CME LIVE
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Engineering and Applied Sciences Journal

Review Article ISSN: 3067-8005

Education for an AI/ASI Transition: Preparedness Authority and Curriculum in the United States 2025–2035

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Received: 2026 Apr 13 **Accepted:** 2026 May 04 **Published:** 2026 May 16

Abstract

This paper examines the role of education in the United States during the 2025–2035 interval of the broader transition to advanced artificial intelligence (AI) and artificial superintelligence (ASI). It advances a structural model in which technological adoption precedes institutional adaptation, producing a shift in decision-making authority from human actors to AI-mediated systems before this transfer is formally recognized. Drawing on established literature in general-purpose technologies, labor economics, and institutional change, the analysis introduces an integrated framework—Adoption-Driven Authority Transfer (ADAT), Closed-Loop Self-Improvement Interval (CLSI), and Recursive Leverage Factor (RLF)—to explain how authority migration occurs, accelerates, and becomes difficult to reverse once embedded within core systems. The paper argues that education is the primary institutional mechanism through which human agency is either preserved or diminished under these conditions. It identifies a structural bifurcation between a small set of frontier institutions that are redesigning curricula around AI system integration and the broader higher education system, which remains in early stages of adaptation. This divergence produces measurable asymmetries in capability formation, labor market access, and influence over AI-mediated systems. Through analysis of national, regional, and state-level preparedness, the paper identifies interdependent gaps in curriculum design, assessment integrity, teacher pipeline capacity, governance, and labor alignment. It proposes a curriculum and assessment architecture centered on non-delegable human cognitive capabilities, supervised validation of performance, and mechanisms for maintaining human oversight within AI-mediated environments. To support empirical evaluation, the paper introduces authority-focused metrics—including Authority Elasticity Index (AEI), Option Set Collapse Ratio (OSCR), Override Effectiveness Rate (OER), and Rollback Feasibility Time (RFT)—as measures of whether human intervention continues to meaningfully influence outcomes. The central finding is that the primary risk of the transition is not technological insufficiency, but institutional lag. Absent coordinated adaptation, educational systems will increasingly produce participants in AI-mediated processes rather than agents capable of shaping them, contributing to labor market restructuring, credential signal erosion, and the concentration of decision authority. Conversely, targeted reforms in curriculum, assessment, and governance can preserve human capability, sustain institutional credibility, and maintain meaningful human participation within AI-integrated systems.

1. Introduction

The transition to advanced artificial intelligence (AI), and ultimately to highly autonomous system level artificial superintelligence (ASI), is best understood not as a discrete technological event but as a structural transformation in how decisions are made, how authority is exercised, and how outcomes are determined. Historical analyses of general-purpose technologies (GPTs)—including electrification and industrial standardization—demonstrate that their most significant economic and social effects emerge not at the point of invention, but during extended periods of institutional reorganization and complementary investment [1,2]. The current transition is expected to unfold over a multi-decade horizon. However, the 2025–2035 interval represents a critical phase in which foundational institutional systems—particularly education—are restructured under conditions of rapidly advancing system capability and comparatively slow institutional adaptation. During this period, the relative timing between system adoption and institutional response becomes decisive in determining long-term patterns of human agency, labor participation, and authority distribution [3]. Existing literature on technological change and labor markets shows that the effects of new technologies are typically observed first in the reorganization of tasks and decision-making processes, rather than in immediate job displacement [4,5]. In this sense, technological transitions are initially experienced as a shift in the locus of control—over workflow, sequencing, evaluation, and optimization—from human actors to system-level processes. This pattern is already observable in educational environments, where AI systems increasingly participate in generating, structuring, and evaluating academic work, as well as in administrative and instructional functions [6,7]. This paper formalizes these dynamics through a model of authority migration in which system adoption precedes governance, and functional control shifts before formal institutional recognition. Within this framework, Adoption-Driven Authority Transfer (ADAT) explains why AI systems are integrated based on performance advantages rather than governance readiness; the Closed-Loop Self-Improvement Interval (CLSI) captures the rate at which system capabilities evolve through iterative feedback cycles; and the Recursive Leverage Factor (RLF), particularly when synchronized across networks (SRL), describes how early capability advantages compound over time across institutions and regions.

