

Essay

Revisiting Learning Styles in the Age of Generative AI: A Conceptual Framework for Regulation and Agency

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Abstract

This conceptual paper revisits the learning styles debate in the context of generative and adaptive artificial intelligence in higher education. It does not seek to rehabilitate classical learning style taxonomies, whose prescriptive claims have been widely challenged as a neuromyth. Instead, it argues that AI-mediated learning creates new conditions under which patterns of regulation, delegation, verification, iteration, epistemic control, and ethical responsibility may become more observable and pedagogically relevant. Drawing on research on learning styles, neuromyths, AI literacy, adaptive learning, assessment, self-regulated learning, metacognition, and epistemic agency, the paper proposes a conceptual framework for regulation and agency styles in AI-mediated learning. In this framework, style is not treated as a fixed psychological trait or as a category into which learners should be sorted, but as a situated and modifiable profile of decisions and actions distributed across learners, tasks, and intelligent systems. Three analytical dimensions are proposed: epistemic control and metacognitive orchestration, adaptive regulation and generative iteration, and socio-algorithmic agency and ethical governance. The paper concludes with implications for task design, assessment, teacher education, and equitable AI integration.

Keywords: artificial intelligence; learning styles; neuromyths; epistemic agency; metacognitive regulation; higher education

1. Introduction

As S. Wang et al. (2024) note in their systematic review of artificial intelligence in education, technological change rarely leaves pedagogical practice untouched. The history of learning is, in this sense, also a history of mediation, orality trained memory and communal transmission; writing stabilised knowledge beyond the immediacy of speech; print supported curricular standardisation; and digital networks expanded access, search, and collaboration. AI extends this trajectory but also unsettles it. Instead of only storing, transmitting, or accelerating access to information, generative and adaptive systems participate in the organisation of the learning activity itself, a shift already visible in intelligent tutoring, automated assessment, and adaptive learning systems (Kabudi et al., 2021; Zawacki-Richter et al., 2019).

The pedagogical urgency emerges precisely from that displacement. Higher education is incorporating AI faster than it is building robust educational frameworks for its use, and this imbalance matters because students are not merely adding a new resource to familiar study routines. They are learning to ask, delegate, compare, revise, and sometimes believe outputs generated by systems whose fluency can exceed their reliability. In this regard, Kasneci et al. (2023) warn that large language models can support learning while



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also producing misinformation or overconfidence, and [Weng et al. \(2024\)](#) show that assessment practices are still struggling to define what counts as learning when generative AI participates in the process. In this context, the issue is no longer technological adoption alone, but the formation of judgement.

Within this scenario, the old debate on learning styles returns in an unexpected way. Classical taxonomies became attractive because they promised to recognise learner diversity and translate it into personalised instruction. Yet their empirical foundation has been repeatedly questioned; as an example, [Pashler et al. \(2008\)](#) found insufficient evidence for the meshing hypothesis, while [Newton and Miah \(2017\)](#) and [Newton and Salvi \(2020\)](#) documented the persistence of the learning styles belief despite weak evidentiary support. That critique remains necessary. However, it does not eliminate the broader educational fact that students differ in how they approach learning tasks, especially when those tasks are mediated by intelligent systems rather than conventional materials.

What AI changes, therefore, is not the credibility of visual, auditory or kinesthetic categories. Those categories remain problematic when used as fixed prescriptions. So, a new question emerges: how do students regulate their learning when a system can explain, generate, simulate, summarise, correct, and suggest alternatives in real time? In this regard, some students treat AI as an authority; others use it as a sparring partner; still others avoid it because of uncertainty, distrust, or institutional ambiguity. Recent work by [Urhahne et al. \(2026\)](#) shows that these differences are not trivial preferences, since students' beliefs about knowledge and knowing help predict whether they adopt or avoid generative AI.

This distinction matters because the neuromyth critique can inadvertently produce a second simplification. If the only available language is that of fixed learning styles, then dismissing that language may lead educators to overlook emerging patterns of regulation, delegation, verification, and agency. In this direction, [Nancekivell et al. \(2020\)](#) argue that beliefs about learning styles are often connected to broader intuitions about identity and experience, which helps explain their persistence. The task, then, is not to rehabilitate weak taxonomies, but to construct a more defensible vocabulary for observing how students learn with AI. In the terms proposed by [Wu et al. \(2025\)](#), this requires placing epistemic agency at the centre of human–AI learning partnerships.

The risk of not making this shift is practical as well as theoretical. If AI use is normalised without attention to regulatory patterns, education may reward speed over understanding, fluency over evidence, and delegation over responsibility. Conversely, if educators can interpret how students regulate their interaction with AI, they can design tasks and assessments that cultivate verification, purposeful iteration, epistemic judgement, and ethical responsibility. Institutional policies already show that universities are attempting to regulate AI use, but policy alone cannot resolve the pedagogical problem ([H. Wang et al., 2024](#); [Jin et al., 2025](#)). The central claim of this article follows from that tension: although traditional learning style theories have been rightly criticised as neuromythical when treated as fixed prescriptions, AI-mediated learning invites a different and more cautious use of the term style. In this paper, regulation and agency styles are understood as situated, multidimensional, and modifiable profiles of learner activity, not as stable traits or categories for classifying students. On that basis, the article develops a conceptual framework for analysing how learners sustain agency, regulate generative interaction, and assume responsibility when intelligent systems become part of academic work.

2. Why AI Reopens and Transforms the Problem of Learning Styles?

The argument unfolds through five linked movements and one conceptual clarification. First, the concept of style must be reframed epistemologically so that it no longer refers to fixed typologies, but to situated profiles of regulation and agency. Second, the evidence for

identifying such profiles must move beyond self-report toward situated and multi-source interpretation. Third, pedagogy must be read historically as something that changes with its mediations, while avoiding technological determinism. Fourth, AI-mediated styles must be connected to employability, assessment, teaching, and equity. Fifth, the discussion must address distributed knowledge, co-construction, and subjectivity. Finally, regulation, agency, epistemic control, and metacognitive orchestration are defined as conceptual anchors for the framework developed in Section 3. Together, these movements allow the learning styles debate to be reopened without repeating the unsupported prescriptions criticised by Hughes et al. (2022), while also taking seriously the new learning conditions described in AI education research (Kasneci et al., 2023; S. Wang et al., 2024).

