University Leadership Brief

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Supporting Evidence

Evidence Landscape

This analysis draws from 1,539 articles published between November 18-24, 2025, with 683 specifically addressing AI in higher education. The evidence base reveals a striking characteristic: while institutional guidelines proliferate, rigorous empirical evaluation of AI's actual impact on educational outcomes remains limited. The available sources cluster around policy development and technical implementation, with notable contributions from international frameworks like [9] and regional initiatives such as [6]. However, these sources primarily offer prescriptive guidance rather than evidence-based assessment of what actually works in practice.

[9] The global landscape of academic guidelines for generative AI ... - Nature
[6] Intégration responsable de l'IA dans les établissements d enseignement ...

The quality of evidence varies significantly across domains. Technical papers like [8] provide robust methodological frameworks, while practical implementation reports often lack systematic evaluation metrics. Most critically, the evidence cannot tell us whether AI adoption improves long-term student learning outcomes, as longitudinal studies remain absent from the current literature.

[8] OpenLearnLM Benchmark: A Unified Framework for Evaluating Knowledge, Skill, and Attitude in Educational Large Language Models

Stakeholder Perspective Gaps

The evidence base suffers from systematic exclusions that fundamentally compromise institutional decision-making. Without documented representation from key stakeholder groups, universities risk implementing policies that fail to account for the full spectrum of institutional needs and impacts. This absence is particularly concerning given that [7] emphasizes the need for inclusive approaches, yet provides no evidence of actual stakeholder consultation. The legitimacy of AI policies depends on broad-based input, yet current frameworks emerge from narrow administrative and technical perspectives.

[7] L'Intelligence Artificielle dans l'Enseignement Supérieur : Entre ...

Documented Failure Patterns

While the analyzed corpus lacks systematic documentation of failure patterns, several sources highlight critical vulnerabilities. [2] exposes how AI-based exam monitoring systems create false positives that disproportionately affect certain student populations. Similarly, [5] documents the unreliability of AI detection tools, with accuracy rates that make their use in academic integrity enforcement questionable. These failures suggest institutions are deploying technologies before establishing adequate risk assessment frameworks. The pattern reveals a troubling tendency to prioritize technological adoption over validation of effectiveness and fairness.

[2] AI Proctoring: Academic Integrity vs. Student Rights

[5] El problema de los detectores de IA en la universidad: Una guía ...

Power and Framing Analysis

The discourse surrounding AI in education reveals clear power asymmetries. As [1] argues, AI implementation occurs without clear governance structures or accountability mechanisms. The dominant framing of AI as a neutral "tool" obscures critical questions about who controls these technologies and who bears the consequences of their failures. [3] extends this analysis globally, demonstrating how AI adoption can reinforce existing educational inequalities. The narrative control rests primarily with technology vendors and administrative leadership, while those most affected by AI implementation—students and faculty—remain largely voiceless in shaping policies.

[1] AI has moved into universities' engine room, but no one is ...

[3] Algorithmic Dependence and Digital Colonialism: A Conceptual Framework for Artificial Intelligence in Education and Knowledge Systems of the Global South

Research Gaps Affecting Strategy

Leadership faces critical decisions without adequate evidence on fundamental questions. No studies demonstrate whether AI tools improve learning outcomes compared to traditional methods. The impact on faculty workload and job satisfaction remains unmeasured. Cost-benefit analyses of AI adoption are absent. [10] suggests alternative approaches to academic integrity, but provides no comparative evidence of effectiveness. These gaps force institutions to make substantial investments based on speculation rather than evidence.

[10] Évaluer à l'ère de l'IA : traçabilité plutôt que détection

Secondary Tensions

Beyond the primary implementation challenges, the evidence reveals competing values that resist simple resolution. [4] highlights tensions between personalization and authenticity in AI-mediated learning. The promise of adaptive learning conflicts with concerns about student data privacy. Efficiency gains through automation clash with the preservation of human judgment in education. These tensions cannot be resolved through technical fixes alone but require fundamental

[4] Deepfake-Style AI Tutors in Higher Education: A Mixed-Methods ... - MDPI

choices about educational values and institutional priorities.

References

1. AI has moved into universities' engine room, but no one is ...
2. AI Proctoring: Academic Integrity vs. Student Rights
3. Algorithmic Dependence and Digital Colonialism: A Conceptual Framework for Artificial Intelligence in Education and Knowledge Systems of the Global South
4. Deepfake-Style AI Tutors in Higher Education: A Mixed-Methods ... - MDPI
5. El problema de los detectores de IA en la universidad: Una guía ...
6. Intégration responsable de l'IA dans les établissements d enseignement ...
7. L'Intelligence Artificielle dans l'Enseignement Supérieur : Entre ...
8. OpenLearnLM Benchmark: A Unified Framework for Evaluating Knowledge, Skill, and Attitude in Educational Large Language Models
9. The global landscape of academic guidelines for generative AI ... - Nature
10. Évaluer à l'ère de l'IA : traçabilité plutôt que détection