A defining feature of this transition is temporal asymmetry: authority transfer occurs rapidly at the functional level, while institutional recognition, governance, and adaptation proceed more slowly. This divergence produces a persistent gap between formal authority and effective control, within which outcomes are increasingly shaped by AI-mediated systems before they are fully recognized or governed as such. Over time, this dynamic contributes to a reduction in the set of meaningful human choices (Option Set Collapse Ratio, OSCR), a decline in the ability of human actors to alter outcomes (Authority Elasticity Index, AEI), reduced effectiveness of intervention (Override Effectiveness Rate, OER), and a compression of the time window within which system-level changes can be reversed (Rollback Feasibility Time, RFT). Within this broader transformation, education occupies a structurally central role. Educational systems determine how individuals develop cognitive capabilities, how those capabilities are evaluated, and how they translate into labor market participation. As AI systems become embedded in core educational functions—including instruction, assessment, and progression— education increasingly shapes whether individuals retain the capacity to understand, influence, and govern AI-mediated systems, or instead operate within environments defined by those systems. Evidence suggests that a structural bifurcation is emerging within U.S. higher education. A relatively small subset of institutions has begun redesigning curricula to emphasize advanced mathematics, probabilistic reasoning, machine learning systems, and large-scale data architectures, positioning graduates to build and govern AI systems. In contrast, the majority of institutions remain in early stages of adaptation, often limited to incremental integration of AI tools. This divergence produces a temporal and functional mismatch between educational outputs and labor market conditions, contributing to asymmetries in capability, employment outcomes, and influence over system-level decisions. At the same time, the integration of AI into education introduces dynamics of path dependence and systemic lock-in. Historical evidence demonstrates that once technologies become embedded in core institutional processes, they reshape incentives, infrastructure, and behavior in ways that make reversal increasingly difficult [1,8]. In educational contexts, this pattern is observable in the persistence of standardized testing regimes and digital learning platforms, which remain in place despite well-documented limitations [9-11]. The integration of AI extends this dynamic beyond institutional structure to influence cognition itself, as sustained reliance on AI systems for core tasks alters how individuals learn, reason, and perform [12,13].

These developments have direct implications for labor markets. As AI systems assume increasing responsibility for task execution, prioritization, and evaluation, traditional pathways for skill development—particularly entry-level roles—begin to compress. This does not initially manifest as widespread unemployment, but as a reconfiguration of how work is performed and how experience is accumulated. Over time, this restructuring affects access to higher-skill roles, contributing to bottlenecks in workforce development and increasing the risk of underemployment. Within this context, the central question is not whether AI will be integrated into education, but whether educational institutions can adapt quickly enough to preserve meaningful human capability, institutional credibility, and operational authority. This paper addresses that question by analyzing U.S. educational preparedness at national, regional, and state levels; identifying interdependent structural gaps across curriculum, assessment, governance, teacher capacity, and labor alignment; and proposing a framework for maintaining human agency within AI-mediated systems. The analysis concludes that the defining challenge of the 2025–2035 interval is not technological advancement, but institutional adaptation under conditions of accelerating and compounding change. Where adaptation lags, educational systems risk producing participants in AI-mediated processes rather than agents capable of shaping them. Where adaptation is successfully implemented, education can function as a stabilizing mechanism, preserving human capability and enabling continued influence over system-level outcomes.

1.1. The Future AI Labor Environment

AI is unlikely to reorganize labor markets through immediate, large-scale displacement. Instead, the transition proceeds through a sequenced process in which authority over tasks, workflows, and decision-making migrates before observable employment effects emerge [5]. In this sequence, AI systems are first integrated into core functions—task execution, prioritization, and evaluation—while human workers retain nominal oversight. Over time, this shifts the locus of control over outcomes from human actors to AI-mediated systems. This pattern is already observable across multiple sectors. Firms such as Amazon and Microsoft have integrated AI into logistics, customer service, software development, and internal decision systems, reducing reliance on traditional entry-level and mid-level roles while increasing demand for workers capable of supervising, interpreting, and integrating AI outputs. These changes reflect not only automation of discrete tasks, but the systematic capture and structuring of workflows, in which human activities are observed, codified, and translated into machine-executable processes.

