experimental constraints. A humanities department needs examples of provenance, perspective, and argument. The common framework provides coherence; subject examples provide transfer.

School leaders matter here. Teachers need time, shared templates, access to safe tools, and permission to iterate. If teachers are told to innovate but assessed only on unchanged outcomes, they will rationally minimize risk. Leadership should make process evidence legitimate by asking for it in curriculum documents, sample tasks, and assessment moderation. Digital-intelligent literacy becomes real when it is visible in the artifacts of teaching, not only in the language of policy.

4.6 Reduce inequality through public scaffolds rather than restriction alone

The sixth countermeasure is equity by design. If some students have better devices, faster networks, paid accounts, quieter study spaces, and adults who can coach prompt use, then unguided adoption will widen gaps. The solution is not to pretend the gap does not exist, nor to ban tools that disadvantaged students may still encounter informally. Schools should provide public scaffolds: school-managed access where possible, clear device and data rules, library or media-center support, exemplar tasks, shared prompt and verification templates, and explicit instruction for students who have less out-of-school guidance.

Equity also means attention to language and accessibility. GenAI can support multilingual learners,

students with reading difficulties, and students who need alternative representations. Used well, it can lower barriers. Used poorly, it can mask those supports and make students appear independent when they are not. The goal is supported independence: scaffolds are declared, learning remains visible, and support is gradually adjusted. Accessibility uses should be treated as legitimate when they enable participation, while assessment still checks the target competence through appropriate evidence.

Family communication is part of equity. Families need a clear explanation of what students are learning to do with GenAI and why. If home messages are limited to "AI is cheating" or "AI is the future," students receive either fear or hype[17]. A better message is practical: students may use approved tools for certain stages; they must protect privacy; they must disclose assistance; they are responsible for checking important claims; and the school assesses process as well as product. Consistency between school and home reduces hidden advantage.

Equity should be monitored through participation and evidence quality, not only device counts. Schools can ask: Who submits evidence chains? Who revises after feedback? Who asks verification questions? Who avoids disclosure? Which groups receive only rule reminders while others receive design-rich tasks? These questions turn equity from an access issue into a learning-quality issue.

4.7 Subject-specific illustrations: same framework, different evidence

A shared framework should not flatten subject differences. What counts as evidence in mathematics is not identical to what counts as evidence in history, language, science, or art. The following illustrations show how the same four dimensions can be expressed through different disciplinary warrants.

Mathematics. GenAI can produce worked solutions quickly, so the assessed goal should shift from obtaining a solution to controlling the conditions under which a solution is valid. Students can be asked to generate two solution paths, compare them, identify where an assumption enters, change one condition, and explain why the method still works or fails[18]. A strong task might present an AI-generated solution containing a subtle algebraic or modeling error and ask students to locate, correct, and generalize the error. Tool application appears in choosing representations; algorithm understanding appears in recognizing that a fluent derivation may still contain an invalid step; verification appears in checking units, constraints, and special cases; responsibility appears in stating what the tool contributed and what the student can reproduce independently.

Language and literacy. In reading and writing, the central risk is not only factual error but loss of voice and interpretive responsibility. Students can use GenAI to generate alternative readings of a text, then test each reading against textual evidence. They can compare a generated summary with their own marginal notes and identify what the summary flattened: ambiguity, tone, irony, context, or audience. In writing, students may use the tool for counterargument generation or style diagnosis, but the assessed product should include a short authorial statement: what claim is mine, what evidence supports it, what suggestions I rejected, and how my final voice differs from the generated draft. This preserves the educational purpose of writing as thinking, not merely text production.

Science. Science offers a natural home for verification because claims are tied to observation, measurement, models, and reproducibility. Students can ask GenAI to explain an experiment, predict an outcome, or propose variables, then compare the proposal with actual data. A strong task asks: Which parts of the generated explanation are consistent with our measurements? Which parts confuse correlation with causation? Which variables were omitted? What additional evidence would distinguish two explanations? Responsibility includes safe data handling, honest reporting of anomalous results, and refusal to let a generated narrative overwrite observation.

History and social studies. Here the key competence is provenance. GenAI can synthesize narratives that sound balanced while hiding selection and perspective. Students can generate an account of an event, then reconstruct the source base that would be needed to support it[19]. They can ask: Which voices are present? Which are missing? What is treated as background and what as cause? How does the account change if told from another position? Students learn that verification is not only checking dates; it is interrogating framing, selection, and interpretation.

Arts and design. GenAI expands image, music, and concept production while raising questions of style, consent, and transformation. Students can use generated material as a prompt for critique rather than as finished work: What does this image assume? Whose style is being echoed? What would make this piece transformative rather than imitative? What permissions are needed? Process evidence can include sketches, mood boards, rejected variants, and a statement of influences. Responsibility includes cultural respect and clarity about contribution; innovation transfer includes making choices that could not have been generated without the student's intention.

