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Commentary

Rethinking evidence-informed policy and practice in the age of generative artificial intelligence

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Abstract

The rise of generative artificial intelligence tools such as ChatGPT is transforming how knowledge is produced, accessed and used across educational systems. While these technologies offer new opportunities for efficiency and scalability, they also challenge foundational assumptions about what counts as evidence, how it is interpreted and who holds epistemic authority. The article argues that models of evidence-informed policy and practice (EIPP), although still valuable, require recalibration to address the emerging demands of educational contexts mediated by artificial intelligence. Drawing on recent research in artificial intelligence, critical thinking and professional practice, the article proposes a reframing model – EIPP-CT (Evidence-Informed Policy and Practice with Critical Thinking) – that places critical thinking at the heart of evidence use. Here, critical thinking is conceptualised not merely as a cognitive skill, but as a professional stance encompassing interpretive judgement, epistemic reflexivity and ethical responsibility. The article outlines key risks of over-reliance on content generated by artificial intelligence, including automation bias and diminished transparency, and advocates for institutional safeguards and professional development that foster context-sensitive, deliberative engagement with evidence. It concludes by calling for more systematic research and policy attention to the shifting epistemic landscape of education. In doing so, it aims to preserve the integrity of evidence-informed decision-making in a world increasingly shaped by algorithmic technologies.

Keywords critical thinking; generative artificial intelligence; AI; evidence-informed practice; educational policy; professional judgement

Introduction: why rethink evidence now?

The widespread adoption of generative artificial intelligence (AI) tools such as ChatGPT, Google Gemini and Microsoft Copilot is reshaping how educators, researchers and policymakers engage with knowledge. These large language models (LLMs) generate fluent, grammatically coherent and seemingly authoritative responses to prompts, ranging from lesson plans and policy drafts to research summaries and feedback reports. While these tools offer powerful affordances – particularly in terms of speed, accessibility and personalisation – they also raise urgent epistemic and ethical questions about what counts as credible evidence in education (Williamson and Eynon, 2020; Xie et al., 2024).

This commentary argues that the emergence of generative AI constitutes more than a technological shift: it disrupts foundational assumptions about how evidence is produced, interpreted and used in education. Evidence-informed policy and practice (EIPP), as a paradigm, has been central to debates on improving decision-making through the judicious use of research, professional expertise and contextual understanding (Nutley et al., 2007; Rickinson et al., 2021). It evolved in part as corrective to rigid 'evidence-based' models that privileged certain research hierarchies (for example, randomised controlled trials) while marginalising practitioner knowledge and local values (Biesta, 2007; Levin, 2013). At its best, EIPP promotes a dialogic and iterative engagement with knowledge, emphasising professional judgement, transparency and responsiveness to context.

However, these assumptions are increasingly challenged by the logic of generative AI. LLMs draw on vast, uncurated and largely opaque corpora of texts, and their outputs are not grounded in explicit evidence chains or methodological transparency (Haverkamp et al., 2023; Peng et al., 2023). Texts produced by generative AI may appear authoritative, but they often lack clear provenance, may reflect algorithmic biases and can include fabricated or outdated information (Giannakopoulos et al., 2023; Sallam, 2023). In such contexts, users are not merely consumers of evidence; they are de facto evaluators, interpreters and, at times, unwitting co-constructors of it.

In response, this commentary argues for a rethinking of EIPP – one that embeds critical thinking (CT) as a central, cross-cutting process in how evidence is engaged with in AI-mediated environments. CT is not understood here as a generic cognitive skill, but as an epistemic disposition and ethical stance: a commitment to questioning assumptions, interrogating sources and considering whose knowledge is being represented and why (Facione, 2011; Lai, 2011). Articulated through a proposed EIPP-CT lens, this reframing recognises that the availability of AI-generated knowledge demands greater scrutiny, not less, and that educational practice and policymaking require renewed attention to interpretive judgement and epistemic care.

The commentary proceeds by examining the promise and peril of AI-generated evidence, problematising current models of evidence use and outlining the implications of adopting a critical stance for educators and decision-makers alike.

The promise and peril of AI-generated evidence

Generative AI systems offer powerful capabilities that are already being harnessed across the educational landscape. Tools such as ChatGPT, Claude and Copilot enable users to generate teaching resources, summarise academic literature, formulate assessment tasks and even simulate policy analysis with minimal input. Trained on massive datasets, these models can produce responses that mimic the form and tone of scholarly writing, creating an illusion of authority that makes them especially appealing for time-constrained professionals and institutions (Peng et al., 2023; Sallam, 2023).

