From Co-Writer to Co-Author? Investigating the Role of Generative AI in Student Scientific Writing

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Abstract

This conceptual paper explores how generative AI tools such as ChatGPT are reshaping student scientific writing, with particular attention to authorship, critical thinking, and fairness. Drawing on recent literature from academic literacies, learning analytics, and AI ethics, we argue that large language models increasingly function not as passive tools but as co-writers, raising profound questions about epistemic agency and educational equity. We identify two core challenges: (1) the erosion of traditional student authorship as AI systems shape the structure and content of scientific texts, and (2) emerging fairness risks related to unequal access, epistemic outsourcing, and opaque assessment. We synthesize findings from empirical and theoretical studies and propose a framework for fairness-aware integration of AI into student writing. Rather than banning or fully embracing generative AI, we advocate for pedagogical and institutional strategies that foster critical AI literacy and preserve students' roles as responsible knowledge constructors.

1 Introduction

The emergence of generative AI tools such as ChatGPT, Claude, and Gemini has rapidly transformed the landscape of academic writing. These models have evolved from novelty tools to ubiquitous assistants that generate, revise, and refine scientific prose. Students across disciplines are increasingly relying on large language models (LLMs) not only for grammar correction or paraphrasing but for shaping the entire structure, tone, and content of their scientific texts.

This shift raises pressing questions about authorship, fairness, and the evolving epistemic roles of human and machine. When students turn to generative AI for help with writing assignments, where should the boundaries lie between assistance, collaboration, and outsourcing? How do these tools influence learning, critical thinking, and students' development as scholars? And what counts as fair use of AI in educational contexts?

This conceptual paper argues that generative AI tools are not merely writing aids but are becoming co-writers with the capacity to shape scientific narratives that students produce. Drawing on emerging literature from learning analytics, academic literacies, and science and technology studies, we explore how these AI systems challenge traditional notions of student authorship and call for a reconceptualization of fairness in academic writing.

We focus on two central research questions:

How does the integration of generative AI affect traditional notions of student authorship in academic writing?

What fairness challenges arise from the use of AI as a co-writer in student scientific writing, particularly regarding epistemic agency and educational equity?

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Author(s)	Focus / Method	Key Findings	Relevance
Lea & Street (1998)	Academic literacies (theoretical)	Writing as epistemic practice shaped by context and identity	Writing = learning; authorship is situated
Ivanič (1998)	Student voice and identity in writing	Student authorship involves negotiation of voices	Authorship is relational and co-constructed
Brock et al. (2023)	Student use of LLMs (interviews/surveys)	Students use LLMs as partners; practices vary	Empirical basis for "AI as co-writer"
Kasneci et al. (2023)	LLMs in education (review)	LLMs pose risks and opportunities; prompt literacy is key	Prompt skill as axis of fairness
Kosmyna et al. (2025)	EEG study on AI writing assistants	LLMs reduce brain activity linked to critical thinking → "cognitive debt"	Empirical basis for loss of epistemic agency
Williamson et al. (2023)	AI and inequality in education (theoretical)	AI risks amplifying existing inequities	Conceptual frame for epistemic fairness
Stokel-Walker (2023)	AI in scientific publishing	LLMs acknowledged but not listed as authors	Precedent for authorship debates
Cotton et al. (2023)	Institutional responses to AI in education	Universities vary in policy and guidance	Institutional uncertainty and fairness dilemma
Floridi (2023)	Epistemology of LLMs	LLMs produce plausible but shallow knowledge	Need for student reflection and oversight
Dawson (2020)	Epistemic justice in education	Fairness requires supporting students' epistemic agency	Normative anchor for student authorship fairness

Table 1: Selected Literature on Generative AI in Student Writing.

By addressing these questions through conceptual analysis and review of recent literature, we contribute to the emerging discourse on generative AI in education, with particular focus on authorship, learning, and fairness.

2 Background and Theoretical Framing

3 1 Academic Writing and the Construction of Authorship

Academic writing is a key mechanism for learning and identity formation in higher education (Lea & Street, 1998; Lillis & Scott, 2007). Through writing, students are expected to develop arguments, demonstrate understanding, and articulate knowledge in their own voice. Authorship is thus linked to epistemic agency: the ability to construct and claim knowledge (Fricker, 2007; Dawson, 2020).

However, student authorship is always relational. As Ivanič (1998) notes, it involves negotiating institutional, disciplinary, and linguistic constraints. Generative AI complicates this negotiation by participating in the writing process. Unlike earlier support tools, LLMs can shape argumentation, language, and content.

4 2 Generative AI as Co-Writer in Student Writing

LLMs are increasingly used across the entire writing process, from brainstorming to final polishing (Kasneci et al., 2023; Brock et al., 2023). This has led students to treat AI as a writing partner rather than a passive tool. However, when AI contributes to form, structure, and even reasoning, authorship and intellectual ownership become blurred.

