Al Infrastructure for Trust and Learning in Education: The Emergence of The 'Learning Provenance' Concept

Abstract

Artificial Intelligence (AI) is increasingly integrated into higher education for personalized learning, assessment, and institutional governance. However, challenges of trust, equity, and faculty adoption hinder its transformative potential. This paper develops a conceptual framework for AI infrastructure in education, emphasizing three layers: trust, learning, and governance. Drawing on literature and a case study of an Entrepreneurship College in the Northeastern US, findings suggest that explainability, equitable access, and institutional oversight are critical to enhancing both student learning and faculty confidence.

Keywords: Al infrastructure, trust, governance, higher education, generative Al, equitable access

Introduction

Al technologies such as large language models (LLMs) and adaptive learning systems are reshaping higher education. Institutions increasingly adopt Al to provide personalized tutoring, automated assessment, and institutional insights (Chen et al., 2020). Yet, the successful integration of Al requires more than technical capacity—it requires infrastructure that builds trust among students, faculty, and administrators.

Students express concerns about bias and fairness, faculty fear loss of academic integrity, and administrators must ensure compliance with privacy regulations (Bosch & D'Mello, 2015). Without trust, Al adoption risks disengagement and resistance. This study develops a framework for Al infrastructure that prioritizes trust and institutional learning, supported by a case study at an entrepreneurship college in the Northeastern US.

Literature Review

AI in Education

Al enables personalization, adaptive assessment, and support for programming, writing, and problem-solving (Bringula, 2024; Liu et al., 2024). Generative Al reduces student frustration and enhances self-efficacy (Yilmaz & Yilmaz, 2023). However, inequities in access and over-reliance on automation remain concerns.

Trust and Governance

Al Infrastructure for Trust and Learning in Education Author: Mohd Qaiser Malik MBA'25 Babson, Co-Author: Trond Undheim, PHD Trust in AI is grounded in transparency, accountability, and equity. Explainable AI models and auditability mechanisms improve user confidence (Bosch & D'Mello, 2015). Governance frameworks such as GDPR, FERPA, and UNESCO AI ethics emphasize privacy, fairness, and institutional responsibility.

Institutional Learning

Institutions must treat Al adoption as both a learning process and a governance challenge. Logging Al use, monitoring equity, and analyzing adoption patterns enable continuous improvement and institutional resilience.

Methodology

This study adopts a conceptual design approach informed by:

- 1. Literature review on AI in education, trust, and governance.
- 2. The case study of deployment of <u>Answerr Al</u> in an entrepreneurship college in the northeastern US, which provided several multi-model Al access, equitable Al usage, and faculty oversight.
- 3. Development of a three-layer AI infrastructure framework.

Results: AI Infrastructure Framework

The framework used in this study emphasized innovation and continuous refinement across the pilot. There were three essential elements: Trust, Learning, and Governance (Table 1).

Table 1. Al Infrastructure Framework

Layer	Mechanisms	Outcomes
Trust Layer	Explainable AI, audit logs, bias detection	Transparent, fair, and equitable Al use
Learning Layer	Adaptive content, multi-model access, usage logs	Improved confidence, reduced frustration
Governance Layer	Data privacy compliance, oversight dashboards, ethics boards	Responsible institutional adoption and continuous learning

Case Study: Deployment of Answerr AI in an entrepreneurship College in the Northeastern US

An entrepreneurship College in the northeastern US adopted <u>Answerr AI</u> in 2025 to address student frustration with programming and faculty concerns about plagiarism and inequity. The Challenge, particularly in computing classes, was that non-technical business students struggled with programming, which led to considerable frustration as well as disengagement with the learning process (Table 2).

Table 2. Learning challenges and solutions

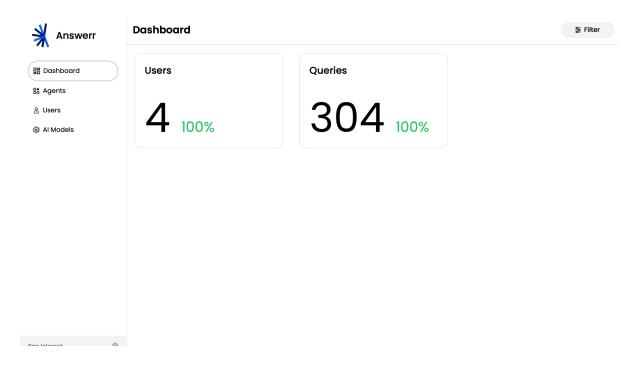
Dimension	Findings
Challenge	Students disengaged due to frustration; faculty feared inequity and plagiarism
Solution	Integration of Answerr AI with multi-model access, auto-logging, and equitable usage

Faculty feared Al plagiarism, loss of critical thinking, and inequity in access. The College addressed these concerns by integrating Answerr Al for equitable usage and transparent monitoring.