These tools appear to lower barriers to knowledge access and facilitate rapid knowledge translation – tasks that once required specialist expertise. In foreign language education, for instance, generative tools have been employed to support reflection, feedback and instructional adaptation (Abdelhalim, 2024; Teng, 2025). In research and policy contexts, they are increasingly used for evidence screening, literature synthesis and report drafting (Nguyen-Trung et al., 2024; Xie et al., 2024). Such uses hold considerable promise for enhancing efficiency and scalability, particularly in settings with limited resources or constrained research capacity.

However, these affordances are tightly coupled with epistemic risks. Unlike traditional forms of evidence grounded in transparent research processes, the outputs of LLMs are generated probabilistically based on training data patterns – not on source-verifiable facts (Giannakopoulos et al., 2023; Williamson and Eynon, 2020). Multiple studies have documented factual errors, hallucinated citations, outdated information and misleading generalisations produced by these systems (Gianola et al., 2024; Haverkamp et al., 2023; Makrygiannakis et al., 2024). In educational settings, where contextual judgement, ethical considerations and local nuance are central, such errors may lead to decisions that are ill-suited to learners' needs, or that unintentionally reinforce bias and inequity.

Moreover, generative AI's surface-level fluency often masks its underlying opacity. Although newer models such as ChatGPT with browsing or DeepSeek can generate outputs with inferred references or reasoning, these citations are often partial, unverifiable or disconnected from peer-reviewed evidence, making interpretive discernment essential. This creates a distinct form of automation bias, wherein users may over-trust outputs that appear polished and coherent but that lack a transparent evidence trail (Gianola et al., 2024; Haverkamp et al., 2023). The risk is not merely informational but pedagogical: educators and policymakers may adopt materials or recommendations without scrutinising their epistemic origins, ethical implications or embedded assumptions.

These epistemic risks are not confined to generative AI tools alone. Broader algorithmic ecosystems, including social media platforms and search engines, similarly shape users' exposure to knowledge. Pariser's (2011) concept of *filter bubble* describes how personalised algorithms tailor content based on users' past behaviours, reinforcing pre-existing beliefs while filtering out disconfirming perspectives. Building on this, the notion of *information cocoons* refers to a deeper entrenchment: a feedback loop in which human preferences and AI-driven personalisation jointly restrict exposure to alternative viewpoints (Piao et al., 2023). While filter bubbles refer to algorithmic sorting, information cocoons result from an adaptive dynamic between human and machine agency, making them harder to escape and more resistant to corrective input. Bibliometric research highlights information cocoons as a growing interdisciplinary concern, particularly in relation to fake news, political polarisation and selective exposure on platforms such as Twitter and Facebook (Yan et al., 2025). These dynamics undermine critical engagement by discouraging epistemic friction and narrowing interpretive horizons.

In educational contexts, where AI-generated tools are increasingly relied upon to assist with summaries, instructional decisions and policy recommendations, such cocooning effects may compound automation bias. When critical engagement is diminished by algorithmic reinforcement and surface-level fluency, the shift from evidence-informed to algorithm-driven practice becomes not only possible but also likely. Without deliberate frameworks for epistemic scrutiny and evaluative discernment, educators and decision-makers risk bypassing the interpretive work that underpins sound educational judgement. What is needed, then, is a renewed commitment to questioning, contextualisation and ethical deliberation in how knowledge is produced, validated and applied – particularly in an era increasingly shaped by generative AI.

The next section examines how EIPP, while still valuable, requires conceptual recalibration to meet the demands of this emerging epistemic landscape.

Why evidence-informed policy and practice needs reframing

EIPP has become a widely endorsed framework across educational systems. Unlike 'evidence-based' approaches that privilege experimental research and standardised hierarchies of proof, EIPP values a more holistic integration of research evidence, practitioner expertise and local knowledge (Nutley et al., 2007; Rickinson et al., 2021). It is designed to support democratic decision-making, professional autonomy and responsiveness to contextual variation – particularly important in complex fields such as education, where outcomes are shaped by social, cultural and relational factors (Biesta, 2007).

