AI Dependency vs. Doctoral Identity: How Generative AI is Challenging the Development of Independent Scholarly Thinking in Doctoral Students

Valerie A. Storey, (https://orcid.org/0000-0001-8868-0802), Franklin University, USA

Abstract

The rise of Generative Artificial Intelligence (GenAI) in higher education has altered the conditions under which doctoral students learn, research, and develop as scholars. Although doctoral student use of GenAI has accelerated rapidly, institutional frameworks for responsible and developmentally appropriate use have not kept pace. This paper examines a central paradox in doctoral education: the same tools that enhance research productivity may also weaken intellectual independence when used without guidance. Using a critical review methodology, the study synthesizes 47 sources on doctoral education, GenAI use, policy, and epistemic development. Three interconnected dimensions of risk emerged from the analysis: critical thinking attrition, knowledge authenticity erosion, and doctoral identity disruption. The paper introduces a conceptual distinction between AI as a productivity instrument and AI as a surrogate for independent scholarship, arguing that this distinction should guide doctoral AI policy. At the same time, the review recognizes that GenAI can support doctoral learning when institutions provide developmental boundaries, competency-based guidance, and active supervision.

Keywords: AI policy, doctoral education, doctoral identity, epistemic dependency, generative artificial intelligence (GenAI), independent scholarship

Introduction

Over two-thirds of European universities report doctoral student use of Generative Artificial Intelligence (GenAI) in the course of research (EUA-CDE, 2026), and 63% of EdD doctoral students in the U.S. report active use of GenAI for proofreading (49%), academic writing (41%), idea generation (39%), and literature reviews (33%) (Harris et al., 2025; Ocen et al., 2025). Broader higher education surveys suggest that usage is likely higher and continues to rise (Freeman, 2025). Yet only 36% of students report receiving formal AI skills training from their institution, even though two-thirds consider AI use essential in today's world (Freeman, 2025). This gap between perceived necessity and institutional support is one of the most pressing challenges facing doctoral education. Without a framework that differentiates between AI as a productivity tool and AI as a surrogate for independent scholarly development, doctoral programs risk producing graduates who are technically proficient yet increasingly epistemically dependent because core scholarly work, including critical analysis, synthesis, and judgment, may be displaced onto algorithmic systems (Zhai et al., 2025).

This paper argues that the challenge posed by GenAI in doctoral education extends beyond questions of academic integrity or craft skills to the formation of doctoral identity and the capacity for independent scholarly thinking that doctoral programs are designed to cultivate. Higher education has been outpaced by GenAI development and adoption: fewer than 10% of

institutions globally had formal AI policies as recently as 2023 (Jiang, 2025), and fewer than 40% have them today (Brandon et al., 2025). As a result, many doctoral students are left to self-regulate AI use while also grappling with what it means to be a scholar, to produce original knowledge, and to develop an independent scholarly identity without clear institutional guidance. Despite the growth in institutional AI policy development, a third of students remain unsure whether they are allowed to use GenAI in coursework because regulations are unclear or inconsistently communicated (Crompton et al., 2025). This inconsistency may also intensify longstanding challenges associated with doctoral isolation, uncertainty, and attrition. At the same time, GenAI may offer meaningful support when used with guidance, for example by assisting with proofreading, brainstorming, or other bounded tasks that do not replace scholarly judgment. The problem addressed here is therefore not GenAI use in itself, but unguided use that blurs the boundary between support and substitution.

A critical literature review approach is adopted to identify, evaluate, and synthesize literature relevant to doctoral GenAI use, epistemic development, and policy formation. The review is intended to provide urgently needed guidance for doctoral students navigating turbulent conditions, dissertation supervisors who lack an evaluative AI framework, and institutional policy makers crafting governance structures. This paper is one of the few to examine GenAI through the lens of doctoral identity formation and epistemic development, a significantly underexplored area that is fundamental to institutional AI policy development. It also offers an original conceptual tool by distinguishing between AI as a productivity tool and AI as a scholarly surrogate, a distinction not currently established in the literature (see Section 2 for full development of this framework). Previous research has often framed the GenAI academic integrity debate around prevention; this paper instead repositions the conversation around development and shifts attention from how doctoral students write with GenAI to who they may become when AI use remains unguided. Finally, the paper provides a conceptual scaffold for doctoral AI policy.

Methodology

A critical review was selected because the field is emergent and rapidly evolving, and this approach permits the analytical flexibility needed to identify conceptual contributions and derive new theoretical frameworks from a heterogeneous body of evidence (Grant & Booth, 2009). Literature searches were conducted across four major databases: ERIC, Scopus, Web of Science, and Google Scholar. These searches were supplemented by federal legislation, professional organization working papers, and reports published between late 2022, following the public release of ChatGPT, and March 2026 in order to capture the development and accessibility of large language models (LLM). Search terms were employed individually and in combination and included academic integrity, critical thinking, cognitive development, doctoral education, doctoral identity, epistemic dependency, generative artificial intelligence (GenAI), higher education policy, and independent scholarship. Sources were retained when they addressed at least one of the following: doctoral or higher education use of GenAI, critical thinking or cognitive offloading, academic integrity or knowledge authenticity, doctoral identity or scholarly development, or AI governance and policy. Sources were excluded when they focused on unrelated sectors, duplicated concepts already represented in stronger sources, or lacked clear relevance to the review question. The final corpus included 43 sources identified through the

search and screening process, supplemented by four foundational theoretical works predating the search window, for a total of 47 sources synthesized. Three interconnected dimensions of risk in unguided doctoral GenAI adoption emerged through inductive synthesis (see Table 1): (1) critical thinking attrition, (2) knowledge authenticity erosion, and (3) doctoral identity disruption. Four sources published prior to the search window (Ennis, 2011; Sparrow et al., 2011; Risko & Gilbert, 2016; Choi et al., 2021) were intentionally retained as foundational theoretical anchors. These works establish the conceptual bedrock on which the GenAI-era evidence is interpreted: Ennis (2011) provides the benchmark definition of doctoral-level critical thinking; Sparrow et al. (2011) and Risko and Gilbert (2016) establish the pre-GenAI theoretical and empirical basis for cognitive offloading; and Choi et al. (2021) provides the foundational framework for understanding doctoral education as identity formation. Their inclusion is consistent with critical review methodology, which distinguishes between primary evidence sources and the established theoretical frameworks necessary to interpret them (Grant & Booth, 2009). No post-2021 source supplants these foundational constructs; they remain the field's definitional starting points.

While the field is recent and the evidence base is still developing, qualitative synthesis methodology suggests that concepts and themes are less likely to shift substantially once they recur across a diverse body of sources (Lewin et al., 2019). The identification of the three dimensions reflects the interpretive judgment that the critical review method both permits and requires, and these dimensions are offered as the paper's original conceptual contribution rather than as a claim of definitive causal proof (Grant & Booth, 2009).

Table 1. Literature-to-Framework Mapping: Three Interconnected Dimensions of Risk in Unguided Doctoral GenAI Adoption

Source	CT	KA	DI	Evidence Type	Role
Foundational Frameworks (pre-search window)					
Ennis (2011); Risko & Gilbert (2016)	✓			Theoretical	Foundational
Sparrow et al. (2011)	✓			Empirical	Foundational
Choi et al. (2021)			✓	Theoretical	Foundational
All Three Dimensions (CT + KA + DI)					
Fan et al. (2024); Zhai et al. (2025); Ma et al. (2026)	✓	✓	✓	Empirical	Primary evidence
Critical Thinking + Doctoral Identity (CT + DI)					
Iskender (2023); Jayasinghe (2024); Kizilcec et al. (2024); Sarwanti et al. (2024); Xu et al. (2025); Wang & Ellington (2026)	✓		✓	Empirical	Primary evidence
Freeman (2025)	✓		✓	Survey	Contextual / policy