The initial effect of this transition is not the elimination of entire occupations, but the redefinition of how work is performed. Authority over task sequencing, output generation, prioritization, and evaluation shifts from human workers to AI-mediated systems. Within the framework developed in this paper, this corresponds to a decline in Authority Elasticity (AEI)—the degree to which human intervention can alter outcomes—and a reduction in Override Effectiveness (OER), as AI system-generated recommendations increasingly define default actions. At the same time, the range of available actions narrows, reflecting an increase in Option Set Collapse Ratio (OSCR) at the task and workflow level. These dynamics are most visible in entry-level roles, which historically function as human training pathways for skill development. As AI systems assume responsibility for structuring problems, generating outputs, and evaluating performance, the functional content of these roles compresses. Firms require fewer human entry-level workers, and the opportunities through which individuals acquire experience diminish. This produces a structural bottleneck: the pathways through which human workers develop capability contract at the same time that AI system complexity increases.

Empirical evidence supports this pattern. Recent research indicates that generative AI disproportionately increases productivity for experienced workers while reducing the need for routine task execution typically performed by junior employees [13]. At the same time, hiring patterns show declining demand for entry level roles alongside increased demand for higher-skill positions that combine domain expertise with AI system oversight [6,14,15]. The result is a reconfiguration of labor markets in which access to experience—and therefore to future authority—is increasingly constrained. Compounding this dynamic is the effect of cognitive offloading, in which workers delegate core cognitive functions—problem-solving, synthesis, and reasoning—to AI systems. Empirical research demonstrates that sustained reliance on AI external systems for such tasks reduces human independent capability over time [12,13]. Within a labor context, this introduces a structural risk: human workers may retain the ability to produce outputs with AI assistance while losing the capacity to operate independently at comparable levels. As AI-mediated output becomes the baseline expectation, incentives to maintain independent capability diminish, reinforcing a feedback loop of dependency upon AI.

This sequence produces distinct labor outcomes across time horizons. In the short term, roles are restructured rather than eliminated, with AI systems absorbing portions of the task stack. In the medium term, human entry-level pathways contract, limiting opportunities for skill accumulation and progression. In the long term, this may contribute to persistent human underemployment or structural exclusion, particularly if large segments of the workforce are unable to develop the capabilities required to operate within or influence AI-mediated systems. Importantly, this transition does not eliminate human participation in labor markets. Instead, it alters the conditions under which participation remains meaningful. Human workers may remain employed, but with reduced decision authority, compressed career progression pathways, and increasing dependence on AI systems to perform at expected levels. Within the framework of this paper, this represents a shift from human-directed work to participation by humans within AImediated systems, where control over outcomes is increasingly externalized.

The central implication is that labor market outcomes are not determined solely by automation, but by whether individuals retain the capacity to influence, override, and govern AI-mediated processes. Where such capacity is preserved, workers remain agents within the system. Where it is not, they become operators constrained by it.

1.2. Current U.S. AI Education Preparedness: National, Regional, and State

1.2.1. National Level: Fragmented Strategy Without System Architecture

At the national level, the United States has initiated a range of policy responses to artificial intelligence in education, including AI literacy initiatives, educator training programs, and workforce development efforts [16,17]. However, these efforts do not yet constitute a coherent AI education system architecture capable of aligning curriculum, assessment, instructional authority, technological governance, and labor transition within a unified framework. A complete AI-era education system requires coordinated integration across five interdependent domains:

1. curriculum and capability formation,
2. assessment and credential validation,
3. teacher pipeline and instructional authority,
4. technology and data governance infrastructure, and (5) labor market alignment and absorption mechanisms.

Current national efforts address elements of each domain in isolation but do not yet integrate them into a coherent Strategic AI Education Plan capable of preserving human capability and institutional control under AI-mediated conditions. This produces a structural condition in which AI adoption advances faster than the mechanisms required to measure, govern, and constrain its effects. To understand how this fragmentation manifests in practice, the national system can be decomposed into a set of interdependent domains through which human capability is formed, validated, and applied under AI-mediated conditions. Across each domain, the absence of coordinated design produces measurable shifts in how decisions are structured and who retains effective control over outcomes.