Yet the emergence of generative AI challenges key assumptions underpinning this model. EIPP is premised on the notion that evidence is produced through transparent, methodologically rigorous processes and can be critically assessed through human deliberation. Generative AI, by contrast, produces content that often resembles evidence in form – summaries, recommendations, data interpretations – but that lacks a traceable methodological foundation. These outputs are frequently presented without citations or are grounded in opaque and uncurated training data, making it difficult for users to verify the quality, relevance or origin of the information provided (Giannakopoulos et al., 2023; Haverkamp et al., 2023).

This opacity presents a dilemma for educators and policymakers. When a policy memo or instructional guide is generated by ChatGPT, should it be treated as evidence? If it synthesises plausible insights but fails to reference primary studies or indicate its sources, how can it be critically appraised? Traditional EIPP frameworks offer limited guidance in such scenarios, as they assume that the 'evidence' in question is externally validated and transparently produced. Moreover, the surface fluency and speed of generative AI may tempt educators to shortcut the interpretive labour at the heart of EIPP. Instead of triangulating evidence, consulting communities or applying accumulated professional wisdom, practitioners may uncritically adopt AI-generated suggestions that appear polished and persuasive. This dynamic risks diminishing professional judgement, narrowing deliberative space and subtly shifting decision-making power from human actors to algorithms (Berendt et al., 2020; Peng et al., 2023).

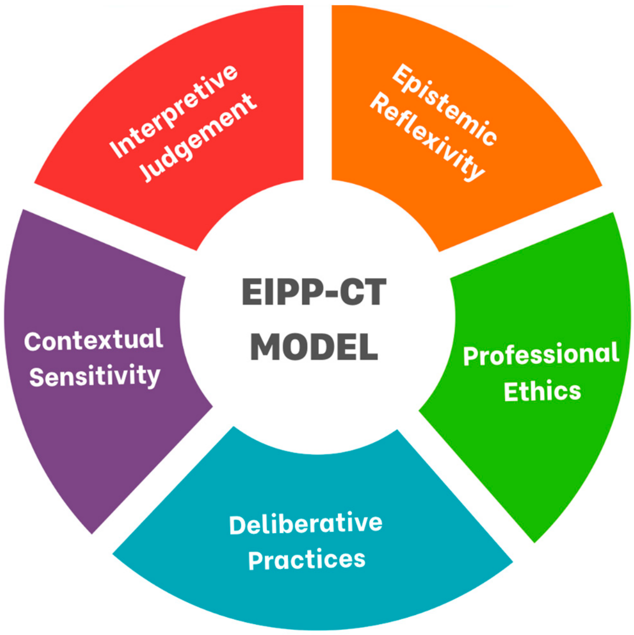
What is needed, then, is not a rejection of EIPP, but its recalibration to meet the epistemic and ethical challenges posed by AI-mediated knowledge environments. Drawing on prior scholarship that frames CT as essential to sound professional judgement (Facione, 2011; Lee et al., 2025), and on calls for more inclusive and context-sensitive approaches to evidence use in education (Cooper, 2014; Levin, 2013), I propose a reframing of EIPP through a CT lens – what I term the EIPP-CT model (see Figure 1). This model reconceptualises CT not as a discrete cognitive skill or student learning outcome, but as a central epistemic and ethical stance embedded across all stages of evidence engagement – from sourcing and appraisal to interpretation and application.

The EIPP-CT model offers a principled framework for navigating evidence use in AI-mediated educational contexts by positioning CT as a situated professional stance, rather than as a discrete individual skill. It integrates five interrelated dimensions that together support epistemically responsible and contextually grounded engagement with evidence. The first, interpretive judgement, involves scrutinising the credibility, coherence and appropriateness of claims across varied sources, including research literature, practitioner knowledge and generative AI outputs. Epistemic reflexivity entails interrogating the assumptions that underpin claims to knowledge and recognising how algorithmic systems shape the framing and perceived authority of such evidence. The third dimension, professional ethics, highlights the moral responsibilities that educators and policymakers carry when working with AI-generated content – particularly the need for transparency, accountability and vigilance against automation bias. Contextual sensitivity draws attention to the importance of aligning evidence use with local values, learner realities and institutional goals, resisting one-size-fits-all applications of generalised AI outputs. Finally, deliberative practices emphasise the role of collaborative, dialogic reasoning in preserving human judgement and resisting the passive adoption of seemingly authoritative machine-generated responses. These five dimensions synthesise insights from CT scholarship – especially on bias detection, ethical reasoning and epistemic caution – and from emerging empirical studies examining how educational professionals interact with generative AI in real-world practice (Abdelhalim, 2024; Cong-Lem et al., 2025; Liang and Wu, 2024; Teng, 2025). Taken together, the EIPP-CT model offers a robust conceptual foundation for sustaining professional agency, ethical responsibility and critical engagement in educational systems increasingly shaped by algorithmic mediation.