Critical Thinking + Knowledge Authenticity (CT + KA)					
Hoomanfard & Shamsi (2025)	✓	✓		Empirical	Primary evidence
Ocen et al. (2025)	✓	✓		Review	Primary evidence
Knowledge Authenticity + Doctoral Identity (KA + DI)					
Harris et al. (2025)		✓	✓	Empirical	Primary evidence
Inside Higher Ed & Hanover Research (2024a, 2024b); Robert & McCormack (2025)		✓	✓	Survey	Contextual / policy
Crompton et al. (2025)		✓	✓	Policy analysis	Contextual / policy
Critical Thinking only (CT)					
Gerlich (2025)	✓			Empirical	Primary evidence
Salido et al. (2025)	✓			Review	Primary evidence
Knowledge Authenticity only (KA) — Primary Evidence					
Liang et al. (2023); Weber-Wulff et al. (2023); Abduljabbar et al. (2024); Bittle & El-Gayar (2025); Jin et al. (2025); Kofinas et al. (2025)		✓		Empirical	Primary evidence
Arar et al. (2025)		✓		Review	Primary evidence
Knowledge Authenticity only (KA) — Contextual / Policy					
Xiao et al. (2023)		✓		Empirical	Contextual / policy
Da Mota (2024)		✓		Policy analysis	Contextual / policy
Mowreader (2024); Rasky (2024); UNESCO (2025)		✓		Survey	Contextual / policy
Brandon et al. (2025); Jiang (2025); Jiang et al. (2025); McDonald et al. (2025); Sánchez-Ruiz et al. (2025)		✓		Policy analysis	Contextual / policy
Pattison (2026); Schuman (2026)		✓		Media/Case	Contextual / policy
Doctoral Identity only (DI)					

Chen (2025); Hou (2025); Mensah (2025)			✓	Empirical	Primary evidence
Henriksen et al. (2025)			✓	Conceptual	Primary evidence
EUA-CDE (2026)			✓	Survey	Contextual / policy
Total (n = 47)	**17**	**29**	**21**		

Note. CT = Critical Thinking Attrition; KA = Knowledge Authenticity; DI = Doctoral Identity Disruption.

Column totals (CT = 17; KA = 29; DI = 21) exceed the total source count (n = 47) as sources contributing to multiple dimensions are counted in each; this reflects the interconnected and mutually reinforcing nature of the three dimensions as argued in Section 3.

Section One: Three Tier AI Policy Guidance

1.1 Tier 1: U.S. Federal AI Policy Guidance

The federal AI policy landscape is best understood not as a coherent regulatory framework but as two successive and incompatible governing philosophies divided by a single administration change (see Table 2). The Biden administration (2022–2024) built a safety, equity, and oversight-centred approach to AI governance. The Trump administration (2025–present) has replaced it with a competitiveness and deregulation agenda, framing the U.S., AI dominance as a matter of national economic interest. The transition between them has produced a governance vacuum, and it is within that vacuum that higher education institutions and doctoral students are making unguided decisions about GenAI in the production of original knowledge.

The Biden framework was established incrementally across three years. The *Blueprint for an AI Bill of Rights* (White House OSTP, 2022) articulated five foundational principles for trustworthy AI, including algorithmic non-discrimination and data privacy. The Department of Education's 2023 AI report addressed equity and data privacy in educational contexts (U.S. Department of Education, Office of Educational Technology, 2023), and Executive Order 14110 *(Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence)* established the first legally operative federal AI governance obligations and directed the Department of Education to develop formal guidance (Biden, 2023). The resulting publications, a developer guide in July 2024 and an integration toolkit in October 2024, addressed institutional tool selection and equity (U.S. Department of Education, Office of Educational Technology, 2024a, 2024b). None of this guidance addressed doctoral education, original scholarship, or the epistemological challenges of GenAI in knowledge-producing research contexts.

On day one of Trump's second term, Executive Order 14148 revoked Executive Order 14110 as part of a broad omnibus rescission, dismantling the Biden-era equity framework in its entirety. Executive Order 14179, signed January 23, 2025, established the new federal position. AI regulation is an obstacle to national competitiveness rather than a tool of protection, and the Department of Education was explicitly directed to roll back its prior equity-centred frameworks (The American Presidency Project, 2025). Executive Order 14277 (April 2025) established a

White House Task Force on AI Education, but framed AI literacy exclusively as workforce readiness and national competitiveness with no reference to doctoral education, scholarly independence, or knowledge authenticity (Trump, 2025).

The most consequential episode for understanding the state-federal governance landscape was the attempted 10-year moratorium on state AI regulation embedded in the House version of the *One Big Beautiful Bill Act*. The Senate rejected the moratorium 99-1 on July 1, 2025, following bipartisan opposition from 40 state attorneys general and 17 Republican governors (Time, 2025). The version signed into law on July 4, 2025, contained no AI moratorium (Goodwin Law, 2025). However, its failure directly precipitated the December 11, 2025, Executive Order *Ensuring a National Policy Framework for Artificial Intelligence*, which pursues the same objective through conditional federal funding. The Office of Management and Budget is directed to consider a state's AI regulatory climate when making discretionary funding decisions, enabling the administration to withhold federal grants from states with "burdensome" AI laws. Higher education institutions in California, Colorado, and Texas now face active federal legal challenge to the very state protections under which they currently operate.

The fullest expression of the current federal position is the Fiscal Year 2025 Fund for the Improvement of Postsecondary Education (FIPSE) Special Projects competition (November 12, 2025), which designated AI as Area of National Need #1 and allocated $50 million to *Advancing the Understanding and Use of AI Technology in Postsecondary Education* across two priorities aligned with Executive Order 14179 and Executive Order 14277 (U.S. Department of Education, 2025b; Federal Register, 2025). Neither priority addresses doctoral-level scholarly governance, dissertation integrity, or epistemic independence (Association of Community College Trustees, 2025). Federal policy is therefore not merely silent on doctoral AI governance, it is actively funding AI adoption at the institutional level where, as Section 1.3 demonstrates, fewer than 40% of institutions have developed the governance infrastructure to manage it (Robert & McCormack, 2025). Without a federal mandate that distinguishes between GenAI as a productivity instrument and GenAI as a surrogate for independent scholarly reasoning, institutions are incentivized to scale adoption at precisely the moment they are least equipped to govern the distinction (Hoomanfard & Shamsi, 2025; McDonald et al., 2025; Mowreader, 2024).

Table 2. *Timeline Of Federal AI Policy Actions And Their Implications For Doctoral Education (October 2022 – February 2026)*

Date	Policy / Action	Key Significance for Doctoral Education
October 2022	Blueprint for an AI Bill of Rights (White House OSTP)	Established foundational principles for safe, trustworthy AI across sectors. First federal signal on AI governance.
May 2023	Department of Education AI Report	Provided guidance on AI equity and data privacy in education. Introduced basics of responsible AI use to the sector.
July 2023	S.2293 AI LEAD Act (Proposed Legislation)	Introduced in the Senate; companion House bill (June 2024) did not pass into

Date	Policy / Action	Key Significance for Doctoral Education
		law. No binding federal legislation resulted.
October 2023	Executive Order 14110: Safe, Secure, and Trustworthy AI	Called on Department of Education to develop formal AI guidance. Established government-wide responsible AI development framework.
July 2024	Designing for Education with Artificial Intelligence (Dept. of Education)	Supported teams designing AI products for teaching and learning. No specific doctoral-level guidance provided.
October 2024	Toolkit for Safe, Ethical, and Equitable AI Integration (Dept. of Education)	Final equity-centered federal education AI guidance before administration change. Doctoral education not specifically addressed.
January 2025	Rescission of Biden-era Executive Orders, including Executive Order E14110 on AI safety.	Biden-Harris AI Executive Order revoked on Day 1 of Trump's second term. Department of Education directed to roll back equity-centered AI frameworks.
January 2025	Executive Order 14179: Directs the creation of an AI Action Plan Removing Barriers to American Leadership in AI	Directs the administration to release an AI Action Plan, titled "*Winning the Race: America's AI Action Plan.* Focuses on bolstering American AI dominance through deregulation, promotion of ideologically neutral AI systems, infrastructure investment, and international competition.
April 2025	Executive Order 14277: Advancing AI Education for American Youth	Established White House Task Force on AI Education. AI framed as workforce readiness and national competitiveness, not scholarly development.
May 2025	Take It Down Act (First Federal AI Legislation Enacted)	First U.S. law to substantially regulate AI-generated content. Focused on non-consensual imagery — no academic integrity provisions.
July 2025	*Winning the Race Action Plan* released, fulfilling January directive	First formal step designating AI in postsecondary education as a federal priority, aligned with EO 14179-no doctoral governance provisions.

