The Double-Edged Algorithm: A Review of AI-Tool Dependency in Education and Education Research

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Abstract. Artificial-intelligence (AI) tools—from writing assistants and automated tutors to literature-search and coding assistants—have moved from novelty to necessity across classrooms, faculty offices, and research laboratories in only a few years. This review examines the phenomenon of AI-tool dependency in education and education research: the degree to which learners, educators, and researchers have come to rely on AI systems to complete cognitive and academic work that they previously performed unaided. We organise the literature and observed practice into a taxonomy distinguishing learner, educator, and researcher dependency, and propose a conceptual feedback-cycle model explaining how convenience-driven adoption can deepen into structural reliance. Reported benefits include efficiency gains, personalised support, and expanded research throughput, while reported risks include erosion of critical thinking and independent problem-solving, academic-integrity concerns, propagation of model bias into scholarly output, and homogenisation of student and research writing. We argue that dependency is best understood not as a binary state but as a spectrum shaped by task design, disciplinary norms, and institutional guidance, and we propose a set of design and policy principles—transparency, scaffolded autonomy, verification literacy, and assessment redesign—intended to preserve the benefits of AI assistance while containing its costs.

Keywords: Artificial Intelligence in Education · AI Dependency · Academic Integrity · Critical Thinking · Educational Technology · Research Methodology

1 Introduction

Within a remarkably short span, generative and predictive AI tools have become embedded in nearly every stage of the educational and research life cycle: students draft essays with writing assistants, teachers generate quizzes and lesson plans with content-generation tools, and researchers use AI systems to search literature, clean data, write code, and even draft manuscript text. The efficiency gains are real and widely reported. Yet the same convenience that makes these tools attractive also raises a structural concern: as more cognitive work is delegated to a system that produces fluent, confident output on demand, do learners and researchers gradually lose the capacity—and the inclination—to perform that work themselves?

This question defines *AI-tool dependency*: a pattern of reliance in which the availability of an AI system changes not just how a task is completed but whether the human user retains the underlying skill, judgement, or verification habit that the task was meant to exercise. Dependency is distinct from ordinary tool use. Calculators did not erode arithmetic literacy uniformly, and word processors did not eliminate the skill of writing; what distinguishes generative AI is the breadth of cognitive tasks it can substitute for, and the fluency with which it does so, which together make substitution easy to reach for and hard to notice.

This paper offers a structured review of AI-tool dependency across three actor groups—learners, educators, and researchers—synthesises the mechanisms that drive dependency into a conceptual feedback-cycle model, and surveys evidence-informed responses. The contribution is an integrative framework rather than a single empirical study: it organises a fast-moving, fragmented literature into a taxonomy that educators, institutions, and researchers can use to diagnose where dependency is emerging and to design proportionate responses.

2 Related Work

Technical work on discriminative feature selection for high-dimensional data illustrates how the same statistical machinery that powers adaptive tutoring and automated assessment tools operates by isolating the signals most predictive of an outcome [5], which is directly relevant to how AI-driven grading and personalisation systems function inside classrooms. Model-analysis studies comparing multiple learners on classification tasks [2] parallel the comparative evaluations increasingly used to select AI tutoring or plagiarism-detection systems in institutional settings. In specialised professional domains, transformer-based classification of medical images [1] demonstrates both the power and the opacity of modern AI systems: high accuracy achieved through representations that even domain experts cannot fully audit, a tension that recurs when AI is used to grade student work or assess research quality. Computational forecasting models applied to financial time series [6] exemplify a broader pattern–extrapolating from historical data with limited transparency about assumptions–that mirrors concerns raised about AI-generated literature summaries and predictive learning analytics. Predictive maintenance systems built on deep neural networks [7] and adaptive, reinforcement-learning-based network routing [3] show how thoroughly AI-driven automation has penetrated technical infrastructure, a trajectory that education systems are now following with comparable speed but considerably less regulatory scaffolding. Hybrid AI frameworks for reasoning under uncertainty in transactional data [4] illustrate the growing willingness to delegate judgement calls to AI systems even where stakes and ambiguity are high, a willingness this review argues is also visible in classrooms and research offices. Finally, work on augmented reality and its sustainability challenges [8] is instructive by analogy: as with AR, the pedagogical promise of AI tools is real, but so are the unresolved

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costs–in AR's case environmental and infrastructural, in AI's case cognitive and epistemic–that adoption tends to outpace.