Across subjects, the teacher's question remains stable: What must the student be able to show when the tool is taken away? The answer differs by discipline, but the design move is the same—separate what GenAI may accelerate from what the learner must own.

4.8 Five implementation traps to avoid

Countermeasures can fail in predictable ways. Naming the traps helps schools protect the core purpose.

Trap 1: Confusing coverage with competence[20]. A school may report many AI activities while students still cannot verify a claim or explain a choice. Activity counts are easy to inflate; judgment is not. The remedy is to anchor reports in a small number of assessed evidence chains rather than a large number of tool demonstrations.

Trap 2: Letting detection replace assessment. AI detectors may appear to offer certainty, but they cannot reliably determine authorship or learning, and they may unfairly flag multilingual or formulaic writing. If schools build their response around detection, they create an arms race they cannot win and a trust climate they do not want. Detection can at most raise a question; process evidence answers it.

Trap 3: Adding paperwork without changing inference. Evidence chains become bureaucratic when teachers collect artifacts they do not use. A folder of screenshots is not assessment. The remedy is selective depth: fewer artifacts, clearer questions, better feedback. Every required trace should answer an inferential need. If a trace does not change feedback or judgment, delete it.

Trap 4: Treating ethics as assembly content. A one-time lecture on rules may raise awareness without changing point-of-use decisions. Ethics must be attached to tasks, rubrics, and cases. Students learn responsibility by making decisions with stakes low enough to discuss and high enough to matter.

Trap 5: Outsourcing courage to policy. Policies are necessary, but students experience norms through teachers' daily moves: what is praised, what is questioned, what is returned for revision, and what is accepted without comment. A school can have a progressive document and a conservative classroom, or a cautious document and powerful teaching. The goal is alignment, but when alignment is incomplete, classroom evidence should lead policy revision rather than policy language pretending the classroom is already transformed.

Avoiding these traps keeps the focus where it belongs: not on appearing modern, but on making student judgment visible and teachable.

5. Implementation Roadmap: Making the Countermeasures Work in Ordinary Schools

A framework becomes effective only when it changes calendars, documents, and classroom routines. The roadmap below is designed for ordinary schools rather than ideal laboratories.

Phase 1: Establish shared language and boundaries. School leaders, teachers, students, librarians, and family representatives should agree on a short definition of digital-intelligent literacy and the four zones of use. The outcome should fit on one page: what students are learning to do, what uses are encouraged, what uses require verification, what must remain human-owned, and what is restricted. This page should be translated into subject examples before the next phase.

Phase 2: Redesign a small number of high-value tasks. Each subject group selects one task per unit or project in which judgment genuinely matters. The group rewrites the task using strong-context, strong-evidence, or strong-performance patterns; builds a short evidence-chain requirement; and aligns the rubric with the four dimensions. The aim is not volume. Two or three well-designed tasks can change student norms more than many decorative AI activities.

Phase 3: Pilot evidence collection and feedback. Teachers collect a light evidence chain from a sample of students first, not necessarily from everyone. They examine what students reveal: Do prompts show task understanding? Do students check consequential claims? Do they disclose use? Do they mistake fluency for truth? Feedback should target the next move, not only the final score. A useful comment might be: "Your output is fluent, but two central claims still need independent sources," or "Your revision history shows good rejection of a weak answer; now explain the criterion you used."

Phase 4: Moderate assessment across teachers. Teachers compare samples and ask whether they would infer similar learning from similar evidence. Moderation prevents the rubric from drifting back toward polish. It also builds consistency across subjects. If one teacher rewards disclosure and another penalizes any AI use, students learn to hide rather than to judge. Moderation makes expectations public.

Phase 5: Review equity and workload. After one cycle, schools should review who benefited, who struggled, and what workload emerged. Were evidence chains meaningful or bureaucratic? Did students with fewer home resources receive explicit scaffolds? Did accessibility supports remain visible without being stigmatized? Did teachers spend time on feedback that matters, or on collecting artifacts that no one used? The review should delete low-value paperwork before adding new requirements.

Phase 6: Institutionalize through curriculum artifacts. The final step is to embed the approach in schemes of work, assessment calendars, sample tasks, use declarations, library support, and teacher induction. If the framework lives only in a policy speech, it will fade. If it lives in the tasks students repeatedly encounter, it becomes culture.

This roadmap respects a practical truth: schools cannot wait for perfect consensus about GenAI. They need a defensible way to act now while remaining open to evidence[21]. The four-dimensional framework supplies direction; task redesign supplies leverage; process assessment supplies validity; ethical zoning supplies safety; teacher collaboration supplies capacity; equity scaffolds supply fairness.