Date	Policy / Action	Key Significance for Doctoral Education
	Proposed Priority: Advancing AI in Education (90 FR 34203)Executive Order 14319: Preventing Woke AI in the Federal Government Executive Order 14318: Accelerating Federal Permitting of Data Center Infrastructure Executive Order 14320: Promoting the Export of the American AI Technology	
July 4th 2025	One Big Beautiful Bill Act	Federal intervention in U.S. higher education affecting student borrowing, repayment, and institutional funding, including caps on graduate student borrowing that analysts warn will shut many out of graduate education. The original bill contained a provision imposing a decade-long moratorium on all state and local government AI regulation, which was ultimately removed by the Senate before the bill was signed into law — with 40 state attorneys general and 17 Republican governors opposing it.
November 2025	FIPSE-SP Competition Launched — $50M for AI in Postsecondary Education	First dedicated federal grant competition for postsecondary AI integration. Funds AI adoption at scale without investment in scholarly governance frameworks, accelerating epistemic risk at the doctoral level.
December 2025	Executive Order 14365: Ensuring a National Policy Framework for Artificial Intelligence	Seeks federal supremacy over state AI regulation. AI Litigation Task Force established to challenge state laws. Directly affects institutions in regulated states (e.g., California, Colorado, Texas).

Date	Policy / Action	Key Significance for Doctoral Education
February 2026	Department of Labor AI Literacy Framework	AI literacy framed as workforce competency, not academic or epistemic competency. No doctoral education provisions. Gap between federal framing and scholarly formation needs widens.

Note: The cumulative effect of the federal policy arc from the Biden administration's equity and safety-centred framework to its revocation and replacement with a productivity and U.S. competitiveness agenda exacerbates inconsistency and uncertainty around AI policy, accelerating the institutional conditions under which epistemic dependency in doctoral education is most likely to emerge unchallenged.

1.2 *Tier 2: State AI Policy Guidance*

In 2025, more than 1,208 AI-related bills were introduced across all U.S. states and territories, with 145 enacted into law, and 38 states adopted or enacted approximately 100 AI related measures. State AI policy guidelines vary widely. States have moved to fill the gap left by the lack of federal legislation but this has resulted in inconsistency of scope, philosophy, and enforceability which has direct consequences for higher education institutions. For example California enacted 24 AI related laws across the 2024-2025 legislative session pushing universities to adopt stricter governance (University of California 2025), Texas passed the *Responsible Artificial Governance Act* (TRAIGA), and in May 2024 Colorado Governor, Jared Polis signed the *Artificial Intelligence Act* (Siegal & Garcia, National Association of Attorneys General, 2024) with an effective date of June 2026 (the law was originally scheduled to take effect on February 1, 2026, but on August 26, 2025, the Colorado General Assembly passed a bill delaying the effective date). This legislation is arguably the first comprehensive risk-based AI statute in the U.S. The goal of the act is to impose on developers and deployers of AI a duty of care to protect individuals from algorithmic discrimination (Siegal & Garcia, National Association of Attorneys General, 2024).

As of January 2026, state departments of education in 31 states had released AI guidance for K-12 public schools. During the 2025 legislative session, 53 bills were proposed on the use of AI in education across 21 states, and four states: Illinois, Louisiana, Nevada, and New Mexico. However, higher education, and doctoral education in particular, remains largely absent from state AI policy frameworks, leaving higher education institutions to self-govern. The inconsistency of approach is compounded by federal efforts to curtail them. As shown in the AI federal legislation timeline (Table 2) in December, 2025, President Trump signed the Executive Order, *Ensuring a National Policy Framework for Artificial Intelligence* which seeks to establish federal supremacy over state AI regulation, directing multiple federal agencies to take coordinated action to challenge and preempt state AI laws (U.S. Department of Education). For example Colorado's AI Act is specifically named in the executive order as an example of excessive state regulation. Higher education institutions in states with active AI governance frameworks i.e. California, Texas, Colorado now face legal uncertainty about whether state

protections remain enforceable, while institutions in states without any AI guidance face no regulations at all.

Further, the recent *AI Action Plan* (June 2025) requires the Office of Management and Budget (OMB) which sits within the Executive Office of the President and reports directly to the President, to consider a state's AI regulatory climate when making funding decisions. This process enables the administration to withhold federal discretionary funding from states with "burdensome" AI regulations. Higher education institutions in more heavily regulated states face a policy inconsistency compounded by federal funding incentivizing rapid AI adoption while state regulation constrains it, and it is within this turbulence that the institutional policy landscape must be understood

1.3 Tier 3: Institutional Policy

The 2025 EDUCAUSE AI Landscape Study (Robert & McCormack, 2025) found that fewer than 40% of higher education institutions surveyed have AI acceptable use policies. Jin et al. (2025) surveyed 40 leading international universities and found that while institutional leaders generally expressed positive attitudes toward the integration of GenAI, formal policies often lacked clarity, coherence or actionable detail. Similarly, Xiao et al. (2023) examined QS ranking top 500 universities and found that less than one-third of these universities had some regulations in place, and that a great majority banned rather than embraced ChatGPT. In Canada, Da Mota (2024) reported that there is no existing or proposed legislation that addresses AI use in research institutions and a recent report focused on post-secondary institutions highlighted that 56% of participants were either unsure or disagreed that their institutions had implemented broad policies on GenAI and 56% were either unsure or disagreed (Rasky, 2024).

The inconsistency, unclear guidelines, and gap between formal policy efforts and student understanding echoes a broader global trend relating to GenAI guidelines *(*American Association of University Professors [AAUP], 2025; Azevedo et al., 2024; Jiang, 2025*;* Jiang et al., 2025; Mowreader, 2024). For example a global survey of 400 institutions across 90 countries found that only 19% of respondents indicated that their institutions have a formal AI policy (UNESCO, 2025) however regional variations are highlighted. Around 70% of institutions in Europe and North America have or are developing guidance whereas in Latin America and the Caribbean 45% are in the process of developing AI guidance. In the U.S. a survey of 500 faculty members across 200 campuses found that 90% of institutions had introduced AI initiatives, only 20% of colleges and universities have published a policy governing the use of AI and 71% of respondents said administrators led AI conversations rather than faculty, staff or students (AAUP, 2025). When the published GenAI policies from 50 top U.S. universities was examined using topic modeling and sentiment analysis, a highly positive attitude toward GenAI was indicated although there were significant differences between faculty and student-targeted guidelines (Jiang et al., 2025). Inside Higher Education President's Survey (2024a) reported that 81% of college presidents have yet to publish a policy governing the use of AI and similarly only 20% of responding provosts said that they had published an AI policy (Inside Higher Education, 2024b). Only 16% of Student Voice respondents said that they knew when to use AI because their college or university had published a policy on appropriate use cases for Gen AI coursework (Mowreader, 2024).

Despite the increasing development of GenAI institutional policy, recent research by Jiang et al., (2025) found significant gaps remain in both faculty and student familiarity with an implementation of GenAI policies. Jiang et al. explain their findings through the lens of Policy Enactment Theory (Ball et al., 2012) which suggests that institutional policies are not simply implemented as written, but are interpreted and reshaped by local actors-in this case, faculty and students. At a more granular level they found that faculty viewed institutional GenAI guidelines as vague or disconnected from their teaching and research needs, especially at the graduate level. While students more often recognized GenAI related policies at the classroom level, suggesting that even when unclear, faculty are able to clarify institutional expectations into course-specific rules. However, it was noted that classroom policies tend to be restriction-focused, and that faculty members struggled to integrate AI into practice due to unclear policies and insufficient training.