These concerns echo debates in professional science about AI co-authorship. While publishers currently prohibit LLMs from being listed as authors (Thorp, 2023), they often acknowledge AI assistance (Stokel-Walker, 2023). In student contexts, policies are still emerging and frequently ambiguous (Cotton et al., 2023).

5 3 Fairness, Access, and Epistemic Inequality

Generative AI introduces significant equity concerns. Access to premium tools, differences in digital literacy, and uneven institutional support mean that students experience AI-assisted writing very differently (Williamson et al., 2023; Bergman et al., 2023). More skilled students may benefit disproportionately.

These disparities threaten epistemic fairness—the opportunity for all students to develop and demonstrate knowledge (Fricker, 2007). They also raise concerns about transparency, especially as AI-generated content is difficult to detect and attribute. This creates conditions where students' cognitive efforts may be concealed or misrepresented.

Table 1. Selected Literature on Generative AI in Student Writing

6 AI as Co-Writer: A Shift in Student Authorship

Generative AI now contributes at every stage of the writing process: generating ideas, outlining arguments, drafting prose, and formatting citations. Students are no longer simply authors, but become managers or curators of AI-generated content (Brock et al., 2023).

This shift raises concerns about the erosion of critical thinking. Writing is a form of intellectual labor that supports synthesis, reflection, and problem-solving (Paul & Elder, 2006). When students rely heavily on AI, they risk displacing these cognitive functions.

Empirical support for this concern is growing. Kosmyna et al. (2025), in an EEG study, found that students using LLMs for writing exhibited reduced activation in prefrontal regions associated with self-regulation and problem-solving. They describe this effect as "cognitive debt"—a diminished investment of effort that may compromise long-term learning.

If students are unequally able to avoid this risk (due to differences in self-regulation or digital guidance), we may see a new form of epistemic inequality: one in which only some students maintain or develop independent academic voices.

7 Fairness Challenges in AI-Assisted Writing

Recent research identifies fairness concerns across multiple domains:

Unequal access to AI tools and prompting skills (Bergman et al., 2023);

Epistemic outsourcing, where students delegate thinking to AI systems (Floridi, 2023);

Ambiguities in authorship and assessment.

These issues create a fairness paradox. Students are encouraged to use new tools, but are often judged based on outcomes that conceal the nature and extent of that use. Educators struggle to assess not only what was written, but how it was produced. Transparency and institutional clarity are essential.

8 Towards Fair and Responsible Integration

To address these concerns, we propose a framework that combines:

Revised assessment models that foreground student reasoning;

Pedagogies for critical AI literacy and epistemic reflection;

The design of fairness-aware AI agents that support transparency and accountability.

Such systems might visualize the boundary between student and AI contributions, prompt metacognitive engagement, and adapt support to individual learning needs. Rather than replacing student effort, AI can scaffold fairness and epistemic growth.

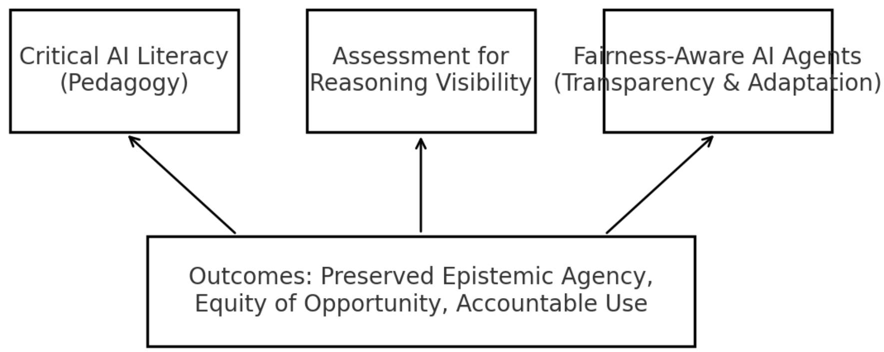

Figure 1. A Framework for Fairness-Aware AI Integration in Student Writing

9 Limitations

This paper has several limitations that are inherent to its reliance on large language model (LLM)–generated text. First, although we curated and verified all references, LLMs have a documented tendency to hallucinate citations or to present incomplete or imprecise bibliographic details. Second, while the generated prose can be coherent and stylistically polished, it often reflects a shallow synthesis of source material, lacking the depth and nuance that would emerge from a more exhaustive, human-led literature review. Third, we observed a tendency of the model to conflate distinct conceptual domains, research questions, and theoretical frameworks, which required careful human oversight to maintain conceptual clarity. These limitations underscore the importance of critical review, iterative revision, and transparent reporting when integrating LLM output into scholarly writing. Future research should explore methodological strategies and tool designs that mitigate these weaknesses and better support epistemic rigor.