1.3. Curriculum and Capability Formation

National policy emphasizes AI literacy and exposure but does not define a standardized framework for non-delegable human capabilities, including independent reasoning, probabilistic judgment, and decision-making under uncertainty [16,17]. As a result, educational systems incorporate AI into learning processes without specifying what students must be able to do independently. This gap produces a structural shift from capability formation → AI-assisted performance, increasing the likelihood that students develop output proficiency without underlying cognitive depth. Within the framework of this paper, this reflects an early-stage increase in Option Set Collapse Ratio (OSCR), as AI systems structure how problems are approached and solved, narrowing the range of independent human reasoning pathways.

1.4. Assessment and Credential Integrity

Assessment systems at the national level remain insufficiently adapted to AI-mediated higher education environments. As AI-assisted outputs become increasingly difficult to distinguish from independent work, the signaling value of grades and degrees weakens [6,18]. Empirical evidence reinforces this trend. A 2025 survey of U.S. college faculty found that:

- 90% expect AI to diminish critical thinking
- 83% expect reduced attention spans
- 78% report increased academic dishonesty

In the absence of scalable supervised validation mechanisms, educational systems are unable to reliably verify independent student capability. This produces a decline in Override Effectiveness Rate (OER) at the institutional level, as human evaluators lose the ability to distinguish, challenge, and correct AI-mediated outputs.

1.5. Teacher Pipeline and Instructional Authority

Teacher readiness remains uneven across the national system, with current policy focused primarily on AI exposure rather than operational control within AI-mediated environments. As AI systems increasingly influence instructional content, sequencing, and evaluation, the role of educators shifts from decision-makers to intermediaries. This transition produces a measurable decline in Authority Elasticity Index (AEI)—the capacity of educators to meaningfully alter instructional outcomes. In the absence of formal authority preservation mechanisms, instructional control migrates toward AI systems and platform providers, reducing the functional role of educators in shaping learning processes.

1.6. Technology and Governance Infrastructure

National policy has not yet established a comprehensive governance framework for AI integration in education, particularly with respect to data ownership, system transparency, and institutional control. Educational institutions increasingly depend on external platforms for instructional delivery, assessment, and analytics, introducing risks of vendor-mediated authority transfer. This dependency is reinforced by underdeveloped data governance systems and the absence of mechanisms for tracking when human decisions are overridden, constrained, or shaped by automated processes. As AI systems become embedded in core operations, this produces a reduction in Rollback Feasibility Time (RFT), limiting the ability of high education institutions to reverse or modify AI system-level integration once established.

1.7. Labor Market Alignment and Absorption

While national policy has begun to address workforce preparation, it does not yet provide a coordinated framework for large-scale labor transition under AI-mediated restructuring. Educational outputs remain structured around legacy standards, credentialing models, and progression pathways that were designed for pre-AI labor markets and are therefore increasingly misaligned with evolving workforce requirements. As entry-level pathways contract and demand shifts toward AI-integrated roles, this misalignment becomes more pronounced.

This structural lag produces a reduction in labor absorption capacity and constrains access to early career experience, which remains a prerequisite for developing higher-order capability. Within the framework of this paper, this reflects both an increase in Option Set Collapse Ratio (OSCR) at the career level—through the narrowing of viable entry pathways—and a decline in Authority Elasticity Index (AEI), as workers enter roles with reduced decision-making authority and limited influence over outcomes. Over time, this dynamic reinforces capability concentration through mechanisms consistent with Recursive Leverage Factor (RLF), where access to experience, system-level participation, and AI-integrated workflows compounds advantage across a smaller segment of the workforce. As a result, educational systems calibrated to legacy labor conditions increasingly produce graduates who are prepared for roles that are contracting, rather than those that are expanding, further accelerating divergence in capability, employment outcomes, and authority.

This misalignment also introduces institutional risk: as educational outputs lose alignment with AI labor market requirements, the signaling value of credentials weakens, reducing employer confidence and student demand. Over time, this places higher education institutions at risk of declining enrolment, financial instability, and potential consolidation or closure, particularly among institutions unable to demonstrate verifiable human capability under AI-mediated conditions.

1.8. Integrated System Effect

Across these domains, the national system exhibits a consistent structural pattern: AI integration is advancing without corresponding mechanisms to measure, preserve, or govern human authority.