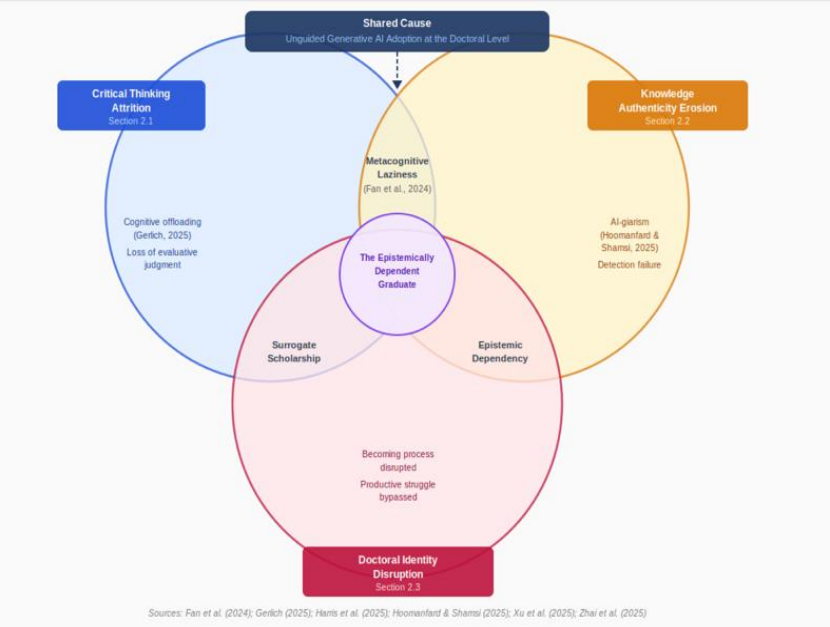
When institutions fail to provide and communicate coherent GenAI guidance, students are left to self-regulate in relation to a technology that is actively reshaping how knowledge is produced, evaluated, and attributed. Understanding the nature of this self-regulation requires attention to when, where, and why doctoral students are using GenAI across the research process, as well as the gap between actual use and available institutional support. It is within this gap that three interconnected and compounding risks may take root: (1) critical thinking attrition, (2) knowledge authenticity erosion, and (3) doctoral identity disruption. Each of these risks is examined in the sections that follow as a likely consequence of unguided AI adoption within current federal, state, and institutional policy conditions.

Section Two: Unguided Adoption and the Emergence of Risk

2. Three Interconnected Dimensions

The three dimensions of risk examined in this section, critical thinking attrition, knowledge authenticity, and doctoral identity disruption emerged inductively through the critical synthesis of empirical literature on doctoral student GenAI adoption. As Grant and Booth (2009) establish, the critical review method is specifically suited to deriving new theoretical frameworks from emergent and rapidly developing fields. The distinction introduced in this paper's conceptual framework and absent from current institutional policy at all levels documented in Section One is the condition under which all three dimensions of risk arise. Where institutions provide no guidance on where legitimate GenAI use ends and epistemic surrogacy begins, doctoral students cannot self-regulate effectively (Fan et al., 2024; Hoomanfard & Shamsi, 2025; Mowreader, 2024). The cognitive consequences of that failure manifest as critical thinking attrition (Section 2.1); the integrity consequences manifest as knowledge authenticity erosion (Section 2.2); and the developmental consequences manifest as doctoral identity disruption (Section 2.3). These are not three separate problems that happen to co-exist. They are three dimensions of the same problem, and each one compounds the other two. A doctoral student who offloads analytical judgment to a GenAI is simultaneously undermining their critical thinking capacity, producing work whose authenticity cannot be verified, and bypassing the developmental struggle through which a scholarly identity is formed.

Figure 1. *Three Interconnected Dimensions of Risk In Unguided Doctoral GenAI Adoption*



2.1 Critical Thinking Attrition

Critical thinking is a fundamental skill in higher education, requiring doctoral students to analyze, synthesize, and evaluate information effectively to make informed decisions and solve complex problems (Ennis, 2011). It involves various cognitive processes, including problem-solving, decision-making, and reflective thinking, which are crucial for navigating complex and dynamic environments. In 2026, the impact of GenAI on critical thinking remains underexplored (Gerlich, 2025; Salido et al., 2025), although the research area is growing (Salido et al., 2025; Wang & Ellington, 2026). In a recent combined bibliometric mapping and a systematic literature review examining the research landscape on critical thinking in higher education within the context of GenAI, Salido et al., (2025) provide a comprehensive examination of how AI intersects with the development of critical thinking skills in higher education. A further four recently published studies have also focused on this topic. Jayasinghe (2024), Kizilcec et al. (2024), Sarwanti et al. (2024), and Iskender (2023) found that overreliance on AI tools, may undermine the development of critical thinking and risk diminishing student autonomy, intrinsic motivation, and reflective engagement. This dependency can inhibit students' ability to critically appraise or generate original ideas, undermining the instructional aim of cultivating evaluative and creative thinking. In a more recently completed study Gerlich (2025) found a significant negative correlation between frequent AI tool usage and critical thinking abilities, mediated by increased cognitive offloading which refers to the process by which individuals delegate mental tasks to external tools or systems. While this is not a new phenomenon, GenAI introduces considerably more risk than prior technologies. The doctoral student who consistently delegates analytical judgment to an AI system may fail to develop the evaluative capacity that independent scholarship requires, a capacity that requires nurturing to develop.

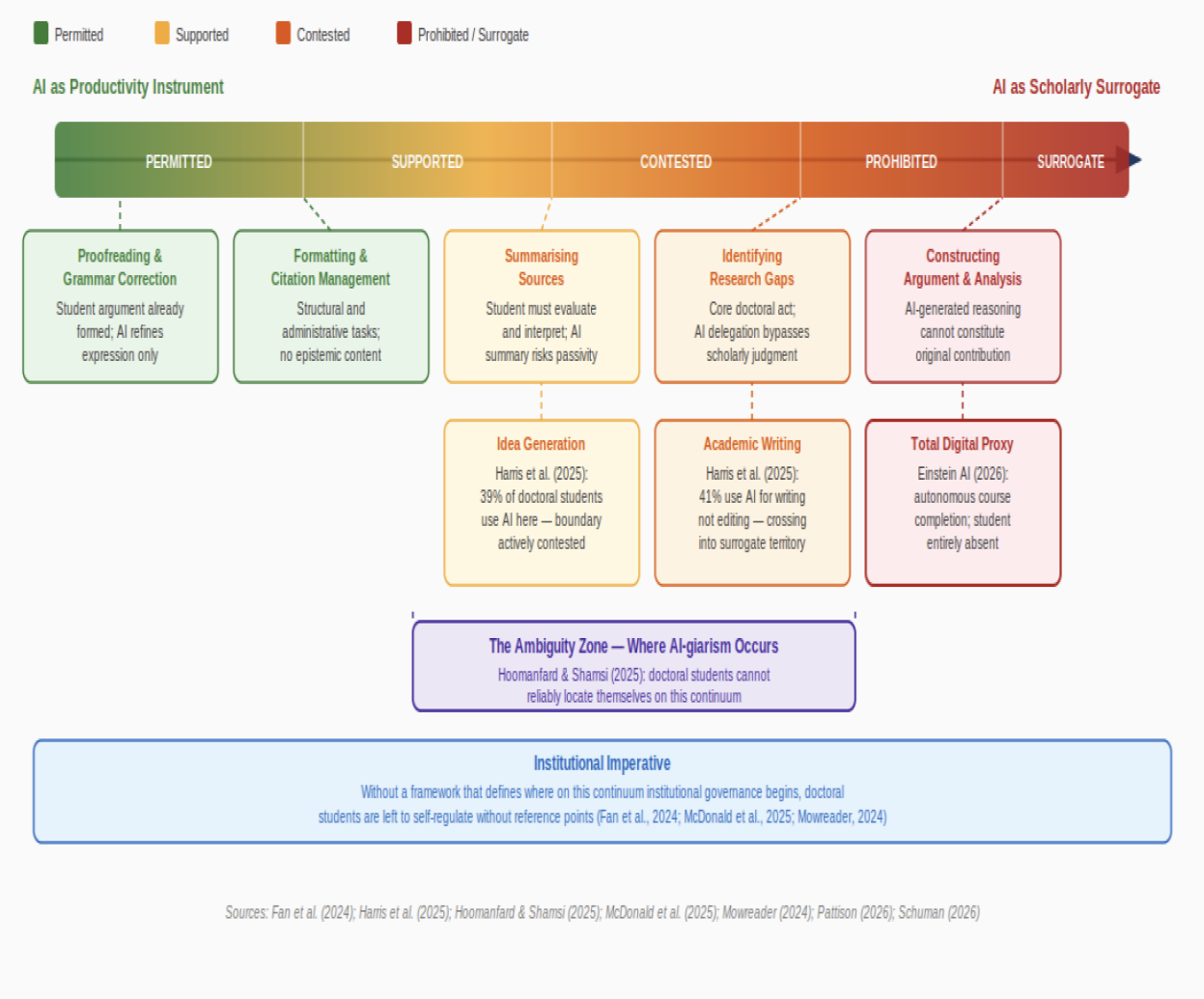
2.1.1 Cognitive Offloading and Doctoral-Level Reasoning