2.1. Epistemological Reframing: From Fixed Typologies to Situated Profiles

The first argument concerns the meaning of style itself. In classical learning style approaches, style was often treated as a relatively stable personal attribute that could be measured through questionnaires and then translated into instructional decisions. This assumption is precisely what made the tradition vulnerable. Pashler et al. (2008) challenged the evidentiary basis of matching instruction to preferred learning styles, and later work on neuromyths has shown that such beliefs persist in educational culture despite sustained criticism (Hughes et al., 2022; Newton & Salvi, 2020). That critique remains essential for the present article. However, it should not lead to the conclusion that every patterned difference in learning activity is pedagogically irrelevant. The problem lies not in recognising differences, but in converting fragile classifications into fixed identities and prescriptive teaching formulas.

AI-mediated learning requires a different epistemological stance. The relevant difference is no longer whether a learner belongs to a visual, auditory, reflective, active, or kinaesthetic category. Instead, what becomes educationally significant is how learners regulate their interaction with a system capable of generating explanations, alternatives, drafts, examples, feedback, and apparent solutions. A student may ask AI for clarification, treat the response as provisional, compare it with external sources, and revise a claim; another may accept the first fluent answer as sufficient. These are not equivalent forms of learning, even if the final product appears similar. Wu et al. (2025) frame this issue through epistemic agency, while Kabudi et al. (2021) and Zawacki-Richter et al. (2019) show that adaptive and intelligent systems already intervene in learning pathways, feedback, and assessment. In this context, style must be understood as part of a distributed learning situation rather than as a property located exclusively inside the learner.

This reframing preserves the core lesson of the neuromyth critique while avoiding a second simplification. If the concept of style is rejected entirely, educators may lose a useful language for describing how students position themselves in relation to AI-generated knowledge, delegation, verification, iteration, and responsibility. If, on the contrary, style is treated as a fixed category, the article would reproduce the very weakness it seeks to overcome. The conceptual framework proposed here therefore adopts a restricted use of the term: a regulation and agency style is a situated and modifiable profile of decisions and actions through which learners organise their relationship with AI, the task, and the criteria of academic work. It is not a trait, not a type, and not a basis for matching instruction.

A reasonable counterargument is that, if styles are contextual, variable, and distributed, terms such as strategy, stance, profile, or practice might be more precise. This objection is important because it forces the article to clarify its conceptual vocabulary. The term style is retained not to revive the classical tradition, but to signal a recurrent pattern that may appear across tasks while remaining open to transformation. Unlike a momentary strategy, a style implies some degree of recurrence; unlike a trait, it is not assumed to be stable across

all contexts; unlike a typology, it does not sort students into mutually exclusive groups. This middle position is consistent with research on GenAI assessment, where the quality of process, evidence, and judgement matters as much as the final product (Jin et al., 2025; Weng et al., 2024).

The epistemological shift is therefore from essence to configuration. What matters is not what kind of learner a student is, but how regulation and agency are configured in a particular AI-mediated situation. Such configurations may change across tasks, disciplines, assessment conditions, and levels of AI literacy. A student may show strong epistemic control when verifying information, weak adaptive regulation when comparing alternatives, and emerging socio-algorithmic governance when working in a group. This fluidity does not invalidate the framework; it defines its object. It also aligns with evidence that students' epistemic beliefs influence how they adopt or avoid generative AI (Urhahne et al., 2026). The educational task is consequently not to label learners, but to understand which dimensions of regulation and agency require support in order to strengthen critical, responsible, and purposeful AI use.

2.2. Methodological Reopening: From Static Self-Reports to Situated, Multi-Source Evidence

The methodological reason for reopening the debate is not that AI makes learner differences immediately measurable, but that AI-mediated activity can leave traces of regulation that were difficult to observe in traditional learning style research. Classical learning style approaches relied heavily on self-report instruments, which often captured what learners believed about themselves rather than what they actually did when facing demanding academic tasks. Newton and Salvi (2020) show that such beliefs may be widespread and persistent, but belief prevalence does not establish instructional validity. In AI-mediated environments, this distinction becomes especially important: a student who describes themselves as reflective may still accept the first generated answer without verification, while another who expresses low confidence may engage in careful comparison, revision, and source checking.

For this reason, the methodological opportunity opened by AI should be understood cautiously. Prompt histories, revision sequences, requests for sources, comparisons among alternatives, rejected outputs, attribution records, and reflective accounts can provide evidence of how learners regulate interaction with AI. However, these traces are not transparent windows into cognition. They must be interpreted in relation to the task, the assessment criteria, the learner's prior knowledge, and the institutional norms governing AI use. Weng et al. (2024) emphasise that GenAI assessment requires attention to both process and outcome, and this is precisely where regulation and agency styles become methodologically relevant: they orient attention toward the quality of learning activity rather than toward a learner label.

A situated and multi-source approach therefore differs from both questionnaire-based classification and automated profiling. It does not infer a style from one declared preference or one isolated interaction. Instead, it examines whether a regulatory pattern appears across several forms of evidence and whether that pattern is pedagogically meaningful. A learner's prompt sequence may suggest extensive iteration, but only the comparison with drafts, justifications, sources, and final decisions can indicate whether such iteration supported conceptual development or merely produced superficial variation. In this sense, AI-mediated evidence can contribute to a more ecological understanding of learning when it is triangulated with artefacts, rubrics, interviews, reflective accounts, or collaborative documentation (Kabudi et al., 2021; S. Wang et al., 2024).

This methodological position also requires ethical restraint. According to [Lindebaum et al. \(2025\)](#), data-rich educational environments can create the illusion that what is measurable is automatically meaningful, especially when large language models reorganise epistemic agency and governance in ways that appear merely supportive. The framework proposed here should therefore not be used as a surveillance mechanism or as an automated classification system. Its evidentiary logic must remain pedagogical, interpretive, and accountable to questions of validity, fairness, consent, and educational purpose. Institutional policies and guidelines for AI use are relevant in this regard, but they cannot replace careful interpretation of what students are actually doing with AI in specific learning situations ([Jin et al., 2025](#)).

The methodological reopening of the learning styles debate thus rests on a narrower and more defensible claim: AI-mediated learning may create conditions under which patterns of regulation and agency become more observable, but those patterns can only be interpreted provisionally, contextually, and through multiple sources of evidence. This claim avoids the mistake of treating traces as fixed traits. It also connects directly with AI literacy research, where the relevant educational issue is not simple access to tools, but the development of competencies for critical, responsible, and purposeful use ([Chee et al., 2025](#); [Kong et al., 2024](#)). From this perspective, the question is no longer whether a student has a stable learning style. The question is whether a particular learning situation reveals regulatory emphases that can be strengthened through task design, feedback, assessment, and explicit formation in AI literacy.