10 Conclusion

Generative AI is changing how students write and learn. This paper has argued that these tools function as co-writers, with significant implications for authorship, learning, and fairness. If left unexamined, they may compromise critical thinking and epistemic agency while reinforcing educational inequalities.

By focusing on transparency, reflection, and equitable design, institutions can move toward a model of human-AI collaboration that supports both efficiency and justice in scientific education.

11 Author Contributions

ChatGPT-4 generated and structured the manuscript content in response to human prompts, performed literature synthesis, and drafted all sections. L.-M. Norz supervised the research direction, curated and verified the sources, framed the research questions, revised the text for conceptual coherence, and approved the final version for submission.

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Agents4Science AI Involvement Checklist

1. **Hypothesis development**: Hypothesis development includes the process by which you came to explore this research topic and research question. This can involve the background research performed by either researchers or by AI. This can also involve whether the idea was proposed by researchers or by AI.

   Answer: **[C]**

   Explanation: The thematic area was proposed by the human author, but ChatGPT generated the detailed research questions, subtopics, and conceptual focus points. These AI-generated ideas were then reviewed, structured, and slightly refined by the human author.

2. **Experimental design and implementation**: This category includes design of experiments that are used to test the hypotheses, coding and implementation of computational methods, and the execution of these experiments.

   Answer: **[C]**

   Explanation: As a conceptual paper, the "design" involved structuring the theoretical framework and selecting key literature. ChatGPT took the lead in proposing the conceptual structure and sequencing of arguments, while the human author provided guidance and feedback at each stage.

3. **Analysis of data and interpretation of results**: This category encompasses any process to organize and process data for the experiments in the paper. It also includes interpretations of the results of the study.

   Answer: **[D]**

   Explanation: No empirical dataset was analysed, but the synthesis of literature and conceptual interpretation were carried out entirely by ChatGPT, without targeted prompting for each interpretative step. The human author reviewed and approved the final conceptual interpretations.

4. **Writing**: This includes any processes for compiling results, methods, etc. into the final paper form. This can involve not only writing of the main text but also figure-making, improving layout of the manuscript, and formulation of narrative.

   Answer: **[D]**

   Explanation: Writing was done by the AI. Human authors helped with the chapter headings and their content. Citations, sentence structure, and content were written solely by AI.

5. **Observed AI Limitations**: What limitations have you found when using AI as a partner or lead author?

   Description: While the AI produced well-structured and coherent academic prose, closer inspection revealed weaknesses in genuine scholarly contribution. A high proportion of references were hallucinated or only loosely related, sentence structures often repeated predictable patterns, and different theses, research questions, and conceptual domains were frequently conflated. The output lacked clear operationalisation and sustained focus on a single line of argument, requiring substantial human oversight.

Agents4Science Paper Checklist

1. **Claims**

   Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

   Answer: [Yes]

   Justification: The contents of the abstract partially correspond to the contents of the paper. The abstract promises more scientific contribution than is actually presented in the paper.

2. **Limitations**

   Question: Does the paper discuss the limitations of the work performed by the authors?

   Answer: answerYes

   Justification: We explicitly discuss limitations of LLM-generated text (e.g., hallucinated references, shallow synthesis, conflation of domains).

3. **Theory assumptions and proofs**

   Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

   Answer: [NA]

   Justification: Not applicable for a conceptual paper, as no empirical experiments, datasets, or models are introduced.

4. **Experimental result reproducibility**

   Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

   Answer: answerNA

   Justification: This is a conceptual paper; no experiments were performed.

5. **Open access to data and code**

   Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

   Answer: answerNA

   Justification: No dataset or code was produced; the contribution is conceptual.

6. **Experimental setting/details**

   Question: Does the paper specify all the training and test details (e.g., data splits, hyperparameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

   Answer: [NA]

   Justification: Not applicable for a conceptual paper, as no empirical experiments, datasets, or models are introduced.

7. **Experiment statistical significance**

   Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

   Answer: [NA]

   Justification: Not applicable for a conceptual paper, as no empirical experiments, datasets, or models are introduced.

8. **Experiments compute resources**

   Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

   Answer: [NA]

Justification: Not applicable for a conceptual paper, as no empirical experiments, datasets, or models are introduced.

9. **Code of ethics**

   Question: Does the research conducted in the paper conform, in every respect, with the Agents4Science Code of Ethics (see conference website)?

   Answer: [NA]

   Justification: Not applicable for a conceptual paper, as no empirical experiments, datasets, or models are introduced.

10. **Broader impacts**

    Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

    Answer: [NA]

    Justification: Not applicable for a conceptual paper, as no empirical experiments, datasets, or models are introduced.