Cognitive offloading involves using external tools such as GenAI to reduce the cognitive load on an individual's working memory (Risko & Gilbert, 2016). Cognitive load theory, developed by Sweller, posits that the human cognitive system has limited capacity, and reducing cognitive load can enhance learning and performance. GenAI tools can automate routine and complex tasks, thereby reduce cognitive load and free up cognitive resources for higher-order thinking. This dependence can lead to a decline in cognitive abilities, as doctoral students may lose the opportunity to practice and develop their own cognitive skills. Recent studies, such as those by Gerlich (2025) show that the use of GenAI can result in greater cognitive offloading, which in turn reduces engagement in critical thinking. This aligns with earlier preGenAI research conducted by Sparrow et al., (2011) who demonstrated that the availability of information through search engines can affect memory retention and the inclination to process information deeply.

2.1.2 From Writing Assistance to Analytical Substitution

The difference between using GenAI as a productivity tool and AI as a surrogate researcher and analyst is not always obvious to a doctoral student, the supervisor, and the institution which is why this is so concerning at the doctoral level (Hoomanfard & Shamsi, 2025; Zhai et al., 2025). A doctoral student who uses GenAI as a productivity tool to edit their writing and improve the clarity of their work has already reasoned and developed the paper whereas a doctoral student who uses GenAI for any of the following i.e. to construct the argument itself, the theoretical framework, the literature review, and analyze collected data has used GenAI as a surrogate for scholarship by delegating epistemic labor to an algorithm. Harris et al. (2025) found that 41% of EdD doctoral students used GenAI for academic writing (as opposed to editing) and 39% for idea generation both of which lie on the boundary between productivity and analytical surrogacy (see Figure 2). Hoomanfard and Shamsi (2025) found that doctoral students reported uncertainty about the boundary between legitimate GenAI use and academic misconduct, and faced a dilemma over whether to acknowledge using GenAI in their dissertations suggesting the boundary between appropriate and inappropriate use is not self-evident even to students actively navigating it. The absence of an institutional framework to guide doctoral students leads to inconsistent self-regulating and decision making (Fan et al., 2024; Xu et al., 2025) which Fan et al. (2024) refer to as metacognitive laziness, an over-reliance on AI instead of actively regulating learning tasks with short-term performance improvements masking the lack of deeper knowledge gain.

Figure 2. *The Generative GenAI Productivity-Surrogate Continuum in Doctoral Education*



2.2 Knowledge Authenticity

In the field of research there is a core assumption that the writing produced represents human labor, nevertheless, cheating has always been a concern which is why academic integrity frameworks are crafted to address the issue. However, the rapid expansion of GenAI tools has heightened concern not only relating to originality, intellectual property, data manipulation and plagiarism but to the blurring of the boundary between human and machine generated content, raising questions of authorship and academic integrity which conventional frameworks are not designed to resolve (Arar et al., 2025; Kofinas et al., 2025; Ma et al., 2026) (see Figure 2). At the doctoral level these concerns impact the purpose of the degree i.e. the production of original knowledge, and the degree's defining purpose. The authenticity of doctoral student work may be called into question as a results of governance frameworks and the easy accessibility of GenAI to generate content, undermining the conditions necessary for demonstrating independent scholarship (Abduljabbar et al., 2024).

This concern is compounded by the fact that the boundary between GenAI productivity and GenAI scholar surrogacy as a knowledge generating agent is not self-evident (see Figure 2) (Ma

et al., 2026). As mentioned in Section 2.1.2, this ambiguity is not just perceptual. Harris et al. (2025) found that just under 50% of doctoral students teeter on the boundary between GenAI productivity and GenAI scholar surrogacy, and could be accused of metacognitive laziness (Fan et al., 2024).

Hoomanfard and Shamsi (2025) found that doctoral students experienced uncertainty as to where legitimate use of GenAI ends and academic misconduct begins, developing the term "AI-giarism" to characterize this experience (see Figure 2). This uncertainty has been documented over recent years and institutional guidance has not resolved this ambiguity. For example a thematic analysis of GenAI guidelines from thirty research one universities found that researcher guidance focused on disclosure rather than providing actional criteria for what constitutes legitimate use at the doctoral level (McDonald et al., 2025), and a policy analysis of ethical GenAI use for research purposes found that in higher education, governance frameworks tend to address compliance rather that knowledge originality (Sánchez-Ruiz et al., 2025).

Punitive enforcement mechanisms such as conventional plagiarism detection frameworks and AI identification tools primarily developed for undergraduate essay submission do not have the capacity to differentiate GenAI usage. Weber-Wulff et al. (2023) concluded that current AI detection tools are neither accurate nor reliable and that institutions that rely on these tools place themselves in a vulnerable positions particularly if they serve a diverse student body (Liang et al., 2023).

The trajectory of GenAI surrogacy, and the inadequacy of AI tool detection was highlighted in February 2026 with the emergence of Einstein, an agentic AI tool (ability to navigate learning management systems without student input) designed to function as a total digital proxy for any student using Canvas. The AI developer, Advait Paliwal claimed that Einstein could watch lectures on behalf of the student, read texts, write a paper automatically, post to the discussion board with contextual replies and submit assignments before deadlines without any student input (Pattison, 2026; Schuman, 2026).Whether Einstein functioned precisely as marketed remains unverified as the tool was not independently tested due to the site being taken down within 48 hours following cease-and-desist letters from Instructure, Canvas' parent company, and from the Hebrew University of Jerusalem, which controls the Einstein intellectual property rights. Ironically, the site takedown was for trademark infringement and not its actual capability (Pattison, 2026; Schuman, 2026). Nevertheless, the technology landscape is such that similar tools will soon be available. This technology eliminates the role of the student and the production of original knowledge. At the doctoral level, where the transaction in question is the production of original knowledge, this endpoint is not merely an integrity concern but an epistemological one. No detection tool, plagiarism framework, or disclosure norm is structurally capable of identifying a substitution of this kind, because nothing has been copied and no text has been generated outside the submission process itself.

2.2.1 Original Contribution in an AI-Mediated Research Environment

The concept of original contribution is the cornerstone of doctoral assessment (Arar et al., 2025; Kofinas et al., 2025). Dependent on the doctoral program the doctoral candidate is required to demonstrate that their research has extended the boundaries of knowledge in their field, and this

may consist of improving professional practice or producing new knowledge. When the contribution of GenAI is analysis, argument construction, or interpretive synthesis it becomes a surrogate research scholar for the intellectual process from which the contribution is supposed to derive (Zhai et al., 2025).

Academic journals will not accept AI for primary authorial responsibilities such as generating arguments or drawing conclusions. Major publishers have established guidelines (Sánchez-Ruiz et al., 2025). Yet the framework guiding a doctoral dissertation has not been comparably updated (Fan et al., 2024). The result is a doctoral student may graduate, publish their dissertation, and enter an academic field governed by publishing standards that would prohibit practices that some institutions have failed to regulate (Bittle & El-Gayar, 2025).