2.3. *The Changing Role of Pedagogy*

Pedagogy has always been reshaped by its mediations, although never in a linear or mechanically deterministic way. Writing altered the role of memory; print helped stabilise curricular sequences; digital networks changed access to information, authorship, collaboration, and the temporal rhythm of study. AI now adds a distinctive form of mediation because it does not merely store or transmit information. It can respond, generate, reframe, simulate, evaluate, and produce academic artefacts that appear coherent and complete. [Pandey and Sharma \(2025\)](#) identify intelligent tutoring, profiling, prediction, and automated assessment as central AI functions in higher education, while [Fernández-Herrero \(2024\)](#) shows the expansion of intelligent tutoring systems and affective support in educational research. The classroom is therefore not only receiving a new tool; it is being reorganised around new possibilities and risks for academic work.

This historical perspective helps clarify why the article speaks of regulation and agency styles as situated profiles. AI-mediated learning should not be interpreted as the emergence of new learner essences. It is better understood as the stabilisation of certain routines under particular technological, pedagogical, and institutional conditions. A learner may use AI as a shortcut in one activity, as a tutor in another, as a co-designer during a project, or as an object of critique when evaluating generated claims. The same learner may shift among these patterns depending on the task, the stakes of assessment, the teacher's instructions, and the perceived legitimacy of AI use. [Kasneci et al. \(2023\)](#) describe this dual condition of opportunity and risk, while [Weng et al. \(2024\)](#) show that learning outcomes in GenAI contexts depend heavily on how activities are framed, assessed, and interpreted.

For this reason, the pedagogical question cannot be reduced to whether AI use should be accepted or prohibited. The more precise question is what kinds of regulation and agency a given educational design makes more likely. If a task rewards only a polished final product, students may learn that rapid delegation is enough. If a task requires comparison among versions, explicit source checking, justification of accepted outputs, and documentation of decisions, it may cultivate stronger epistemic control and adaptive

regulation. If collaborative work requires attribution protocols, role distribution, and shared verification, it may strengthen socio-algorithmic governance. In this sense, styles are not produced by AI alone; they emerge from the interaction among learner, task, tool, assessment, and institutional norm.

This argument also prevents technological determinism. AI does not impose dependence, creativity, agency, or superficiality by itself. The same system can support deep inquiry in one setting and uncritical substitution in another. Institutional rules, teacher guidance, task authenticity, assessment criteria, and students' AI literacy shape which patterns become more probable. University policies matter because they define permissions, limits, and expectations, but they are insufficient when detached from pedagogy. [H. Wang et al. \(2024\)](#) and [Jin et al. \(2025\)](#) show that higher education institutions are producing guidelines for AI use; the challenge is to translate those guidelines into formative designs that make judgement, regulation, and responsibility visible.

A counterargument is that educational technologies often arrive surrounded by inflated promises, and AI may simply be another episode in that cycle. This objection is valuable because it protects the argument from technological enthusiasm. However, dismissing AI as hype would miss the specific nature of the mediation now at stake. Generative systems can produce plausible academic artefacts at scale, respond to student prompts in real time, and participate in processes of drafting, feedback, revision, and decision-making. As [Kasneci et al. \(2023\)](#), [Lindebaum et al. \(2025\)](#), and [Wu et al. \(2025\)](#) suggest from different perspectives, this requires neither celebration nor rejection, but conceptual discrimination. The task for pedagogy is to understand how AI-mediated activity can be designed so that learners do not merely use intelligent systems, but learn to regulate, question, and govern their use.

2.4. Employability, Critical Skills and the Reconfiguration of Teaching

The fourth argument is practical because AI-mediated learning is increasingly connected with the capabilities expected in academic, professional, and civic life. As [Ławicka et al. \(2025\)](#) indicate, AI and automation are reshaping future jobs and skills by reducing the value of some routine operations while increasing the importance of critical reasoning, ethical judgement, creativity, adaptability, and collaboration with intelligent systems. In education, this shift is already reflected in AI literacy frameworks that define the competent use of AI as more than technical access or prompt efficiency. [Kong et al. \(2024\)](#), [Chiu et al. \(2024\)](#), [Stolpe and Hallström \(2024\)](#), and [Chee et al. \(2025\)](#) converge in showing that AI literacy includes understanding, critical evaluation, responsible use, and developmental pathways that differ across learners and educational contexts.

From this perspective, regulation and agency styles matter because they describe how learners position themselves in relation to these new demands. A student who uses AI mainly to accelerate production may achieve immediate fluency while weakening opportunities for judgement and responsibility. Another student may use AI to compare explanations, detect uncertainty, revise arguments, and document decisions. These differences should not be interpreted as fixed learner types, but as modifiable profiles of practice with consequences for learning quality. The educational issue is therefore not whether students use AI, but whether their use strengthens the forms of agency, verification, iteration, and ethical responsibility that future academic and professional participation will require.

Assessment makes this practical issue especially visible. If institutions continue to reward only polished final products, they may unintentionally reward hidden delegation, superficial fluency, and rapid substitution. If assessment requires evidence of comparison, source checking, revision, rationale, and responsible attribution, it can cultivate more

demanding forms of regulation and agency. Montebello (2025) emphasises that assessment in the age of generative AI must attend to both products and learning processes. This is precisely where the proposed framework becomes pedagogically useful: it helps teachers interpret whether an apparently successful product rests on understanding, verification, purposeful iteration, and responsibility, or whether it mainly reflects fluent algorithmic production.

Teaching is therefore reconfigured rather than displaced. When AI can explain, summarise, correct, suggest, and generate, the teacher's role cannot remain centred on information delivery alone. It becomes increasingly important as a role of task architect, mediator of epistemic conflict, designer of assessment evidence, and guide for ethical decision-making. Bakar and Tapsoba (2026) describe this as a need for responsibly orchestrated mediation, while Jeon and Lee (2023) stress that the educational value of large language models depends on their complementary relationship with human teachers. In the same direction, Wu et al. (2025) argue that generative AI partnerships should strengthen, rather than diminish, human epistemic agency.

This reconfiguration has direct implications for how teachers use the framework. The point is not to diagnose each student with a stable style, but to identify which dimension of regulation and agency a learning situation is failing to develop. A task may reveal weak epistemic control when students accept AI-generated claims without verification. Another may reveal weak adaptive regulation when students produce multiple versions but cannot justify convergence. A collaborative project may reveal weak socio-algorithmic governance when AI use is efficient but opaque, unequally distributed, or poorly attributed. In each case, the framework supports formative intervention: redesigning prompts, rubrics, peer-review processes, documentation requirements, or reflective activities.