3 Methodology

This review follows a narrative-synthesis approach suited to a fast-evolving, cross-disciplinary topic where randomised evidence is still sparse. Observed practices and reported concerns were organised thematically across three actor groups (learners, educators, researchers) and three dimensions of impact (skill development, academic integrity, and quality of output). Technical literature on the AI methods underlying classroom and research tools [5, 2, 1, 6, 7, 3, 4] was reviewed to characterise how these systems function and where their opacity or bias could propagate into educational and scholarly outcomes. From this synthesis, a taxonomy and a conceptual feedback-cycle model were developed to structure the discussion that follows.

3.1 A Taxonomy of AI-Tool Dependency

Figure 1 organises the phenomenon into three dependency types. *Learner dependency* arises from cognitive offloading of writing, problem-solving, and revision tasks onto AI writing and tutoring tools, with reported risks including reduced critical thinking, skill atrophy, and overtrust in fluent but sometimes incorrect output. *Educator dependency* arises from automating grading, lesson planning, and content generation, which can save time but also risks integrity concerns when AI-generated materials are not reviewed carefully and risks propagating the biases embedded in training data into assessment criteria. *Researcher dependency* arises from AI-assisted literature review, code generation, and manuscript drafting, with risks including homogenised writing style across papers, uncritical acceptance of AI-suggested citations or claims, and reduced first-hand engagement with primary sources.

3.2 A Conceptual Feedback-Cycle Model

Dependency rarely appears suddenly; it accumulates through a self-reinforcing cycle. Figure 2 depicts this cycle: an AI tool offers quick, fluent output; the task is completed faster and with less effort; the user's perceived competence rises even as their own effortful engagement declines; reliance on the tool deepens for similar tasks; and, over repeated cycles, independent skill and the habit of verifying output erode, which in turn increases the perceived necessity of the tool for the next task. Formally, if d_t denotes the degree of dependency at cycle t and each cycle of convenience-driven use increments dependency by a fraction α of the remaining independent capacity $(1 - d_t)$, then

$$d_{t+1} = d_t + \alpha\,(1 - d_t), \qquad 0 < \alpha < 1, \tag{1}$$

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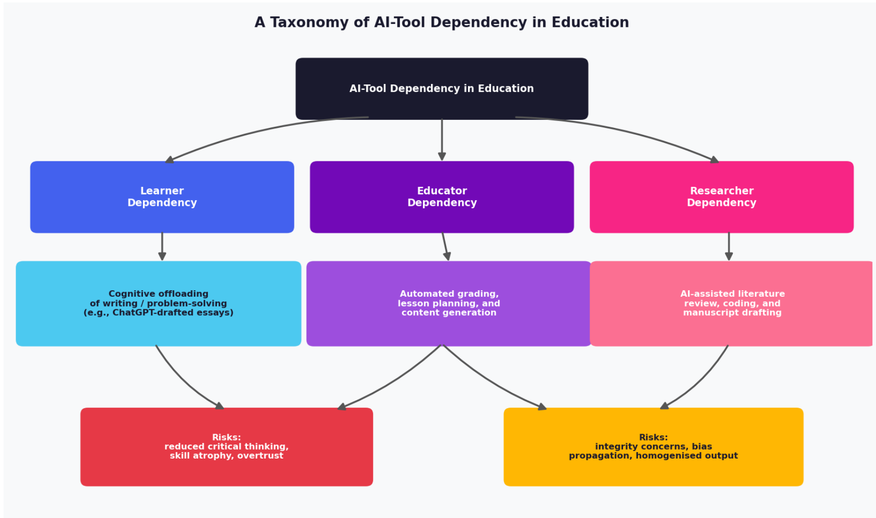

Fig. 1: A taxonomy of AI-tool dependency across learners, educators, and researchers

which converges toward $d_t \to 1$ in the absence of any counteracting force. The parameter α is not fixed: it is lowered by deliberate friction such as scaffolded tasks, verification requirements, and assessment redesign, and raised by unstructured, unsupervised tool access—which is precisely where institutional and pedagogical policy can intervene.

4 Results and Discussion

4.1 The Scale of the Shift

While no single canonical survey captures the full picture, the direction and pace of reported adoption are consistent across sources: regular self-reported use of AI tools among both students and researchers has risen sharply since general-purpose generative AI systems became widely available. Figure 3 presents an illustrative composite trend consistent with the qualitative pattern described across recent institutional surveys and reported classroom practice, intended to convey trajectory and relative magnitude rather than to serve as a citation to any single dataset.