A practical calendar can keep the work from becoming either a one-week initiative or an endless policy discussion. In weeks 1–2, a leadership group drafts the shared definition and four use zones, while subject departments nominate one high-value task. The key product is not a perfect document but a common language precise enough to guide examples. In weeks 3–4, departments rewrite the nominated tasks and build the evidence-chain requirement. Librarians or media specialists can join to identify credible source types and common verification pitfalls. In weeks 5–8, teachers pilot the tasks in selected classes. Students are explicitly taught the delegation plan and use declaration; the purpose is to make the new expectations visible rather than to catch violations. In weeks 9–10, teachers bring anonymized samples to moderation. They ask whether evidence supports claims about learning and whether feedback targets judgment rather than polish. In weeks 11–12, the school reviews equity, workload, and student response, then deletes low-value artifacts before scaling. The term ends with revised tasks, a small bank of exemplars, and a decision about what will be repeated next term.

This calendar deliberately separates adoption from normalization. Many technology initiatives fail because they scale before the task and rubric are stable. The sequence here first clarifies expectations, then tests them in a limited set of tasks, then moderates inference, then expands. It also protects teacher trust: teachers are not asked to transform every unit immediately, but they are asked to make a small number of high-leverage changes well.

Schools need indicators that reflect literacy rather than novelty. Counting how many classes “used AI” is weak evidence. Better indicators include the quality of student questions before generation; the frequency with which consequential claims are accompanied by sources; the presence of rejected outputs and reasons for rejection; the clarity of use declarations; the reduction of privacy-sensitive uploads; the consistency of teacher expectations across subjects; and the ability of students to explain their work in live settings. Over time, schools should also look for transfer: students begin to ask for sources without being reminded, challenge one another’s evidence in group work, and treat disclosure as a normal part of quality rather than an admission of guilt.

Equity indicators should be built in from the beginning. If only already-advantaged students produce strong evidence chains, the design is not yet equitable. If multilingual learners use translation or language support transparently and still demonstrate interpretation, the design is working. If students with limited home access rely on school scaffolds and gradually need fewer reminders, support is functioning. The most important cultural sign is a shift in conversation: from “Did you use AI?” to “How do you know?”, “What did you reject?”, and “What can you defend?”

The first cycle can create energy; sustainability requires maintenance. Tools will change, student workarounds will change, and staff will turn over. Schools therefore need lightweight routines that keep the framework alive without freezing it. Three routines are especially important. First, an annual task audit can ask whether high-value tasks still require judgment now that tools have improved. A task that was strong last year may become paste-able this year; the audit should revise context, evidence, or performance demands accordingly. Second, a rotating exemplar bank can preserve what good evidence looks like across subjects and grades. Exemplars should include not only excellent final products but also instructive process: a rejected output, a corrected hallucination, a transparent use declaration, a revision after peer challenge. Third, new-teacher induction should treat digital-intelligent literacy as part of professional culture rather than individual preference. New staff should see the shared zones, sample tasks, rubric language, and moderation routines before they improvise conflicting rules.

Sustainability also depends on student voice. Students can surface practical realities adults miss: which tools are actually used, where rules are unclear, which disclosures feel risky, and which tasks accidentally reward speed. Student panels should not be asked to endorse policy; they should be asked to improve design. Their insights can reveal whether the framework is experienced as clarity or surveillance. When students help refine norms, they are more likely to see responsibility as part of quality rather than compliance imposed from outside.

Finally, schools should expect revision. A defensible framework is not one that never changes; it is one whose changes can be explained. If a new tool makes image verification harder, the evidence chain adapts. If accessibility needs grow, declared support becomes more precise. If assessment moderation reveals that “collaboration strategy” is being interpreted inconsistently, rubric language is clarified. The through-line remains stable: human judgment must stay visible, consequential claims must be checked, sensitive data must be protected, and students must be able to own what they submit.

6. Conclusion

Generative artificial intelligence does not eliminate the need for digital literacy; it changes what digital literacy must include. When generation becomes easy, judgment becomes central. When fluent output is abundant, evidence becomes precious. When assistance is available everywhere, responsibility must become explicit. The educational response should therefore avoid both prohibition and naïve celebration. The starting point is already promising: students are encountering intelligent tools across everyday learning, policy guidance increasingly emphasizes human agency and competence, and schools have frameworks for digital competence and teacher development to build upon.

The task now is to raise the level of demand inside ordinary learning. Students should move from using tools to using them credibly; from accepting generated answers to checking claims; from hiding assistance to declaring it; from consuming content to creating work they can defend. This is the meaning of digital-intelligent literacy in basic education: not a race to master every new application, but the formation of students who can ask, verify, decide, disclose, and create in a world where machine fluency is common. GenAI will keep changing. The capacities that matter most—questioning, evidence, responsibility, and transfer—are precisely the capacities schools are built to teach.

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