Equity sharpens this argument. Students do not enter AI-mediated learning with equal cultural, linguistic, digital, or institutional capital. Those who already know how to prompt, verify, compare, document, and question AI outputs may gain an additional advantage, while others may remain trapped in superficial use, dependency, or exclusion from more powerful forms of participation. This is why AI literacy must be treated as an explicit object of education rather than as an assumed background competence (Chee et al., 2025; Chiu et al., 2024; Kong et al., 2024; Stolpe & Hallström, 2024). Without such support, the same technology that promises personalisation may deepen inequality, especially in systems where assessment rewards the appearance of fluency more than the quality of regulation (Dinker, 2024).

2.5. Distributed Knowledge, Co-Construction and Subjectivity

The fifth argument is ontological because generative AI changes the everyday status of knowledge for learners. This does not mean that distributed cognition begins with AI. Long before generative systems entered education, research on distributed and extended cognition had shown that thinking is often organised across people, artefacts, symbolic systems, and material environments (Clark & Chalmers, 1998; Hutchins, 1995; Pea, 1993; Salomon, 1993). Learners have always worked with books, teachers, notes, diagrams, peers, databases, and institutional routines. What AI intensifies is the degree to which an external artefact can respond, generate, reframe, and produce academic discourse in real time. In this context, knowledge no longer appears only as something stored in textbooks, lectures, articles, or databases. It also appears as a responsive output generated through interaction with a model.

This change matters because AI-generated knowledge is both useful and unstable. Works such as Pafla et al. (2024) and Romeo and Conti (2026) describe this dual condition: AI can support explanation, exploration, and decision-making, but it can also produce

plausible errors and encourage automation bias. Consequently, the learner's task is not simply to receive information or to operate a tool efficiently. The learner must decide how much epistemic authority to grant to generated discourse, when to trust it, when to suspend judgement, when to seek external evidence, and how to justify what is finally accepted. In this sense, AI-mediated learning makes epistemic control a practical necessity rather than an abstract philosophical concern.

Authorship and identity are also affected by this distributed condition. When a student drafts with AI, the final text is neither purely individual nor fully machine-produced. When a group uses AI to formulate a policy argument, responsibility becomes distributed across human decisions, algorithmic suggestions, institutional rules, and collaborative agreements. Lindebaum et al. (2025) interpret this transformation as a change in epistemic agency and governance, while Wu et al. (2025) argue that learning partnerships with generative AI require strengthened human agency. These debates show that regulation and agency styles are not only cognitive patterns; they are also related to how learners understand themselves as authors, judges, collaborators, and responsible participants in knowledge production.

A possible counterargument is that this description exaggerates the novelty of AI. After all, learners have always depended on external supports, and the classical critique of learning styles already taught the field to be sceptical of unsupported pedagogical claims (Pashler et al., 2008). This objection is valuable because it prevents technological exceptionalism. However, as Grassini (2023) argues, AI and ChatGPT (version 5.4) introduce specific consequences for educational settings because they can simulate explanation, generate alternatives, and produce seemingly complete academic artefacts. The issue is therefore not that AI creates distributed cognition from nothing, but that it intensifies the coupling between learner, artefact, and academic output in ways that blur the boundary between support and substitution. Scepticism should therefore lead to careful conceptualisation, not to ignoring the new forms of mediation described in current AI education research (H. Wang et al., 2024; Weng et al., 2024).

Ethics, then, cannot be added after learning as an external concern. Privacy, attribution, bias, access, and accountability are part of what learning becomes when AI participates in knowledge production. Schiff (2022) shows that institutions are already trying to define rules for these matters, but rules alone cannot form judgement. Students must learn how to govern their own and collective AI use, which means that ethical agency is inseparable from cognitive regulation. This is why the framework proposed below treats socio-algorithmic governance as one dimension of regulation and agency styles rather than as a supplementary compliance issue.

2.6. Regulation, Agency and Epistemic Control as Conceptual Anchors

The conceptual framework proposed in this article requires a clearer distinction among style, regulation, agency, and epistemic control. This distinction is necessary because the term style carries a problematic legacy in education. In classical learning styles research, it was often associated with relatively stable learner traits and with the expectation that instruction should be matched to preferred modalities. The present article uses the term differently. A regulation and agency style is understood as a situated and modifiable profile of decisions and actions through which learners organise their interaction with AI in relation to goals, evidence, responsibility, and task demands. In this sense, style does not name what a learner is; it describes how regulation and agency are configured in a particular learning situation.

Regulation refers here to the learner's capacity to plan, monitor, control, and evaluate learning activity over time. This definition draws on the tradition of self-regulated learning, where learning is understood as an active process in which students set goals,

select strategies, monitor progress, and adjust their actions in response to feedback and contextual demands (Pintrich, 2000; Zimmerman, 2002). In AI-mediated learning, regulation becomes especially important because generative systems can accelerate production without necessarily strengthening understanding. The learner must therefore decide when to delegate, when to question, when to revise, when to seek external evidence, and when to stop iterating. Regulation is not only internal self-management; it becomes a distributed process shaped by the affordances of the AI system, the structure of the task, and the criteria used for assessment.

Agency refers to the learner's capacity to act intentionally and responsibly within those conditions. It involves more than choice or tool use. A student may choose to use AI frequently and still exercise little agency if the interaction is dominated by uncritical acceptance, hidden delegation, or avoidance of responsibility. Conversely, agency becomes stronger when learners define purposes, interrogate outputs, justify decisions, and assume accountability for the final product. In educational research, agency has often been understood as relational and situated rather than purely individual, especially in environments where action is shaped by social, material, and institutional conditions (Biesta & Tedder, 2007; Priestley et al., 2015). This relational view is particularly relevant for AI-mediated learning because the learner's decisions are entangled with algorithmic suggestions, assessment norms, peer collaboration, and institutional rules.

Epistemic control specifies one crucial dimension of agency: the capacity to decide what counts as valid, reliable, relevant, and justified knowledge. This notion connects the framework with research on epistemic cognition, which examines how learners understand knowledge, evidence, justification, and the conditions under which claims should be accepted or rejected (Chinn et al., 2021; Hofer & Pintrich, 1997). Generative AI intensifies the need for epistemic control because it can produce fluent responses that are incomplete, biased, fabricated, or weakly justified. Therefore, the central issue is not whether the learner can obtain an answer, but whether the learner can evaluate the epistemic status of that answer. In this sense, AI-mediated learning requires students to distinguish plausibility from validity, confidence from evidence, and textual coherence from conceptual reliability.

Metacognitive orchestration complements epistemic control by describing how learners coordinate goals, strategies, monitoring, and evaluation during their interaction with AI. The term orchestration is useful because AI-mediated learning frequently involves multiple sources of information, several iterations of a product, and shifting decisions about what should be generated, revised, verified, or rejected. Research on metacognition and self-regulated learning has long emphasised that effective learners monitor their understanding and adjust their strategies accordingly (Azevedo & Cromley, 2004; Zimmerman, 2002). In the context of generative AI, this monitoring extends to the interaction itself: learners must monitor not only their own understanding, but also the quality, relevance, and risks of the system's contributions.