4.2 Benefits Reported Alongside the Risks

Dependency and benefit are not mutually exclusive, which is precisely what makes the phenomenon difficult to regulate. AI tutoring can personalise pacing and feedback beyond what is feasible for a single teacher managing a large class;

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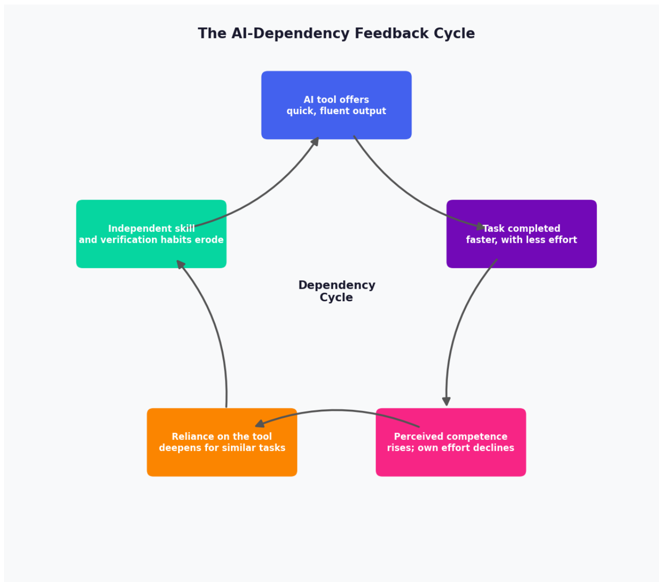

Fig. 2: Conceptual feedback cycle by which convenience-driven AI use can deepen into structural dependency

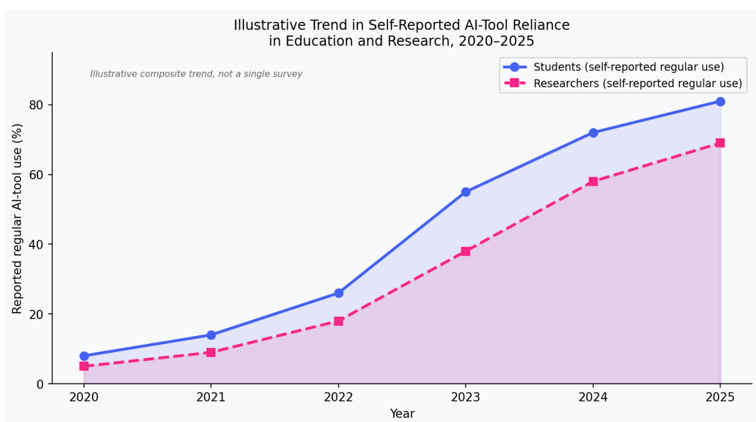

Fig. 3: Illustrative trend in self-reported regular AI-tool use among students and researchers, 2020–2025

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automated literature search and summarisation can expand a researcher's coverage of a fast-growing field; and AI-assisted coding and analysis can shorten the time from research question to result, echoing the efficiency gains documented in predictive-maintenance and adaptive-routing systems in other technical domains [7, 3]. The same feature-selection and classification techniques that raise fairness questions when embedded in automated grading [5, 2] also make it possible, in principle, to build more responsive and individualised learning systems. The policy challenge is therefore not to reject AI assistance but to structure its use so that efficiency gains do not come at the cost of the skills the educational process is meant to build.

4.3 Toward Contained Dependency

Four design and policy principles follow from the taxonomy and the feedback-cycle model. *Transparency* requires that AI-generated contributions–whether in a student essay, a lesson plan, or a literature review–be disclosed, so that dependency remains visible rather than hidden. *Scaffolded autonomy* sequences AI assistance so that learners and early-career researchers first attempt tasks independently before consulting an AI tool, directly lowering the parameter α in the feedback-cycle model. *Verification literacy* treats the ability to check, question, and correct AI output as a core competency in its own right, particularly given the demonstrated opacity of high-accuracy AI classifiers in specialised domains [1, 4]. *Assessment redesign* shifts evaluation toward process, reasoning, and oral defence of work rather than final written products alone, reducing the incentive to substitute AI output for genuine engagement. None of these principles asks institutions to prohibit AI tools; each asks that adoption be deliberate rather than incidental.

5 Conclusion

AI-tool dependency in education and education research is not a fringe concern but an emergent structural feature of how learning and scholarship are now conducted. This review organised the phenomenon into a taxonomy across learners, educators, and researchers, proposed a conceptual feedback-cycle model explaining how convenience-driven use deepens into reliance, and outlined benefits that make simple prohibition an inadequate response. The path forward lies in deliberate design: transparency about AI's role, scaffolded autonomy that preserves independent skill-building, verification literacy suited to opaque AI systems, and assessment methods that reward genuine understanding over fluent output. Future work should pursue longitudinal, discipline-specific empirical studies to test the feedback-cycle model directly and to quantify how particular policy interventions change its trajectory.

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