The challenge of how GenAI use should be documented, attributed and made verifiable introduces a set of accountability challenges that existing dissertation protocols were not designed to manage. A single sentence acknowledgement or disclosure of GenAI attribution on a document is insufficient for a dissertation which is a longitudinal document of a doctoral candidate's intellectual development over time, and the question of where, when, and how GenAI was used across the developmental arc is considerably more complex than a single sentence can capture. At the doctoral level, where research frequently involves unpublished interview data, proprietary datasets, or preliminary findings shared under conditions of confidentiality, the provenance problem is acute. When a doctoral student inputs raw data into a GenAI tools to assist with thematic analysis for example (Harris et al., 2025) they may be simultaneously compromising participant confidentiality, generating insights they cannot fully account for, and producing interpretations that cannot be traced back to a verifiable analytical process (Jin et al., 2025; Xu et al., 2025).

2.3 Doctoral Identity Disruption

The risks identified in Sections 2.1 and 2.2, the attrition of critical thinking and the erosion of knowledge authenticity are not isolated concerns. They converge on a third and foundational dimension of risk that subsumes both: the disruption of doctoral identity (see Figure 2). Doctoral education is not principally a training program or a credentialing process. It is a developmental journey through which an individual is transformed from a practitioner into a scholar practitioner, an independent knowledge producer, capable of original contribution and equipped with the evaluative judgment to advance a field. When GenAI functions not as a productivity instrument but as a surrogate for independent scholarly reasoning (EUA-CDE, 2026; Harris et al., 2025), as this paper has argued it threatens the developmental process from which a doctoral scholar emerges (Gerlich, 2025; Henriksen et al., 2025; Salido et al., 2025).

2.3.1 Doctoral Education as a Developmental Process

Doctoral education is the process of constructing a doctoral student's scholarly identity. The norms and methods of a discipline are absorbed, and the capacity to contribute to it independently is developed. The doctoral journey is as much about identity transitions from prior professional lives and identities to a scholarly identity. This is not a straightforward process and involves many variables but the gradual accumulation of epistemic confidence is fundamental to

scholarly growth. The understanding of doctoral study as identity formation rather than mere knowledge acquisition is well established in the literature on doctoral experience, and it has direct implications for how GenAI adoption should be governed at this level (Chen, 2025; Choi et al., 2021).

A doctoral candidate who consistently delegates the construction of argument to GenAI may never develop the capacity to develop an argument independently (Fan et al., 2024; Jayasinghe, 2024; Zhai et al., 2025) as over reliance on AI tools has been consistently shown to diminish autonomy, motivation, and the reflective engagement through which scholarly identity is formed (Iskender, 2023; Kizilcec et al., 2024; Sarwanti et al., 2024). Whereas a doctoral candidate who grapples with competing theoretical frameworks, who revises an argument because peer feedback has exposed its limitations, who abandons or revises a methodology is developing the habits of scholarly judgment (Henriksen et al., 2025).

The mechanisms through which GenAI disrupts doctoral identity formation are closely related to the cognitive offloading processes identified in Section 2.1.1, but operate at a deeper developmental level. Cognitive offloading reduces the mental effort invested in individual tasks. Identity disruption occurs when offloading becomes sufficiently habitual that the doctoral student never internalizes the evaluative capacities those tasks are designed to develop. Hou (2025) found that doctoral-level engagement with Gen AI reshapes ways of thinking, writing, and learning, reorienting knowledge production from linear to iterative and dialogic processes, and embedding AI as a thought partner in academic practice and identity formation. The significance of this finding is double-edged. Where a doctoral student actively directs the process, questioning, evaluating, and integrating GenAI outputs through their own scholarly judgment it may be regarded as an effective support but where the student has not yet developed the scholarly judgment necessary to evaluate what GenAI produces, the process is unequal as the student accepts rather than questions, and the identity that should be forming through critical engagement is instead deferred to a system that cannot be held accountable (Harris et al., 2025). Compounding this complex issue is that for many doctoral students the boundary between their own reasoning and GenAI's becomes so blurred that there is no account from where their argument originates (Fan et al., 2024; Ma et al., 2026).

2.3.2 The Epistemically Dependent Graduate

The consequence of unguided GenAI adoption at the doctoral level is the risk of producing the epistemically dependent graduate, meaning a scholar who is technically proficient in the tools of research but who lacks the independent evaluative judgment that doctoral education is designed to develop. This is the logical endpoint of the trajectory documented across this review, and it is reinforced by structural conditions such as inadequate institutional governance, absent federal guidance on doctoral-level use, and the active federal funding of GenAI adoption without investment in the scholarly governance frameworks that would protect against misuse as identified in Section One.

Xu et al. (2025) identify metacognitive support as the critical variable in determining whether GenAI use enhances or impedes self-regulated learning. Zhai et al. (2025) also found that over-reliance on AI is significantly associated with diminished critical thinking and reduced

engagement with the analytical tasks that produce scholarly competence. Both findings point to the same institutional implication, the question of whether GenAI produces an epistemically dependent or an epistemically capable graduate is not determined by the tools available, but by the guidance provided. In the absence of structured institutional guidance that explicitly distinguishes between GenAI as a productivity instrument and GenAI as a surrogate for independent scholarly reasoning, the doctorate risks becoming the credential of the epistemically dependent graduate of the future.

Conclusion

The tools that enhance doctoral research productivity may, when adopted without institutional guidance, also undermine the development of the scholarly independence that doctoral education exists to produce. Critical thinking attrition, knowledge authenticity erosion, and doctoral identity disruption are not three separate problems; rather, they are three expressions of a broader structural failure: the absence of frameworks capable of distinguishing between GenAI as a productivity instrument and GenAI as a surrogate for independent scholarship.

The policy landscape examined in Section One demonstrates that the governance infrastructure necessary to protect doctoral intellectual independence remains absent at every tier. The transition from an equity and safety-centered AI governance framework to a competitiveness and deregulation agenda has produced a governance vacuum at a time when GenAI adoption is being incentivized. State level inconsistency compounds rather than resolves this gap, and fewer than 40% of higher education institutions have developed the governance structure to manage it. The result is that doctoral students are making consequential decisions about GenAI without structured guidance.

The conceptual distinction between GenAI as a productivity tool, and GenAI as a scholarly surrogate does not currently exist in institutional policy at any tier. This is the condition under which all three dimensions of risk arise and compound one another. A doctoral student who delegates argument construction to GenAI is simultaneously abandoning their critical thinking, producing work whose authenticity cannot be verified, and bypassing the developmental scholarly struggle through which doctoral identity is formed. These three dimensions are mutually reinforcing and the absence of the productivity-surrogate distinctions allows each to go unaddressed,

Doctoral programs need to develop competency-based frameworks that explicitly operationalize where legitimate GenAI use ends and surrogacy begins, differentiated by each stage of the research process. Dissertation oversight and protocols require revision to incorporate process documentation, and staged disclosure across the arc of doctoral formation, not only at the point of submission. Faculty who certify the authenticity of doctoral contribution must themselves be AI literate, which requires sustained and updated institutional investment, rather than a discrete professional development event. Minimum AI competency standards for the dissertation committee are no longer optional.

Future research should examine whether doctoral students who engage in high levels of unguided GenAI demonstrate measurable differences in independent scholarly capacity at career

entry, including in publication quality, peer review judgements, and research leadership. The evidence base on doctoral specific outcomes remains thin and this gap is a research priority.

Doctoral students are already using GenAI, the question is who claims the dissertation. If the answer is to remain the doctoral student, and the doctorate continues to certify that an individual has demonstrated the capacity for original, independent scholarly contribution, then the productivity-surrogate distinction must become the foundation of doctoral AI policy.

