Mini Review

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A study on the reconstruction bias of textile knowledge by generative AI and its teaching risks

Abstract

AIGC has become increasingly embedded in textile education, promoting an automatic and advanced teaching process. However, its autonomous production of textile-related content often exhibits reconstruction bias and poses teaching risks due to limitations in training data and the inherent complexity of textile systems. Therefore, this study adopts a focused review of representative literature examines how such bias occurs in three core domains of textile knowledge from textile material knowledge, textile machinery knowledge, and textile process knowledge aspects. The result shows that AIGC frequently misrepresents fiber properties and yarn structures, conflates machinery components and operational constraints, and oversimplifies multi-stage textile processes into inaccurate or incomplete workflows. These bias create substantial teaching risks, including the formation of flawed conceptual models, disruption of skill acquisition, and long-term misconceptions that may hinder learners' professional competence. By identifying the mechanisms underlying AIGC-induced reconstruction bias and its teaching risks, this study provides guidance for the critical and informed integration of generative AI into textile education.

Keywords: generative AI, textile knowledge, reconstruction bias, teaching risks

Volume 12 Issue 1 - 2026

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Received: January 26, 2026 | **Published:** February 10, 2026

Introduction

Generative AI (AIGC) is a technology capable of autonomously producing text, images, and multimodal content based on large-scale data learning.[1] It has rapidly expanded its influence across various domains. In particular, for textile education, AIGC tools are increasingly used to suggest fabrics, visualize structures, simulate craft procedures, and support learners in acquiring complex textile knowledge.[2] However, textile knowledge is inherently material-dependent, process-oriented, and rich in tacit expertise.[3] Consequently, the content generated by these models often contains reconstruction biases in both visual and conceptual aspects.[4] This kind of reconstruction bias usually refers to the systematic deviation that occurs when generative models reconstruct domain-specific knowledge by compressing, blending, or re-mapping concepts in ways that differ from expert-validated structures. In addition, the above bias pose substantive teaching risks, particularly in textile programs where students rely heavily on precise technical knowledge and procedural accuracy.[5] Specifically, misleading AIGC outputs may hinder conceptual understanding, disrupt skill acquisition, or produce long-term misconceptions that affect learners' professional competence.[6] Therefore, this study adopts a qualitative conceptual analysis supported by a focused review of representative literature to investigate the reconstruction biases produced by AIGC when generating textile knowledge, analyze their underlying mechanisms, and assess potential risks in teaching contexts. By clarifying how these biases occur in textile knowledge, the study provides practical guidance for integrating AIGC into textile education in a way that supports, rather than disrupts, learners' understanding.

Reconstruction bias of textile knowledge generated by AIGC

The reconstruction bias of AIGC in textile knowledge primarily appear in three major aspects including textile material knowledge, textile machinery knowledge, and textile process knowledge.[7,8]

Reconstruction bias of textile material knowledge

From the aspect of textile material knowledge, AIGC commonly exhibits reconstruction bias in two subdomains of textile material knowledge, which are fiber properties and yarn structure. In particular, AIGC may confuse mechanical and physical parameters.[9] In addition, Errors frequently appear in twist direction, twist level, fiber alignment, and yarn morphology. Image-based AIGC outputs may generate smoothness with real yarns. Text descriptions often oversimplify the yarn-forming mechanics.[9]

Reconstruction bias in textile machinery knowledge

From the aspect of textile machinery knowledge, AIGC-generated bias primarily affect spinning, weaving, and finishing equipment. Due to the model's reliance on heterogeneous and sometimes contradictory training data, it frequently simplifies or blends machinery components, leading to inaccurate descriptions such as mixing drafting and twisting units in spinning frames.[10,11] Common examples include the blending of ring-spinning and rotor-spinning drafting paths, mislabeling of creel and let-off systems in weaving machines, or representing finishing equipment as single-function units without heat-setting, chemical, and mechanical subsystems. Such distortions illustrate that the model reconstructs machinery knowledge by approximating structures based on superficial similarity rather than technical hierarchy. Consequently, the reconstructed knowledge lacks the precision needed to accurately convey equipment structure and operation principles.

Reconstruction bias in textile process knowledge

Bias in AIGC-generated textile process knowledge mainly appears in its representation of spinning, weaving, and finishing workflows. Generative models tend to oversimplify complex, multi-stage processes into linear sequences, often confusing the order or function of key steps, such as merging carding and drawing in spinning, omitting warping and sizing in weaving, or treating dyeing and finishing as a single-step treatment.[12,13] As a result, the reconstructed process knowledge may mislead learners by presenting workflows that are incomplete.

