Teaching the Past in the Age of Algorithms: Algorithmic Source Pedagogy

Cody Montana Dalton
American College of Education
Danville, VA
DaltonInquiry@gmail.com

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Abstract: This article introduces Algorithmic Source Pedagogy (ASP), a novel pedagogical framework for secondary history education. It integrates generative artificial intelligence (AI) as both a tool for inquiry and an object of critical analysis. Drawing from recent developments in AI literacy, critical algorithmic literacy, culturally responsive pedagogy, and digital epistemology, this approach equips students to evaluate, critique, and responsibly use AI-generated historical content. The framework treats AI as a socio-technical construct rather than a neutral source of knowledge. It aligns traditional historical thinking practices with the demands of digital information environments, emphasizing equity, ethical reasoning, and student agency. This paper outlines the theoretical foundations of ASP, practical strategies for classroom implementation, and its implications for curriculum design, civic education, and educational equity.

Keywords: Historical Thinking, AI Literacy, Critical Pedagogy, Culturally Responsive Teaching, Digital Epistemology, Secondary Education

1. Introduction

Generative artificial intelligence (AI) tools such as ChatGPT, Claude, and DALL·E have rapidly entered classrooms, challenging educators to reconsider how students learn, evaluate, and create historical knowledge (Long & Magerko, 2020; Jin et al., 2025). These tools can synthesize information, simulate historical figures, generate timelines, and produce persuasive narratives. Yet, their outputs are not neutral: they reflect the data they were trained on, encode biases of their designers, and often produce factual inaccuracies (Bond et al., 2024; Dastin, 2018; Boateng & Boateng, 2025; Ferrero & Gewerc, 2019; Panch et al., 2019). In a world where students increasingly consult AI for homework, essays, and source interpretation, historical thinking must evolve to meet the challenges and possibilities of AI.

This article proposes Algorithmic Source Pedagogy (ASP), a framework designed to integrate AI tools into history education not as shortcuts or substitutes for critical thinking but as catalysts for inquiry. ASP encourages students to treat AI outputs as historical sources—constructed, fallible, and worthy of critique. It builds on established practices of sourcing, contextualization, corroboration, and perspective-taking while layering in new competencies such as prompt literacy, algorithmic scrutiny, and digital ethics (Dawson et al., 2019; Morris & Stommel, 2018, p. 231). By embedding AI within culturally responsive and justice-oriented pedagogy, ASP supports a vision of historical learning that is both rigorous and relevant to the digital age (Wang et al., 2025).

The rapid advancements in AI capacities, described as "super-exponential" growth (Baklaga, 2024), necessitate a proactive approach to integrating these technologies into education responsibly. While AI offers unprecedented opportunities for personalized learning and access to information (Ouyang & Jiao, 2021; Wu, 2024), its deployment also brings significant ethical challenges, particularly concerning algorithmic bias (Akgün & Greenhow, 2021; Baker & Hawn, 2022; European Union Agency for Fundamental Rights, 2022; Boateng & Boateng, 2025; Panch et al., 2019). Studies have shown that AI systems can exhibit biases that perpetuate societal injustices. For instance, in an example of a biased AI recruiting tool, Amazon scrapped a secret AI recruiting tool in 2018 that showed bias against women (Dastin, 2018). Similarly, concerns about algorithmic bias have been raised in educational systems (Baker & Hawn, 2022; Boateng & Boateng, 2025). Predictive models used in higher education have been found to contribute to racial inequities (Bird et al., 2024). Some machine learning models used in admissions have been linked to societal injustices (Gándara et al., 2024). These biases can be embedded in various AI applications, from automated essay scoring systems (Litman et al., 2021) to image recognition (Kizhner et al., 2021). Recognizing these risks, some researchers propose removing race data from applicant ranking algorithms to mitigate bias (Turner Lee, 2018). ASP directly addresses these concerns by equipping students to identify, analyze, and challenge such biases, fostering a more equitable and critical engagement with digital information.

2. Theoretical Foundations

Algorithmic Source Pedagogy is built upon a synthesis of several key educational and technological theories, each contributing to its comprehensive approach to teaching historical thinking in the AI era.

2.1 Historical Thinking

Wineburg's (1991) foundational work defined historical thinking as a discipline-specific mode of reasoning centered on sourcing, contextualization, corroboration, and empathetic understanding of the past. ASP preserves these heuristics but updates them to include AI-generated content, positioning such content as pseudo-sources requiring similar interrogation. This approach aligns with the understanding that historical thinking involves evaluating evidence and considering multiple perspectives (Baron, 2012; Wineburg, 1991).

2.2 AI Literacy

AI literacy encompasses the knowledge and skills necessary to understand, use, and critique artificial intelligence tools (Long & Magerko, 2020). For students, this means grasping how AI systems generate responses, understanding their limitations, and evaluating their credibility. Recent work emphasizes ethical and critical engagement with AI, principles directly incorporated into ASP (Bond et al., 2024; Jin et al., 2025; Tabassi, 2023). This includes understanding concepts like different types of algorithmic discrimination (European Union Agency for Fundamental Rights, 2022) and learning to use fairness metrics and bias assessments (Pagano et al., 2023).