Such a reframing aligns with broader calls for more reflective and inclusive approaches to evidence use in education (Cooper, 2014; Levin, 2013). It also resonates with recent empirical studies showing that users with higher levels of metacognitive awareness and critical engagement are better equipped to evaluate and adapt AI-generated content responsibly (Abdelhalim, 2024; Teng, 2025).

Figure 1 conceptualises the EIPP-CT model as a principled stance for engaging with evidence in AI-mediated educational environments. At the centre of the model is the EIPP-CT orientation itself, which is not treated as a discrete skill but as an integrated disposition grounded in five interrelated dimensions: interpretive judgement, epistemic reflexivity, professional ethics, contextual sensitivity and deliberative practices. These dimensions collectively represent the cognitive, ethical and dialogic capacities required for professionals to navigate increasingly complex and algorithmically shaped evidence landscapes. Rather than illustrating a flow of information from specific sources (for example, generative AI, research, practitioner expertise), the model emphasises the internal processes by which professionals critically evaluate any form of information they encounter. Its design reflects the recursive and interdependent nature of these dimensions, suggesting that CT is not linear but dynamically sustained across diverse situations of evidence use. In doing so, the model offers a coherent foundation for sustaining professional agency, ethical vigilance and context-aware decision-making in educational systems increasingly shaped by automated outputs and epistemic uncertainty.

Figure 1. The EIPP-CT model for AI-mediated evidence engagement



The next section develops this argument by elaborating on what a CT stance entails, and how it might be supported in professional and policy contexts.

A critical thinking stance for educators and policymakers

If EIPP is to remain relevant in the generative AI era, it must be anchored in a renewed conception of CT – one that is both epistemically robust and ethically situated. In educational settings, CT has traditionally been framed as a desirable learning outcome, often linked to problem-solving, analysis and argumentation. Yet in the context of generative AI, CT must also be understood as a professional disposition: a mode of inquiry through which educators, leaders and policymakers navigate the uncertain epistemic terrain that AI technologies create.

This stance requires the capacity to evaluate AI-generated content not simply for surface-level plausibility, but also for coherence with disciplinary norms, contextual appropriateness and ethical alignment (Knox et al., 2022; Lee et al., 2025). For instance, when a teacher uses ChatGPT to generate differentiated learning activities, or when a policymaker asks an LLM for an evidence-based summary of an intervention, they must be equipped to ask: Where might this information come from? What assumptions are embedded in this output? What alternative perspectives are missing?

Such a stance goes beyond technical skill. It draws on metacognition, digital literacy and professional ethics – and it includes the ability to weigh competing claims, triangulate sources and remain attentive to power and bias in algorithmic outputs (Facione, 2011; Liu and Wang, 2024). It also demands a degree of humility and reflexivity: acknowledging that no single tool or model, no matter how sophisticated, can replace the judgement formed through sustained professional dialogue and contextual knowledge.

The EIPP-CT model (see Figure 1) offers a distinctive contribution by framing CT not merely as an individual cognitive skill, but also as a socially situated and professionally embedded stance that operates at the intersection of individual and collective agency. While earlier scholarship (for example, Knox et al., 2022; Lee et al., 2025) has explored CT primarily in relation to learning outcomes or ethical reflection, the EIPP-CT model extends this focus to encompass how educators and policymakers interpret, evaluate and act upon diverse forms of evidence in AI-saturated contexts. Its five interrelated dimensions – interpretive judgement, epistemic reflexivity, professional ethics, contextual sensitivity and deliberative practices – foreground the collaborative and context-dependent nature of responsible evidence use. In doing so, the model acknowledges that CT is not exercised in isolation but emerges through professional dialogue, institutional constraints, cultural values and algorithmic mediation. This situated orientation enables the model to bridge epistemic caution with collective responsibility, offering a recalibrated framework for sustaining transparency, care and professional judgement amid the growing influence of generative AI.