Students reported improved collaboration and skill transfer. One MBA student noted: "Answerr AI helped me access the latest AI models with ease and enabled me to learn how to build AI assistants."

Faculty also shifted from content delivery to Al-augmented coaching. The lead instructor reflected: "Answerr showed me how to teach better Al collaboration. Students learn faster, and I see how they develop critical thinking with Al." Governance was supported through faculty dashboards that logged usage and flagged inequities. (Figure 1)

Figure 1. Faculty Dashboard



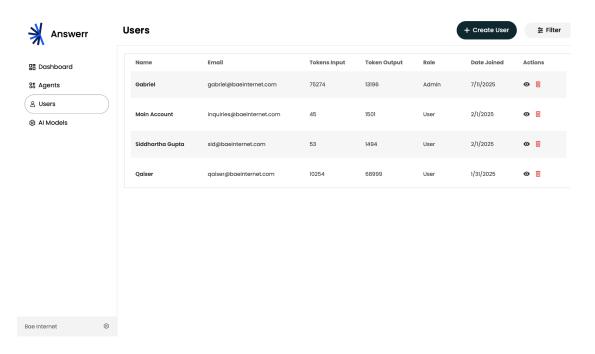


Figure 2. Dashboard - Students List

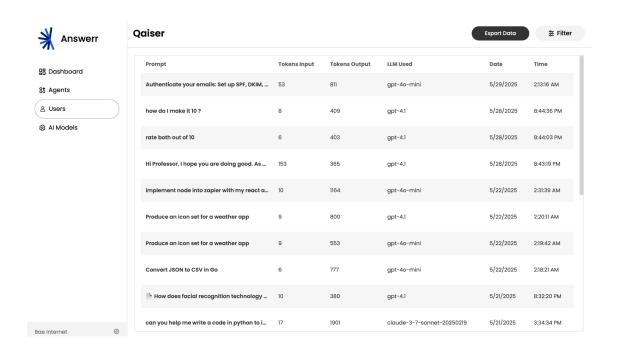


Figure 3. Dashboard - Logging prompts

This case demonstrates how AI infrastructure can simultaneously support student learning, build faculty trust, and strengthen institutional governance.

Discussion

The case study of an Entrepreneurship College in the Northeastern US case illustrates the interdependence of trust and learning. Students improved planning and collaboration skills, while faculty embraced Al-supported coaching because oversight reassured them about integrity. Governance was reinforced by real-time usage monitoring, which reduced fears of inequity and dishonesty.

For adoption to succeed, students, faculty, and administrators must perceive immediate benefits. Simplicity and transparency proved essential: the pilot was quick to implement and minimized friction. Punitive approaches would likely have failed due to legal and cultural barriers. Instead, the concept of *learning provenance*—the recorded history and origin of learning resources, experiences, and outcomes—proved central.

Learning provenance captures the lineage of education, including:

- Resources: textbooks, Al-generated content, faculty materials, peer contributions.
- Experiences: study sessions, projects, Al-assisted problem-solving, drafts.
- Outcomes: assignments, assessments, skills, reflections.

By documenting this chain, learning provenance establishes trust in authenticity, much like provenance in art or data lineage in information systems. It reframes educational authenticity by shifting focus from product to process. Borrowing from provenance science, it adapts principles of origin and authenticity to education. It functions as a trust infrastructure, creating accountability without punitive enforcement, and is designed for AI compatibility where knowledge is co-created with generative tools.

This layered approach—trust, learning, governance—suggests that sustainable AI adoption depends not only on technical integration but also on institutional design that foregrounds provenance, equity, and oversight.

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Conclusion

Al infrastructure must be designed not solely for technical performance but for trust, equity, and governance. The Entrepreneurship College in the Northeastern US case study demonstrates that when Al systems embed explainability, equitable access, and institutional oversight, they can reduce student frustration, increase faculty confidence, and position institutions as leaders in Al-integrated education.

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