Teaching risks caused by bias in textile knowledge

Although the bias originates from textile material knowledge, its teaching risks extend far beyond the technical domain from textile material knowledge, textile machinery knowledge, and textile process knowledge aspects.

Teaching risks caused by bias in textile material knowledge

When AIGC presents incorrect or oversimplified descriptions of material properties or structural relationships, students may form inaccurate conceptual foundations.[14] Such misleading information affects learners' cognitive development by reducing their ability to distinguish essential attributes, evaluate information critically, or build coherent mental models. Over time, these misconceptions may interfere with students' overall learning progression and weaken their confidence in interpreting educational materials, regardless of the specific textile content involved. Thus, the primary teaching risk lies not only in technical inaccuracies but also in the disruption of learners' fundamental conceptual reasoning processes.[15]

Teaching risks caused by bias in textile machinery knowledge

Bias related to machinery knowledge also produces broader teaching challenges. Students frequently rely on visualizations or descriptive narratives to understand complex systems, and when AIGC generates oversimplified or logically inconsistent representations, it can hinder the development of accurate system thinking.[16] These flawed representations may cause learners to misinterpret relationships among components, misunderstand operational logic, or overlook critical constraints. In an educational context, such confusion can undermine students' ability to analyze problems independently, transfer knowledge across contexts, or engage effectively in classroom tasks that require integrative thinking. As a result, the teaching risk extends beyond machinery knowledge itself and affects students' overall capacity for structured reasoning and practical judgment.[17]

Teaching risks caused by bias in textile process knowledge

Bias in process-related content poses additional risks by affecting students' understanding of procedural logic and decision-making patterns. When AIGC presents linear, idealized, or incomplete workflows, learners may develop unrealistic expectations about how real-world processes unfold, potentially underestimating complexity, variability, and the need for continuous evaluation.[18] Such misconceptions weaken students' ability to plan, sequence, and adjust tasks—skills that are central to many forms of professional and academic learning. This affects not only procedural learning in textile contexts but also students' general competencies in problem-solving, critical analysis, and adaptive thinking. As a result, the teaching risks manifest in both domain-specific and cross-disciplinary learning outcomes.

To further strengthen the educational relevance of the analysis, the teaching risks identified in this study can be directly connected to instructional design and assessment practices in textile education. Specifically, when reconstruction bias distorts material, machinery, or process knowledge, its impact extends beyond conceptual misunderstanding and affects how learners engage with designed learning activities. For example, oversimplified workflows may lead students to misinterpret procedural requirements in laboratory tasks, while inaccurate machinery representations may weaken their ability to transfer knowledge during equipment demonstrations or technical drawing exercises. These distortions highlight the need for instructional designs that position AIGC as a guided, critically mediated learning tool rather than an autonomous source of authoritative knowledge. In practice, such integration requires educators to incorporate explicit opportunities for verification, comparison, and reflection, encouraging students to detect and correct AI-generated inaccuracies as part of their learning process. Likewise, formative assessment strategies can be adapted to evaluate not only students' technical understanding but also their capacity to recognize reconstruction bias and articulate why certain AI-generated outputs deviate from established textile principles. By aligning teaching strategies and assessment practices with an awareness of AIGC's limitations, educators can mitigate potential risks while leveraging the technology's strengths to support deeper conceptual, procedural, and critical learning.

Conclusion

This study demonstrates that generative AI, when applied to textile knowledge, often reconstructs materials, machinery, and processes in ways that deviate from real-world logic due to limitations in training data and the complexity of textile systems. Although these bias appear as technical inaccuracies, their educational consequences are broader. Biased outputs can distort learners' conceptual understanding, weaken system-level reasoning, and disrupt the development of accurate procedural cognition. These findings indicate that the teaching risks posed by AIGC arise not merely from incorrect content but from the ways in which such content interacts with students' cognitive processes during learning. Therefore, effective integration of AIGC into textile education requires deliberate instructional design, critical evaluation of AI-generated materials, and strengthened learner guidance. By acknowledging both the strengths and limitations of generative AI, educators can harness its teaching potential while minimizing the propagation of misconceptions and safeguarding the quality of learning outcomes.

Acknowledgments

None.

Funding

None.

Conflicts of interest

The authors declare no conflict of interest.

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Citation: Wu Q. A study on the reconstruction bias of textile knowledge by generative AI and its teaching risks. *J Textile Eng Fashion Technol.* 2026;12(1):40–42. DOI: 10.15406/jteft.2026.12.00447