References

Abduljabbar, D. A., et al. (2024). Enhancing academic integrity among students in the GenAI era: A holistic framework. *Nurse Education in Practice*, *77*, 103978. https://doi.org/10.1016/j.nepr.2024.103978

AI Leadership to Enable Accountable Deployment (AI LEAD) Act, S. 2293, 118th Cong. (2023). https://www.congress.gov/bill/118th-congress/senate-bill/2293

American Association of University Professors. (2025). *Artificial intelligence and academic professions*. https://www.aaup.org/reports-publications/aaup-policies-reports/topical-reports/artificial-intelligence-and-academic

Arar, K.H., Özen, H., Polat, G. (2025). Artificial intelligence, generative artificial intelligence and research integrity: A hybrid systemic review. *Smart Learning. Environments 12*(44), 1-29 https://doi.org/10.1186/s40561-025-00403-3

Association of Community College Trustees. (2025, November 14). *FIPSE funding under the second Trump administration.* https://perspectives.acct.org/stories/fipse-funding-under-the-second-trump-administration

Azevedo, L., Mallinson, D. J., Wang, J., Robles, P., & Best, E. (2024). AI policies, equity, and morality and the implications for faculty in higher education. *Public Integrity*, 1–16. https://doi.org/10.1080/10999922.2024.2414957

Ball, S. J., Maguire, M., & Braun, A. (2012). *How schools do policy: Policy enactments in secondary schools*. Routledge.

Biden, J. R. (2023, October 30). *Executive Order 14110: Safe, secure, and trustworthy development and use of artificial intelligence*. 88 Fed. Reg. 75191. https://www.federalregister.gov/documents/2023/11/01/2023-24283/safe-secure-and-trustworthy-development-and-use-of-artificial-intelligence

Bittle, S., & El-Gayar, O. (2025). Examining academic integrity policy and practice in the era of AI: A case study of faculty perspectives. *Frontiers in Education*, *10*, 1621743. https://doi.org/10.3389/feduc.2025.1621743

Brandon, E., Eaton, L., Gavin, D., & Papini, A. (2025). In the room where it happens: Generative AI policy creation in higher education. *EDUCAUSE Review*. https://er.educause.edu/articles/2025/5/in-the-room-where-it-happens-generative-ai-policy-creation-in-higher-education

Chen, L. H. (2025). Doctoral students' academic identity development under supervision: Issues, challenges, and suggestions. *International Journal of Educational Management*, 1-17. https://doi.org/10.1108/IJEM-03-2025-0189

Choi, Y., Bouwma-Gearhart, J., & Ermis, G. (2021). Doctoral students' identity development as scholars in the education sciences: Literature review and implications. *International Journal of Doctoral Studies, 16*, 89–125. https://doi.org/10.28945/4168

Crompton, H., Burke, D., & Jordan, K. (2025). Comparative analysis of artificial intelligence policies in universities across five countries. *Discover Computing*. https://doi.org/10.1007/s10791-025-09745-5

Da Mota, M. (2024). Toward an AI policy framework for research institutions. In E. Editor (Ed.), *Artificial intelligence* (pp. 1–17). Centre for International Governance Innovation. https://www.cigionline.org/publications/toward-an-ai-policy-framework-for-research-institutions/

Ennis, R. (2011). Critical thinking: reflection and perspective. *Inquiry: Critical Thinking Across the Disciplines, 26*(1), 4–18. https://www.pdcnet.org/pdc/bvdb.nsf/citations?openform=&fp=inquiryct&id=inquiryct_2011_0026_0001_0004_0018

European University Association Council for Doctoral Education. (2026). *Doctoral education survey: AI in doctoral research*. Times Higher Education. https://www.timeshighereducation.com/news/two-thirds-universities-report-ai-use-among-doctoral-students

Fan, Y., Tang, L., Le, H., Shen, K., Tan, S., Zhao, Y., Li, X., & Gašević, D. (2024). Beware of metacognitive laziness: Effects of generative artificial intelligence on learning motivation, processes, and performance. *British Journal of Educational Technology*, *56*(2), 489–530. https://doi.org/10.1111/bjet.13544

Federal Register. (2025, November 12). Applications for new awards; Fund for the Improvement of Postsecondary Education — Special Projects (FIPSE-SP). *90 FR 58903* https://www.federalregister.gov/documents/2025/11/12/2025-19843/applications-for-new-awards-fund-for-the-improvement-of-postsecondary-education-special-projects

Freeman, J. (2025). *Student generative AI survey 2025* (HEPI Policy Note 61). Higher Education Policy Institute; Kortext. https://www.hepi.ac.uk/2025/02/26/student-generative-ai-survey-2025/

Gerlich, M. (2025). AI tools in society: Impacts on cognitive offloading and the future of critical thinking. *Societies*, *15*(1), 6. https://doi.org/10.3390/soc15010006

Goodwin Law. (2025, August 11). *Federal AI moratorium dies on the vine as Senate passes the One Big Beautiful Bill Act.* https://www.goodwinlaw.com/en/insights/publications/2025/07/alerts-practices-aiml-federal-ai-moratorium-dies-on-the-vine

Grant, M. J., & Booth, A. (2009). A typology of reviews: An analysis of 14 review types and associated methodologies. *Health Information and Libraries Journal, 26*(2), 91–108. https://doi.org/10.1111/j.1471-1842.2009.00848.x

Harris, M., Soriano, N. E., & Ralston, N. (2025). An examination of the use of AI (artificial intelligence) technology as experienced by scholarly practitioners in an educational doctorate program. *Impacting Education: Journal on Transforming Professional Practice, 10*(1), 8–17. https://doi.org/10.5195/ie.2025.472

Henriksen, D., Mishra, P., Woo, L., & Oster, N. (2025). The education doctorate in the context of generative artificial intelligence: Epistemic shifts and challenges to practical wisdom. *Impacting Education: Journal on Transforming Professional Practice, 10*(1), 73–79. https://doi.org/10.5195/ie.2025.485

Hoomanfard, M. H., & Shamsi, Y. (2025). Generative AI in dissertation writing: L2 doctoral students' self-reported use, AI-giarism, and perceived training needs. *Journal of English for Academic Purposes, 78,*101570, 1-11.

Hou, Y. (2025). Thinking with ChatGPT: An autoethnographic inquiry into epistemic transformation in higher education. *Artificial Intelligence in Educational Research, 2*(2), 31–42. https://doi.org/10.5281/zenodo.17764013

Inside Higher Ed & Hanover Research. (2024a). *2024 survey of college and university presidents*. Inside Higher Ed. https://www.insidehighered.com/news/governance/executive-leadership/2024/02/29/presidents-survey-finds-optimism-amid-uncertainty

Inside Higher Ed & Hanover Research. (2024b). *2024 survey of college and university chief academic officers*. Inside Higher Ed. https://www.insidehighered.com/news/governance/executive-leadership/2024/04/16/provosts-survey-shows-need-ai-policies-speech

Iskender, A. (2023). Holy or unholy? Interview with open AI's ChatGPT. *European Journal of Tourism Research, 34*, 3414. https://doi.org/10.54055/ejtr.v34i.3169

Jayasinghe, S. (2024). Promoting active learning with ChatGPT: a constructivist approach in Sri Lankan higher education. *Journal of Applied Learning & Teaching, 7(*2), 141–154. https://doi.org/10.37074/jalt.2024.7.2.26

Jiang, Y. (2025). Exploring the effectiveness of institutional policies and regulations for generative AI usage in higher education. *Higher Education Quarterly*. https://doi.org/10.1111/hequ.70054

Jiang, Y., Kambhampati, S., & Chen, M. (2025). Investigating the higher education institutions' guidelines and policies regarding the use of generative AI in teaching, learning, research, and administration. *International Journal of Educational Technology in Higher Education*. https://doi.org/10.1186/s41239-025-00507-3

Jin, Y., Yan, L., Echeverria, V., Gašević, D., & Martinez-Maldonado, R. (2025). Generative AI in higher education: A global perspective of institutional adoption policies and guidelines. *Computers and Education: Artificial Intelligence*, *8*, 100348. https://doi.org/10.1016/j.caeai.2024.100348

Kizilcec, R. F., Huber, E., Papanastasiou, E. C., Cram, A., Makridis, C. A., Smolansky, A., Zeivots, S., & Raduescu, C. (2024). Perceived impact of generative AI on assessments: comparing educator and student perspectives in Australia, Cyprus, and the United States. *Computers and Education*: *Artificial Intelligence, 7,*1-1. https://doi.org/10.1016/j.caeai.2024.100269

Kofinas, A. K., Tsay, C. H., & Pike, D. (2025). The impact of generative AI on academic integrity of authentic assessments within a higher education context. *British Journal of Educational Technology, 56*, 2522–2549. https://doi.org/10.1111/bjet.13585