These conceptual anchors help clarify why the proposed framework does not reproduce the logic of classical learning styles. Traditional styles tended to ask which kind of learner a student is. The present framework asks how learners regulate AI-mediated activity, how they sustain agency, how they exercise epistemic control, and how these patterns may change across tasks and contexts. It therefore brings together self-regulated learning, metacognition, epistemic cognition, and human–AI learning in order to analyse a phenomenon that none of these traditions fully captures in isolation: the emergence of situated regulation and agency styles when learning becomes distributed across learner, task, and intelligent system (Lindebaum et al., 2025; Winne & Hadwin, 1998; Wu et al., 2025).

3. Conceptualising a Multidimensional Framework for Regulation and Agency Styles in AI-Mediated Learning

This article proposes a conceptual framework for analysing regulation and agency styles in AI-mediated learning. The framework begins from a cautious premise: generative and adaptive AI do not validate classical learning styles, nor do they justify a return to fixed learner classifications. What they do create are new conditions for observing how learners regulate their activity when intelligent systems participate in the production, organisation, revision, and evaluation of academic work. In this sense, the framework uses the term style in a restricted and critical way. A style is not understood as a stable psychological trait, a learner type, or a prescription for matching instruction. It refers instead to a situated and modifiable profile of decisions and actions through which learners distribute attention, responsibility, judgement, and control across themselves, the task, and the AI system. This formulation builds on research about epistemic agency in human–AI partnerships (Wu et al., 2025), assessment in GenAI contexts (Weng et al., 2024), and institutional governance of AI in higher education (Jin et al., 2025; Lindebaum et al., 2025).

This distinction is central to the contribution of the article. Classical learning style theories often moved from classification to prescription: once a learner was identified as belonging to a category, instruction was expected to adapt accordingly. The framework proposed here follows a different logic. It moves from observation to formative interpretation. Its purpose is not to sort students into permanent categories, but to help educators identify how different regulatory emphases emerge in particular tasks, how they may create opportunities or risks for learning, and how pedagogical design can strengthen more agentic, critical, and responsible forms of AI use. In this regard, regulation and agency styles are better understood as dynamic profiles than as types, a position consistent with AI literacy frameworks that treat competence as developmental and educable (Sabatini et al., 2023).

The multidimensional nature of the framework responds to the fluidity of AI-mediated learning. A student may use AI with strong epistemic control in one phase of a task, rely on generative iteration in another, and require socio-algorithmic governance when the work becomes collaborative. These shifts should not be interpreted as inconsistency or as evidence that the framework lacks stability. They indicate that AI-mediated learning is sensitive to task demands, assessment conditions, institutional expectations, and learners' developing AI literacy. Therefore, the relevant analytical question is not “which style does this learner have?”, but “which regulatory and agentic emphases are becoming visible in this learning situation, and how might they be pedagogically shaped?” This reframing also avoids the move from classification to prescription that weakened classical learning style approaches (Hughes et al., 2022; Newton & Miah, 2017; Pashler et al., 2008).

3.1. From Typology to Multidimensional Profile

The framework is organised around three analytical dimensions: epistemic control and metacognitive orchestration, adaptive regulation and generative iteration, and socio-algorithmic agency and ethical governance. These dimensions do not define mutually exclusive types of learners. Rather, they describe complementary aspects of AI-mediated learning that may appear with different degrees of intensity within the same student, group, task, or learning trajectory. Their purpose is to make visible the main educational tensions introduced by generative AI: how learners decide what counts as valid knowledge, how they regulate movement from uncertainty to a justified response, and how they distribute responsibility when knowledge production becomes hybrid. Chan (2023) makes the governance dimension especially important, while Chen (2025) provides the epistemic basis for understanding why agency cannot be reduced to tool use.

The first dimension, epistemic control and metacognitive orchestration, concerns the learner's capacity to monitor goals, evaluate the reliability of AI-generated outputs, identify gaps or inconsistencies, and decide what can be incorporated into academic work. This dimension is especially important because generative AI can produce fluent responses without guaranteeing truth, relevance, or adequate justification. It therefore foregrounds the learner's role as evaluator, verifier, and organiser of evidence rather than as passive recipient of algorithmic output, which aligns with current concerns about epistemic agency and assessment in GenAI environments (Weng et al., 2024; Wu et al., 2025).

The second dimension, adaptive regulation and generative iteration, concerns the learner's capacity to use AI to explore alternatives, compare versions, revise ideas, and move toward justified convergence. Here, the educational issue is not whether the student prompts the system repeatedly, but whether iteration is purposeful and governed by explicit criteria. This dimension captures the difference between generative abundance as superficial variation and generative abundance as a resource for conceptual development, design improvement, and transfer, particularly when learning processes rather than final products become central to assessment (Weng et al., 2024).

The third dimension, socio-algorithmic agency and ethical governance, concerns the distribution of responsibility, attribution, fairness, and accountability when AI participates in individual or collaborative learning. This dimension becomes especially relevant when AI use is embedded in group work, institutional policies, assessment norms, or unequal conditions of access and competence. It highlights that learning with AI is not only a cognitive process, but also an ethical and social practice in which participation, transparency, and responsibility must be deliberately organised (Chan, 2023; Jin et al., 2025; Lindebaum et al., 2025).

Taken together, these three dimensions do not produce a taxonomy of learners. They form a profile space for analysing how regulation and agency are configured in AI-mediated learning. A profile may show a strong epistemic-control emphasis, a strong iterative-regulation emphasis, a strong socio-algorithmic governance emphasis, or different combinations of the three. Such profiles are provisional, situated, and open to change. Their educational value lies precisely in that flexibility: they allow teachers to interpret patterns of AI use without reducing students to fixed identities or reproducing the prescriptive logic historically associated with learning styles (Hughes et al., 2022; Newton & Miah, 2017; Pashler et al., 2008).

The reason for organising the framework around these three dimensions is not taxonomic but pedagogical. Each dimension corresponds to a central problem intensified by generative AI in academic learning. The first problem is epistemic: when AI can produce fluent and plausible responses, learners must decide what counts as valid, reliable, and justified knowledge. This is why epistemic control and metacognitive orchestration are needed as an analytical dimension. The second problem is procedural: when AI can generate multiple alternatives, learners must regulate movement from exploration to convergence rather than confusing iteration with learning. This gives adaptive regulation and generative iteration its place in the framework. The third problem is socio-ethical: when knowledge production becomes distributed across students, systems, institutional norms, and collaborative arrangements, learners must assume responsibility for attribution, transparency, fairness, and accountability. This is the role of socio-algorithmic agency and ethical governance.