2.3 Critical Algorithmic Literacy

Critical algorithmic literacy extends media literacy by focusing on how algorithms mediate knowledge. Moss (2022) argued that students must interrogate the power structures behind algorithmic outputs. ASP incorporates these insights, teaching students to question the motivations, limitations, and biases embedded in algorithmically generated content (Baker & Hawn, 2022; Boateng & Boateng, 2025). This pedagogical approach also considers how AI applications in higher education relate to learning theories (Ouyang & Jiao, 2021) and the importance of interdisciplinary collaboration for AI systems (Thomas, 2024).

2.4 Culturally Responsive Pedagogy

Culturally responsive pedagogy affirms students' identities and positions their experiences as assets in learning. ASP applies these principles by prompting students to analyze how AI tools represent or erase culturally diverse histories, empowering them to reframe narratives through deliberate prompt design and critical analysis (Wang et al., 2025; Wu, 2024). This framework supports the development of culturally relevant pedagogy, particularly in the context of K-12 education with the support of large language models (Wang et al., 2025).

2.5 Digital Epistemology and Critical Digital Pedagogy

Digital epistemology explores how knowledge is constructed, accessed, and trusted in online environments. Critical digital pedagogy resists the uncritical adoption of technological tools and centers learner agency (Morris & Stommel, 2018, p. 232). ASP positions students as co-constructors of digital historical knowledge, capable of challenging both the form and content of AI-generated material. This perspective aligns with calls for increased ethics, collaboration, and rigor in the integration of AI in higher education (Bond et al., 2024) and the need for educators to critically assess AI outputs (Hanover Research, 2024).

3. Pedagogical Design: Algorithmic Source Pedagogy (ASP)

ASP offers a structured yet flexible framework for integrating AI into history education, emphasizing critical engagement and ethical use.

3.1 Principles

The core principles guiding ASP include:

- Treat AI-generated historical content as constructed and interrogatable, akin to traditional historical sources (Wineburg, 1991).
- Reinforce traditional historical thinking alongside algorithmic critique, ensuring students develop both sets of competencies (Long & Magerko, 2020; Moss, 2022).
- Use culturally responsive methods to surface and challenge bias, acknowledging that AI can perpetuate existing inequities (Wang et al., 2025; Wu, 2024).
- Promote ethical AI use and digital citizenship, encouraging responsible interaction with AI tools (Akgün & Greenhow, 2021;Tabassi, 2023).
- Center student voice, agency, and inquiry, empowering learners to actively shape their understanding of history in the digital age (Morris & Stommel, 2018).

3.2 Instructional Practices

ASP proposes a range of instructional practices to put these principles into action:

- AI sourcing exercises: Students analyze AI-generated texts, images, or timelines, identifying potential origins, implicit biases, and factual accuracy, much like they would with traditional primary or secondary sources.
- Chatbot interviews: Students interact with generative AI models, posing questions about historical events or figures, and then critically evaluate the AI's responses for nuance, perspective, and potential inaccuracies (Lee & Ompok, 2025).
- Corroboration challenges: Students compare AI-generated historical narratives with established historical accounts and other sources to identify discrepancies and build a more complete understanding.
- Bias audits: Students intentionally prompt AI tools to explore how they represent or omit certain historical narratives, particularly those related to marginalized groups, fostering an awareness of algorithmic bias (Baker & Hawn, 2022; Boateng & Boateng, 2025).
- Image analysis: Students critically examine AI-generated historical images for authenticity, contextual accuracy, and potential stereotypical representations, enhancing visual literacy (Kizhner et al., 2021).
- Simulations and Virtual Reality (VR): While not directly AI-generated, these technologies offer immersive experiences that can be analyzed through an ASP lens. Students can engage with historical simulations (Walters et al., 2017; Chernikova et al., 2020; Jones & Bursens, 2015) and VR environments (Sümer & Vaněček, 2024; Radianti et al., 2020), assessing their historical fidelity and potential biases in representation (Harris et al., 2020).
- Authentic Learning Environments: Utilizing an instructional design framework for authentic learning environments (Herrington & Oliver, 2000) can further enhance the practical application of ASP, encouraging students to engage in real-world historical problem-solving.

- Pedagogical Agents: Integrating pedagogical agents in learning environments (Sikström et al., 2024) can provide interactive support for students as they navigate AI tools and historical content, serving as a guide in their critical inquiry.

3.3 Assessment

Assessment in ASP is designed to reflect the multi-faceted learning objectives. It includes:

- Annotated critiques of AI content: Students provide detailed analyses of AI outputs, highlighting strengths, weaknesses, and biases.
- Reflective journals on digital inquiry: Students document their process of interacting with AI tools, their critical insights, and their evolving understanding of digital epistemology.
- Portfolios combining traditional and AI-augmented projects: Students showcase their ability to integrate AI tools responsibly while demonstrating strong historical reasoning.
- Rubrics integrating historical thinking with AI literacy benchmarks: These rubrics evaluate students' proficiency in both traditional historical skills and emerging AI competencies (Long & Magerko, 2020).
- Formative and summative assessments that leverage AI: This includes practices such as automated essay scoring systems (Litman et al., 2021), though with careful consideration of their potential biases, and other innovative assessment methods transformed by generative AI (Xia et al., 2024).