Emerging research supports this view. Studies show that learners and educators who engage critically with AI outputs – by revising prompts, cross-checking information or reflecting on the limitations of the system – develop stronger metacognitive and evaluative skills (Abdelhalim, 2024; Liang and Wu, 2024; Teng, 2025). Similarly, Shen and Tao (2025) found that metacognitive strategies and AI-based self-efficacy were positively associated with lower writing anxiety and more purposeful engagement with AI-assisted writing tools.

At the policy level, CT implies not only questioning AI-generated advice but also embedding safeguards into decision-making processes. These might include mechanisms for cross-validation, transparency audits and participatory review panels to assess the use of AI-generated evidence in policy formation. Without such structures, education systems risk substituting human deliberation with algorithmic approximation – undermining the very principles of responsiveness, inclusion and care that evidence-informed approaches seek to uphold (Haverkamp et al., 2023; Peng et al., 2023).

In this light, CT becomes the connective tissue between AI-enhanced knowledge and responsible practice. It is the means by which professionals resist overreliance on automation, preserve interpretive agency and uphold the integrity of educational decision-making in an increasingly mediated world.

Conclusion: moving forward with epistemic responsibility

As generative AI systems become increasingly embedded in educational practice and policy, the boundaries between human- and machine-produced knowledge appear to be growing more porous, and the epistemic terrain more complex. These technologies introduce powerful new affordances – streamlining lesson planning, synthesising research or drafting policy documents – but they also raise important questions about how evidence is sourced, validated and interpreted. In this evolving landscape, the concept of EIPP may need to be re-examined. What counts as evidence? Whose knowledge is being represented? And how might educational actors engage with outputs that resemble evidence in form but often lack methodological transparency or verifiable provenance?

This commentary has suggested that EIPP, while continuing to serve as a valuable framework, may benefit from recalibration in contexts increasingly shaped by generative AI technologies. In particular, it may be useful to foreground CT not as an optional skillset but as a foundational epistemic and ethical stance – one that enables educators, researchers and policymakers to interpret and apply both conventional and AI-generated knowledge with greater care. The proposed EIPP-CT model is not presented as a tool for optimising AI use alone; rather, it can be understood as a framework for supporting professional judgement, interpretive space, and contextual responsiveness in an era of growing algorithmic influence.

A key consideration going forward involves how such a stance might be meaningfully embedded in institutional practice. Professional development programmes, teacher education curricula and policy guidelines could usefully expand their conception of AI literacy to include not only technical proficiency, but also the capacity for critical evaluation, ethical reasoning and context-sensitive judgement. This might involve the development of citation norms for AI-generated outputs, collaborative review protocols and verification mechanisms – particularly in settings where generative tools are used to summarise research, develop assessments or inform strategic decisions.

In parallel, future research may play a crucial role in examining how educational actors work with, resist or adapt to generative AI in practice. Longitudinal, design-based and collaborative studies could help to illuminate how trust, agency and accountability are negotiated in AI-mediated environments (Peng et al., 2023; Xie et al., 2024). Such work might also consider how professional cultures, incentive systems and institutional norms support – or constrain – critical engagement with AI-generated knowledge.

Importantly, generative AI does not eliminate the need for human inquiry, judgement and care in education; if anything, it may heighten the importance of these qualities. In a context marked by the rapid proliferation of fluent but often unverifiable content, the call to think critically, act ethically and engage reflectively becomes increasingly urgent. Reframing EIPP around these commitments may offer one constructive way forward for educators, researchers and policy actors navigating an educational landscape in transition.

Declarations and conflicts of interest

Research ethics statement

Not applicable to this article.

Consent for publication statement

Not applicable to this article.

Conflicts of interest statement

The author declares no conflicts of interest with this work. All efforts to sufficiently anonymise the author during peer review of this article have been made. The author declares no further conflicts with this article.

Declaration of generative AI use

During the preparation of this work, the author used OpenAI's ChatGPT-4 solely to support language refinement and editorial clarity, such as improving grammar, sentence structure, and readability. No AI-generated content was used to develop ideas, arguments, or analysis. All revisions were critically reviewed and edited by the author, who takes full responsibility for the integrity and originality of the final manuscript.

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