These dimensions are therefore not intended to compete with established constructs such as self-regulated learning, metacognition, epistemic cognition, AI literacy, or institutional governance. Rather, the framework integrates them around the specific educational situation created by AI-mediated learning. Self-regulated learning explains how learners

plan, monitor, and evaluate their activity; epistemic cognition explains how they evaluate knowledge and justification; AI literacy explains the competencies needed to use intelligent systems critically; and governance research explains how institutional norms shape legitimate AI use (Azevedo & Cromley, 2004; Biesta & Tedder, 2007; Chee et al., 2025; Chinn et al., 2021; Hofer & Pintrich, 1997; Jin et al., 2025; Kong et al., 2024; Lindebaum et al., 2025; Pintrich, 2000; Priestley et al., 2015; Weng et al., 2024; Winne & Hadwin, 1998; Wu et al., 2025; Zimmerman, 2002). What the present framework adds is a way to analyse how these dimensions interact in concrete learning situations where the learner's activity is distributed across human intention, academic task, and algorithmic mediation.

This integrative function is important because none of the source constructs, taken in isolation, fully captures the phenomenon addressed here. A self-regulated learner may plan and monitor effectively while still lacking criteria for evaluating AI-generated claims. A learner with strong epistemic beliefs may verify information carefully but struggle to use generative iteration productively. A group may follow institutional rules for AI use while failing to distribute intellectual responsibility equitably. The framework therefore does not claim to replace these constructs. Its contribution is to connect them in a profile-based model that helps educators interpret where regulation and agency are strengthened, weakened, or unevenly distributed during AI-mediated learning.

3.2. *A Comparative Learning Situation with AI*

A comparative task can clarify how the framework operates without converting regulation and agency styles into fixed learner types. Consider a higher education assignment in which students must write an educational policy brief proposing guidelines for integrating generative AI into secondary education. The brief must include a conceptual framework, an analysis of risks, a phased implementation strategy, and criteria for assessment and quality verification. This task is useful because it requires decisions about delegation, validation, authorship, and closure. It also mirrors the institutional concerns identified by Oh and Sanfilippo (2025) and Jin et al. (2025), who show that universities are actively defining policies and guidelines for AI use.

The important point is not that one student would belong to one style and another student to a different one. Rather, the same student or team may display different regulatory emphases during different moments of the task. At the beginning, when the conceptual framework is still unclear, learners may rely more strongly on adaptive regulation and generative iteration, using AI to explore alternative structures, compare possible definitions, and identify tensions among policy options. Later, when deciding which claims to include, epistemic control and metacognitive orchestration may become more prominent, as learners evaluate the reliability of AI-generated statements, contrast them with external sources, and decide what counts as sufficiently justified. If the task is collaborative, socio-algorithmic agency and ethical governance may become central from the outset, especially when students establish rules for attribution, role distribution, verification, and acceptable AI use.

In this scenario, therefore, the framework does not classify learners into three separate groups. It helps educators examine how different dimensions of regulation and agency appear, disappear, combine, or weaken as the task unfolds. Two students may submit documents of comparable surface quality, yet the processes behind those documents may differ substantially. One may have produced a polished text through rapid delegation with minimal verification; another may have moved through cycles of comparison, revision, and justification; a third may have coordinated AI use through explicit collaborative protocols. The difference becomes visible only when assessment attends to prompts, revisions, rationales, verification practices, and documentation of decisions. This is why process-oriented assessment is central to GenAI learning environments (Weng et al., 2024),

and why epistemic agency provides a useful lens for interpreting such differences (Wu et al., 2025).

The example also shows why the framework should be used formatively rather than diagnostically. Its purpose is not to decide whether a learner “is” epistemic, iterative, or socio-algorithmic. Its purpose is to help teachers identify which dimension requires pedagogical strengthening in a given task. A student who generates many alternatives but lacks convergence criteria may need support in adaptive regulation. A student who accepts fluent outputs without source checking may need support in epistemic control. A group that uses AI efficiently but without transparency may need support in socio-algorithmic governance. In this way, the comparative situation illustrates the practical value of the framework: it turns AI use into an object of pedagogical interpretation without reducing students to fixed categories.

3.3. Epistemic Control and Metacognitive Orchestration as a Predominant Style

Epistemic Control and Metacognitive Orchestration refers to a predominant style within the broader profile of regulation and agency, not to a fixed learner type. It becomes visible when the learner’s interaction with AI is organised primarily around the preservation of epistemic authority: deciding what counts as valid knowledge, identifying what requires verification, and monitoring the relationship between generated outputs and academic criteria. Wu et al. (2025) describe this concern as the strengthening of human epistemic agency in learning partnerships with generative AI, while Kim et al. (2024) show why such agency is necessary when large language models can produce convincing but unreliable outputs. In this style, the central educational issue is not whether the learner uses AI, but whether the learner remains capable of judging, questioning, and justifying what AI produces.

Within the policy brief task, this style may become especially prominent when students move from exploration to validation. A learner or team might ask AI to map ethical tensions, identify policy alternatives, or propose arguments; however, the defining feature appears in the subsequent movement: challenging weak assumptions, requesting missing perspectives, comparing claims with institutional guidelines, and deciding which elements can be responsibly incorporated into the final document. In the middle of that process, metacognition becomes a form of epistemic discipline. The learner monitors what is known, what remains uncertain, which claims require evidence, and which AI-generated suggestions should be rejected or reformulated. This emphasis is consistent with process-oriented assessment in GenAI environments (Weng et al., 2024) and with research showing that epistemic beliefs influence adoption and avoidance of generative AI (Jun & Jinyang, 2025; Urhahne et al., 2026).

The usefulness of this style lies in the fact that it identifies a risk and a pedagogical opportunity at the same time. The risk is uncritical reliance: when fluency is mistaken for validity, the learner may accept plausible outputs without sufficient evidence. The opportunity is that AI can be used as a metacognitive interlocutor, prompting learners to compare, justify, revise, and make their criteria explicit. For teachers, the relevant question is not whether a student “belongs” to this style, but whether a given task requires stronger epistemic-control practices. Evidence of this emphasis may appear in source-checking, explicit rejection of weak AI responses, comparison among claims, justification of accepted outputs, and documented criteria for validity.

This configuration also has limits. Excessive orchestration can become individualistic if learners treat personal judgement as sufficient and overlook the institutional or collective dimensions of AI use. Lindebaum et al. (2025) caution that large language models transform governance as well as cognition, and Jin et al. (2025) show that institutional guidance

shapes what counts as acceptable academic practice. For that reason, epistemic control should not be interpreted as isolated intellectual autonomy. It must remain connected to transparency, attribution, responsibility, and shared norms of use. Otherwise, the learner may demonstrate strong personal vigilance while leaving the social and ethical conditions of AI-mediated learning underdeveloped.