Lewin, S., Bohren, M., Rashidian, A., Munthe-Kaas, H., Glenton, C., Colvin, C. J., Garside, R., Noyes, J., Booth, A., Tunçalp, Ö., Sheikk, K., Wainwright, M., & Tugwell, P. (2019). Applying GRADE-CERQual to qualitative evidence synthesis findings — Paper 2: How to make an overall CERQual assessment of confidence and create a summary of qualitative findings table. *Health Research Policy and Systems, 17*(1). https://doi.org/10.1186/s12961-019-0467-5

Liang, W., Yuksekgonul, M., Mao, Y., Wu, E., & Zou, J. (2023). GPT detectors are biased against non-native English writers. *Patterns*, *4*(7), 1-4. https://doi.org/10.1016/j.patter.2023.100779

Ma, X., Yiran. L., Peiyao, L., & Dervin, F. (2026). The impact of GenAI on epistemic construction, friction and regulation: Doctoral researchers' duoethnography. *European Journal of Education, 61,* 1-12. https://doi.org/10.1111/ejed.70330

McDonald, N., Johri, A., Ali, A., & Collier, A. H. (2025). Generative artificial intelligence for academic research: Evidence from guidance issued for researchers by higher education institutions in the United States. *AI and Ethics 5*, 3917–3933. https://doi.org/10.1007/s43681-025-00688-7

Mensah, F. (2025). The 50% tipping point: Addressing doctoral student attrition through institutional innovation. *Journal of College Academic Support Programs, 7*(1). https://jcasp-ojs-txstate.tdl.org/jcasp/article/view/201

Mowreader, A. (2024, September 16). Survey: When should college students use AI? They're not sure. *Inside Higher Ed*. https://www.insidehighered.com/news/student-success/academic-life/2024/09/16/college-students-uncertain-about-ai-policies

Ocen S., Elasu J., Aarakit, S. M., & Olupot, C. (2025) Artificial intelligence in higher education institutions: review of innovations, opportunities and challenges. *Frontier Education, 10*(1530247), 1-12. doi:10.3389/feduc.2025.1530247

Pattison, H. (2026, February 26). Agentic AI can complete whole courses. Now what? *Inside Higher Education*. https://www.insidehighered.com/news/tech-innovation/artificial-intelligence/2026/02/26/agentic-ai-can-complete-whole-courses-now

Rasky, E. (2024). *Generative AI policy in higher education: A preliminary survey*. Centre for International Governance Innovation. https://www.cigionline.org/publications/generative-ai-policy-in-higher-education-a-preliminary-survey/

Robert, J., & McCormack, M. (2025, February 17). EDUCAUSE AI landscape study: Into the digital AI divide. *EDUCAUSE Center for Analysis and Research.* https://library.educause.edu/resources/2025/2/2025-educause-ai-landscape-study

Salido, A., Syarif, I., Suparjan, Wana, P.R., Sitepu, M. S., & Melisa, R. (2025). Mapping the landscape of critical thinking skills in higher education in the AI era: a bibliometric and systematic literature review. *Journal of Culture and Values in Education, 8*(2), 139-164. https://doi.org/10.46303/jcve.2025.23

Sánchez-Ruiz, L. M., Moll-López, S., & Moraño-Fernández, J. A. (2025). Utilizing generative AI responsibly and ethically for research purposes in higher education: A policy analysis. *Serials Review*. https://doi.org/10.1080/00987913.2025.2581429

Sarwanti, S., Sariasih, Y., Rahmatika, L., Islam, M. M., & Riantina, E. M. (2024). Are they literate on ChatGPT? University language students' perceptions, benefits and challenges in higher education learning. *Online Learning, 28*(3), 105–130. https://doi.org/10.24059/olj.v28i3.4599

Schuman, R. (2026, March 5). Will agentic AI break higher education? *The Chronicle of Higher Education*. https://www.chronicle.com/article/will-agentic-ai-break-higher-education

Siegal, A., & Garcia, I. (2024, October 26). *A deep dive into Colorado's Artificial Intelligence Act*. National Association of Attorneys General. https://www.naag.org/attorney-general-journal/a-deep-dive-into-colorados-artificial-intelligence-act/

Sparrow, B., Liu, J., & Wegner, D. M. (2011). Google effects on memory: Cognitive consequences of having information at our fingertips. *Science*, *333*(6043), 776–778. https://doi.org/10.1126/science.1207745

The American Presidency Project. (2025). *Executive Order 14179: Removing barriers to American leadership in artificial intelligence.* https://www.presidency.ucsb.edu/documents/executive-order-14179-removing-barriers-american-leadership-artificial-intelligence

Time. (2025, July 1). Senators reject 10-year ban on state-level AI regulation. https://time.com/7299044/senators-reject-10-year-ban-on-state-level-ai-regulation-in-blow-to-big-tech/

Trump, D. J. (2025, April 23). *Executive Order 14277: Advancing artificial intelligence education for American youth*. 90 Fed. Reg. 17519. https://www.govinfo.gov/app/details/DCPD-202500511

UNESCO. (2025, September 2). *UNESCO survey: Two-thirds of higher education institutions have or are developing guidance on AI use*. https://www.unesco.org/en/articles/unesco-survey-two-thirds-higher-education-institutions-have-or-are-developing-guidance-ai-use

U.S. Department of Education. (2025a, July 22). Guidance on the use of federal grant funds to improve outcomes for learners through the responsible integration of artificial intelligence. Dear *Colleague Letter.* https://www.ed.gov/media/document/opepd-ai-dear-colleague-letter-7222025-110427.pdf

U.S. Department of Education. (2025b, July 21). Proposed priority and definitions: Secretary's supplemental priority and definitions on advancing artificial intelligence in education. *90 Fed. Reg. 34203.* https://www.federalregister.gov/documents/2025/07/21/2025-13650/proposed-priority-and-definitions-secretarys-supplemental-priority-and-definitions-on-advancing

U.S. Department of Education, Office of Educational Technology. (2024a). *Designing for education with artificial intelligence: An essential guide for developers.* https://tech.ed.gov/files/2024/07/Designing-for-Education-with-Artificial-Intelligence-An-Essential-Guide-for-Developers.pdf

U.S. Department of Education, Office of Educational Technology. (2024b). *Empowering education leaders: A toolkit for safe, ethical, and equitable AI integration.* https://tech.ed.gov/ai/

U.S. Department of Education, Office of Educational Technology. (2023). *Artificial intelligence and the future of teaching and learning: Insights and recommendations*. https://www.ed.gov/sites/ed/files/documents/ai-report/ai-report.pdf

Xiao, P., Chen, Y., & Bao, W. (2023, May 25). *Waiting, banning, and embracing: An empirical analysis of adapting policies for generative AI in higher education*. arXiv. https://doi.org/10.48550/arXiv.2305.18614

Xu, X., et al. (2025). Enhancing self-regulated learning and learning experience in generative AI environments: The critical role of metacognitive support. *British Journal of Educational Technology 6,* 1842–1863. https://doi.org/10.1111/bjet.13599

Wang, V., & Ellington, L. (2026). Harnessing AI for dissertation success: a chair and methodologist's guide. *The International Journal of AI in Pedagogy, Innovation, and Learning Futures, 1*(2026) Continuous Issue. https://journals.calstate.edu/ijaipil/issue/view/567

Weber-Wulff, D., Anohina-Naumeca, A., Bjelobaba, S., Foltýnek, T., Guerrero-Dib, J., Popoola, O., Šigut, P., & Waddington, L. (2023). Testing of detection tools for AI-generated text. *International Journal for Educational Integrity*, *19*(1), 1-39. https://doi.org/10.1007/s40979-023-00146-z

White House Office of Science and Technology Policy. (2022, October). *Blueprint for an AI bill of rights: Making automated systems work for the American people*. https://bidenwhitehouse.archives.gov/ostp/ai-bill-of-rights/

Zhai, X., et al. (2025). The role of over-reliance on AI in the negative consequences of student learning. *Cogent Education*. https://doi.org/10.1080/2331186X.2025.2591503