4. Implications for Equity and Civic Literacy

Algorithmic Source Pedagogy holds significant implications for advancing educational equity and fostering robust civic literacy in an increasingly digital world. ASP supports equity by equipping students from all backgrounds to engage critically with dominant and emerging narratives (Bond et al., 2024). It leverages AI to surface underrepresented voices while preparing students to identify and challenge digital bias. For instance, by critically examining how AI models, often trained on imbalanced datasets, might misrepresent or erase the histories of marginalized groups, students develop a crucial awareness of power dynamics in information creation (Baker & Hawn, 2022; Boateng & Boateng, 2025; Panch et al., 2019). This approach empowers students, particularly those from underrepresented backgrounds, to become active participants in shaping historical narratives rather than passive consumers. By understanding how resource allocation can affect schooling (Hanushek, 1989), ASP also implicitly encourages a broader discussion about equitable access to digital tools and literacy.

Moreover, ASP fosters civic literacy by teaching learners how algorithmic media shape public memory and historiography, positioning them to navigate a disinformation-rich society with historical rigor and ethical awareness (Dawson et al., 2019; Morris & Stommel, 2018). In an era where mis- and disinformation can spread rapidly through algorithmic amplification, the ability to critically evaluate AI-generated content becomes paramount for informed citizenship. By understanding the sources of bias in educational systems (Ferrero & Gewerc, 2019) and AI systems in general (Panch et al., 2019), students are better prepared to discern reliable information from

misleading content, contributing to a more resilient and informed democracy. The framework also aligns with the broader goal of fostering critical algorithmic literacy, bridging computer science and critical media literacy (Moss, 2022), which is essential for navigating modern information landscapes.

5. Implementation Considerations and Future Directions

Successful implementation of Algorithmic Source Pedagogy (ASP) requires careful consideration of several key factors to ensure its effectiveness and equitable reach.

5.1 Implementation Considerations

Professional Development: Teachers will need targeted professional development to effectively integrate AI literacy with historical inquiry. Schools should provide training that emphasizes not only technical proficiency with AI tools but also ethical reflection, critical engagement with AI outputs, and strategies for culturally responsive pedagogy in the context of AI. This is crucial given observed educator hesitation to adopt AI (Michigan Virtual, 2024). The focus should be on building confidence in teaching AI literacy and understanding its implications for historical thinking, rather than solely on the mechanics of using AI.

Access to Resources: Equitable access to reliable and robust technological resources remains a critical consideration, particularly in schools with limited infrastructure. Disparities in access to devices, high-speed internet, and AI software can exacerbate existing educational inequalities. Policymakers and administrators must prioritize investments to bridge these digital divides, ensuring that all students have the opportunity to engage with ASP.

Curriculum Alignment: Policymakers and curriculum designers must collaborate closely with educators to ensure ASP aligns with state and national educational standards for history and social studies. Integrating ASP requires a thoughtful restructuring of existing curricula, identifying key areas where AI can serve as a catalyst for deeper historical inquiry. This also involves considering institutional adoption policies and guidelines for generative AI in higher education, as these frameworks often trickle down to secondary education (Jin et al., 2025).

5.2 Future Directions

Empirical Research: Further empirical research is necessary to assess ASP's effectiveness across diverse educational settings. Studies should investigate how varying levels of student familiarity with technology affect outcomes, as well as the pedagogical strategies most effective in teaching algorithmic literacy within historical contexts. Qualitative research methods (Freebody, 2003) and self-study of teacher education practices (LaBoskey, 2004) could provide rich insights into the lived experiences of implementing ASP. Research could also explore the impact of gamification on student engagement within ASP frameworks (Vlachopoulos & Makri, 2017).

Adaptability to Other Disciplines: Additionally, future scholarship might explore ASP's adaptability to other disciplines, thereby extending its impact beyond history education. The core principles of critical source evaluation, algorithmic literacy, and culturally responsive engagement are transferable to subjects like civics, literature, science, and art, where AI is increasingly used to generate content and analyze data. This broader application could foster a more universally AI-literate and critically engaged student body. Systematic reviews of AI in higher education (Bond et al., 2024; Zawacki-Richter et al., 2019) can provide valuable insights for expanding this framework.

6. Conclusion

Algorithmic Source Pedagogy offers a timely, critical, and inclusive framework for history education in the AI era. By combining traditional historical inquiry with essential AI literacy and culturally responsive practice, ASP prepares students to become thoughtful historians and responsible digital citizens. As generative AI continues to evolve and its capacities grow "super-exponentially" (Baklaga, 2024), educators must cultivate discernment, ethics, and agency among their students. ASP is a significant step in that direction, fostering a generation capable of critically navigating the complexities of AI-driven information landscapes and actively shaping a more just and historically informed future.

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