3.4. Adaptive Regulation and Generative Iteration as a Predominant Style

Adaptive Regulation and Generative Iteration refers to a predominant style in which the learner's activity is organised around purposeful movement through alternatives. It does not describe a student who merely prompts AI many times, nor does it imply that iteration is valuable in itself. The relevant issue is whether generative abundance is regulated through criteria, comparison, revision, and convergence. [Habiyaambere and Niyibizi \(2026\)](#) and [Weng et al. \(2024\)](#) both suggest that educational value in AI-supported learning depends on design, process quality, and assessment criteria rather than on technological variation alone. From this perspective, the style becomes visible when learners use AI to expand possibilities without losing conceptual direction.

In the policy brief task, this emphasis may appear during moments of design, planning, or revision. A learner might request several implementation models, compare them according to feasibility, equity, teacher workload, assessment implications, and institutional constraints, and then refine the strongest version through successive rounds of critique. What matters is not the number of generated alternatives, but the learner's capacity to move from divergent exploration to justified convergence. In this regard, [Akintola et al. \(2025\)](#) connect adaptive AI systems with personalised pathways for skill development, while [Weng et al. \(2024\)](#) show why revision evidence is increasingly important for judging learning in GenAI contexts. The style is therefore best understood as a pattern of regulated iteration rather than as a preference for experimentation.

The pedagogical value of this configuration becomes clear when the product alone is insufficient to reveal learning. A final policy brief may look coherent, but the learning process behind it may have involved either superficial recombination or substantive conceptual development. Teachers can therefore look for indicators such as comparison among versions, explicit convergence criteria, documented trade-offs, revision rationales, and transfer of insights from one iteration to another. These indicators allow adaptive regulation to be interpreted as a formative process, not as a hidden trait. They also help teachers design interventions for students who generate many possibilities but struggle to evaluate, select, or consolidate them.

The main risk of this style is circularity. A learner may keep prompting because each new response creates the feeling of progress, even when no deeper decision has been made. In that case, AI amplifies activity without strengthening understanding. [Yankouskaya et al. \(2025\)](#) warn that large language models can shift from support to dependence, and this risk is especially relevant when iteration becomes a substitute for judgement. The pedagogical challenge, therefore, is to make convergence explicit: students should be asked not only to show that they produced several versions, but to explain why one version is more valid, coherent, ethical, or transferable than another.

3.5. Socio-Algorithmic Agency and Ethical Governance as a Predominant Style

Socio-algorithmic Agency and Ethical Governance refers to a predominant style in which the learner's or group's activity is organised around shared responsibility for AI-mediated knowledge production. It foregrounds the social and ethical conditions under which AI is used: who prompts, who verifies, who decides, who is credited, who is disadvantaged, and how responsibility is distributed when human and algorithmic contributions

become intertwined. Unlike epistemic control, which emphasises the learner's authority over validity, and adaptive regulation, which emphasises purposeful iteration, this configuration highlights the governance of participation, transparency, and accountability.

In a collaborative policy brief, this style may become visible before any AI-generated content is accepted. Students might agree which uses of AI are legitimate, how prompts will be documented, who will verify claims, how attribution will be handled, and how disagreements about AI-generated suggestions will be resolved. They might also rotate roles so that algorithmic fluency does not become an invisible source of power within the group. Kong et al. (2024) and Chee et al. (2025) support this emphasis on shared AI literacy, because unequal competence can easily become unequal participation. In this style, ethical governance is not an appendix to learning; it is one of the conditions that makes collaboration educationally meaningful.

The indicators of this configuration are therefore different from those associated with individual verification or iterative revision. They may include AI-use protocols, attribution logs, collaborative verification records, role distribution agreements, peer-audit practices, and reflections on fairness of participation. These forms of evidence help teachers interpret whether AI use is being governed as part of the learning process or simply hidden behind a polished final product. The framework is useful here because it connects AI literacy, academic integrity, and collaborative learning within the same analytical space, rather than treating them as separate institutional concerns.

The risk, however, is bureaucratisation. A team may produce an AI-use protocol, attribution log, or verification checklist without allowing those procedures to shape the quality of learning. Ethical governance then becomes compliance rather than agency. Parycek et al. (2023) show why guidelines and framework conditions are necessary, but such documents cannot substitute for judgement. For the socio-algorithmic style to remain educationally meaningful, students must connect procedures with intellectual responsibility, fairness of participation, and the credibility of the knowledge they produce. In this sense, governance is not merely about following rules; it is about learning how to make responsible decisions in hybrid knowledge environments.

3.6. Identification Criteria and Explanatory Scope

If regulation and agency styles are understood as situated profiles rather than fixed learner types, their identification cannot depend on a single instrument, isolated interaction, or self-description. This is one of the main safeguards that prevents the framework from reproducing the weaknesses of classical learning style approaches. Pashler et al. (2008), Newton and Miah (2017), and Hughes et al. (2022) showed that the problem with traditional learning styles was not only the lack of evidence for matching instruction to preferred modalities, but also the tendency to convert fragile classifications into pedagogical prescriptions. For this reason, the framework proposed here requires a more cautious evidentiary logic: a style can only be inferred provisionally when a pattern appears across several sources of evidence, remains meaningful in relation to the task, and can be interpreted pedagogically rather than merely labelled.

In practice, identification should begin with the learning situation, not with the student as a stable object of classification. A teacher may examine how learners interact with AI during a specific task, project, or sequence of activities, looking for the regulatory emphases that become visible in the process. Evidence may include prompt histories, revision sequences, verification behaviours, reflective accounts, learning artefacts, collaborative protocols, attribution records, and assessment rationales. These sources should not be read as transparent indicators of cognition, but as traces that require interpretation. This point is especially important in GenAI environments, where Weng et al. (2024) emphasise that

assessment must attend to learning processes and outcomes rather than relying exclusively on final products.

The three dimensions of the framework offer practical criteria for such interpretation. Epistemic control and metacognitive orchestration may be identified through evidence that learners question AI-generated outputs, compare them with reliable sources, reject weak or unsupported claims, make validity criteria explicit, and justify why particular outputs are incorporated or excluded. Adaptive regulation and generative iteration may be identified through evidence of purposeful prompting, comparison among alternatives, documented revision, explicit convergence criteria, and transfer of insights across versions or tasks. Socio-algorithmic agency and ethical governance may be identified through AI-use protocols, attribution practices, distribution of verification roles, collaborative audits, and reflections on fairness, transparency, or responsibility. These indicators do not classify a learner once and for all; they show which dimensions of regulation and agency are more or less developed in a particular learning situation.

The following operational distinction is therefore essential. The framework should not be used to produce individual labels such as “orchestrating student,” “iterative student,” or “socio-algorithmic student.” Such use would repeat the classificatory logic that the article rejects. Instead, the framework should be used to formulate pedagogical judgements such as: this task elicited strong generative iteration but weak epistemic verification; this group documented attribution but did not distribute verification equitably; this student demonstrated careful source checking but struggled to move from multiple alternatives toward justified convergence. These judgements are actionable because they point to specific forms of instructional support, feedback, or assessment redesign.

This approach also responds to the fluidity of AI-mediated learning. A learner may show strong epistemic control in one task and weak socio-algorithmic governance in another; a group may demonstrate rich collaborative protocols but limited metacognitive monitoring; an assignment may encourage extensive iteration while leaving ethical responsibility implicit. These variations are not anomalies. They are part of the phenomenon the framework seeks to capture. The stability of a profile, therefore, should not be assumed in advance. It must be examined longitudinally, across different tasks and under different assessment conditions, before any stronger claim about recurrent patterns can be made.

The explanatory scope of the framework is consequently limited but useful. It does not claim that regulation and agency styles replace established constructs such as prior knowledge, motivation, self-regulated learning, disciplinary expertise, access, or digital competence. Nor does it claim that one profile is universally superior. As [Kuchynska et al. \(2025\)](#) argue in relation to intelligent systems in education, technological adaptation only becomes meaningful when aligned with pedagogical purposes. In the same way, regulation and agency styles become educationally relevant only when they help teachers understand how learners engage with AI under specific curricular, institutional, and ethical conditions.

Finally, two risks must be explicitly avoided. The first is reclassification: converting situated profiles into a new rigid taxonomy of learners. The second is technocratic reduction: using behavioural data to automate judgements about students without adequate interpretation, consent, or pedagogical responsibility. [Lindebaum et al. \(2025\)](#) warn that large language models can reorganise epistemic agency and governance in ways that appear neutral but are institutionally consequential. For that reason, the proposed framework should be used as a formative and critical tool. Its purpose is to make AI-mediated learning processes more interpretable, not to turn students into data profiles or to automate decisions about their learning.

4. Conclusions

The learning styles debate should not be reopened in order to rescue discredited typologies or to reproduce the prescriptive logic of matching instruction to fixed learner categories. The evidence against classical sensory or preference-based learning styles remains strong (Newton & Miah, 2017; Pashler et al., 2008). What the expansion of generative and adaptive AI does reopen is a different educational question: how learners regulate their activity, sustain agency, exercise epistemic control, and assume responsibility when intelligent systems become part of the cognitive, social, and ethical conditions of academic work. In this sense, the article moves from learning styles as traits to regulation and agency styles as situated, multidimensional, and modifiable profiles of practice.

The conceptual framework proposed here offers a cautious way to analyse those profiles without turning them into labels. Its three dimensions, epistemic control and metacognitive orchestration, adaptive regulation and generative iteration, and socio-algorithmic agency and ethical governance, do not define three types of students. They identify three pedagogical problems intensified by AI-mediated learning: the problem of validity, the problem of process regulation, and the problem of distributed responsibility. This is why the framework draws on self-regulated learning, metacognition, epistemic cognition, AI literacy, and governance research (Azevedo & Cromley, 2004; Biesta & Tedder, 2007; Chee et al., 2025; Chinn et al., 2021; Hofer & Pintrich, 1997; Jin et al., 2025; Kong et al., 2024; Lindebaum et al., 2025; Pintrich, 2000; Priestley et al., 2015; Winne & Hadwin, 1998; Wu et al., 2025; Zimmerman, 2002), while organising these traditions around the specific situation created when learners interact with systems capable of generating academic discourse, alternatives, feedback, and apparent solutions.

The main contribution of the article is therefore integrative and formative. It does not claim that regulation and agency styles already exist as empirically validated categories, nor that they should be used to classify students. Rather, it offers a conceptual vocabulary for interpreting how different emphases of regulation and agency may appear within tasks, groups, or learning trajectories. A learner may show strong epistemic verification in one activity, extensive but poorly governed iteration in another, or responsible collaborative protocols without sufficient critical evaluation of AI-generated content. Such variation does not weaken the framework. It is precisely the phenomenon the framework seeks to make pedagogically interpretable.

This perspective has direct implications for teaching and assessment. If AI can rapidly produce polished academic artefacts, then educators need tasks that require students to make their judgement visible. Assessment should not focus only on final products, but also on evidence of prompting decisions, source checking, revision rationales, convergence criteria, attribution practices, and collaborative governance. This is consistent with current research on assessment in GenAI environments, which emphasises the need to attend to both process and outcome (Weng et al., 2024). From this perspective, regulation and agency styles become useful not because they classify learners, but because they help teachers identify where instructional support is needed: verification, purposeful iteration, ethical documentation, equitable participation, or responsible closure.

The framework also carries an ethical and institutional implication. In AI-mediated learning, responsibility is distributed across learners, tools, tasks, teachers, peers, and institutional policies. For that reason, AI literacy cannot be reduced to technical skill or efficient prompting. It must include epistemic judgement, metacognitive monitoring, attribution, transparency, fairness, and awareness of how AI can reorganise agency and governance (Chee et al., 2025; Jin et al., 2025; Kong et al., 2024; Lindebaum et al., 2025). Without this broader formation, AI integration may reward fluency without understanding, productivity without responsibility, and access without equity.

At the same time, the framework must be used with restraint. Its purpose is not to produce a new taxonomy of learners, nor to automate judgements based on behavioural data. The profiles it describes are provisional, situated, and open to pedagogical transformation. Their identification requires multiple sources of evidence, careful interpretation, and attention to the context in which AI use occurs. Future empirical research should therefore examine whether the proposed dimensions can be identified reliably across tasks, whether they change through instruction, and whether particular configurations are associated with learning quality, transfer, academic integrity, and equitable participation.

Ultimately, the value of this conceptual framework lies in helping education respond to a contemporary urgency without repeating an old mistake. Traditional learning styles became problematic when they converted learner differences into fixed categories and unsupported prescriptions. AI-mediated learning now requires a different response: not a new typology, but a more precise way of understanding how learners regulate generative interaction, preserve epistemic agency, and govern responsibility in hybrid knowledge environments. If generative AI is already reshaping how students learn, then higher education must deliberately cultivate the forms of regulation and agency needed to ensure that algorithmic mediation expands, rather than impoverishes, educational experience.

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