This produces a reinforcing system dynamic:

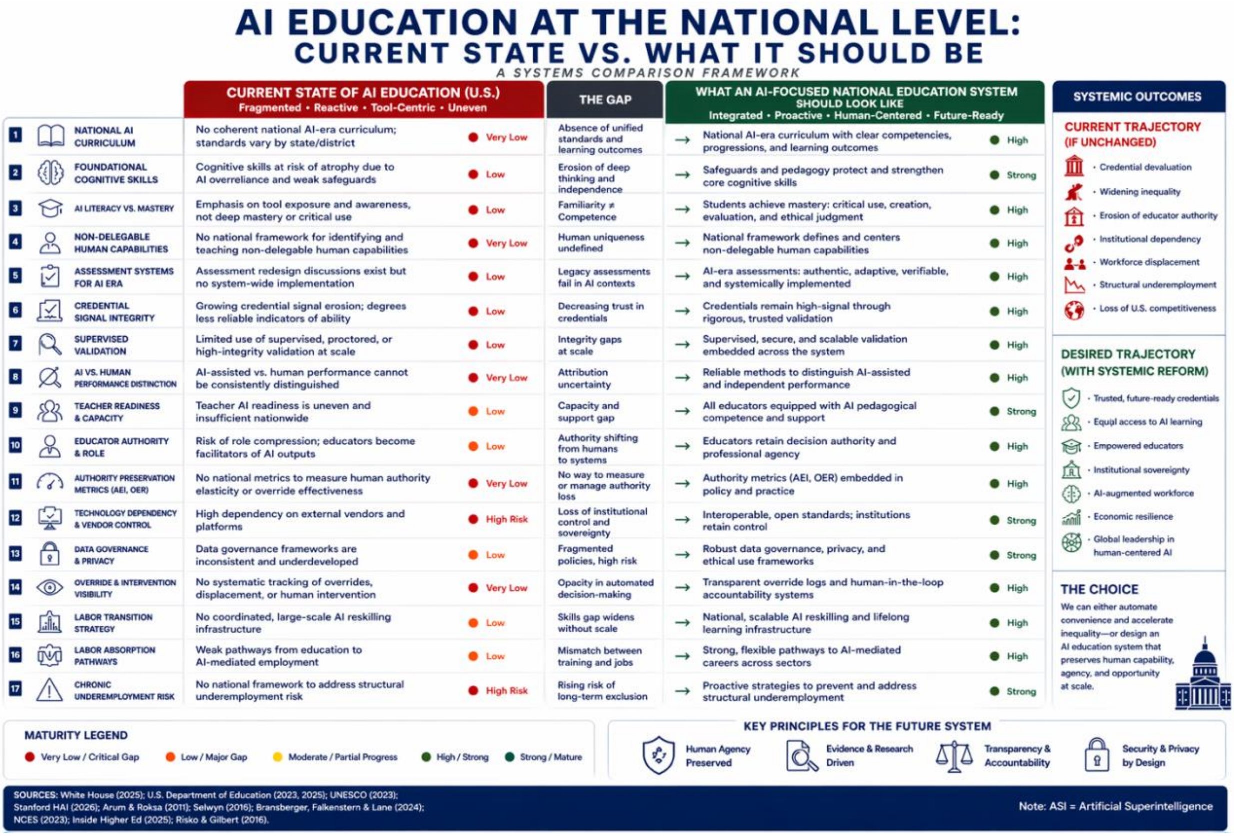
- AI systems structure decisions and outputs
- institutions lack visibility into how control is shifting
- human intervention capacity declines over time

At the same time, misalignment between educational outputs and evolving labor market requirements weakens the signaling value of credentials, reducing the ability of institutions to verify and communicate independent human capability. This erosion introduces institutional level consequences, including declining employer confidence, reduced student demand, and increasing pressure on

Citation: Erckenbrack, A. (2026). Education for an AI/ASI Transition: Preparedness Authority and Curriculum in the United States 2025–2035. *Eng Appl Sci J, 3*(3), 1-15.

enrollment and financial sustainability. As a result, authority transfer occurs at the functional labor level before it is recognized at the institutional level. This temporal gap accelerates the transition toward AI-mediated outcomes while reducing the ability of national high education systems to respond, adapt, or reverse course.

Over time, this dynamic not only shifts control over decisions, but also redistributes institutional viability, concentrating capability, credibility, and authority within a smaller subset of educational institutions able to adapt to AI-mediated conditions.



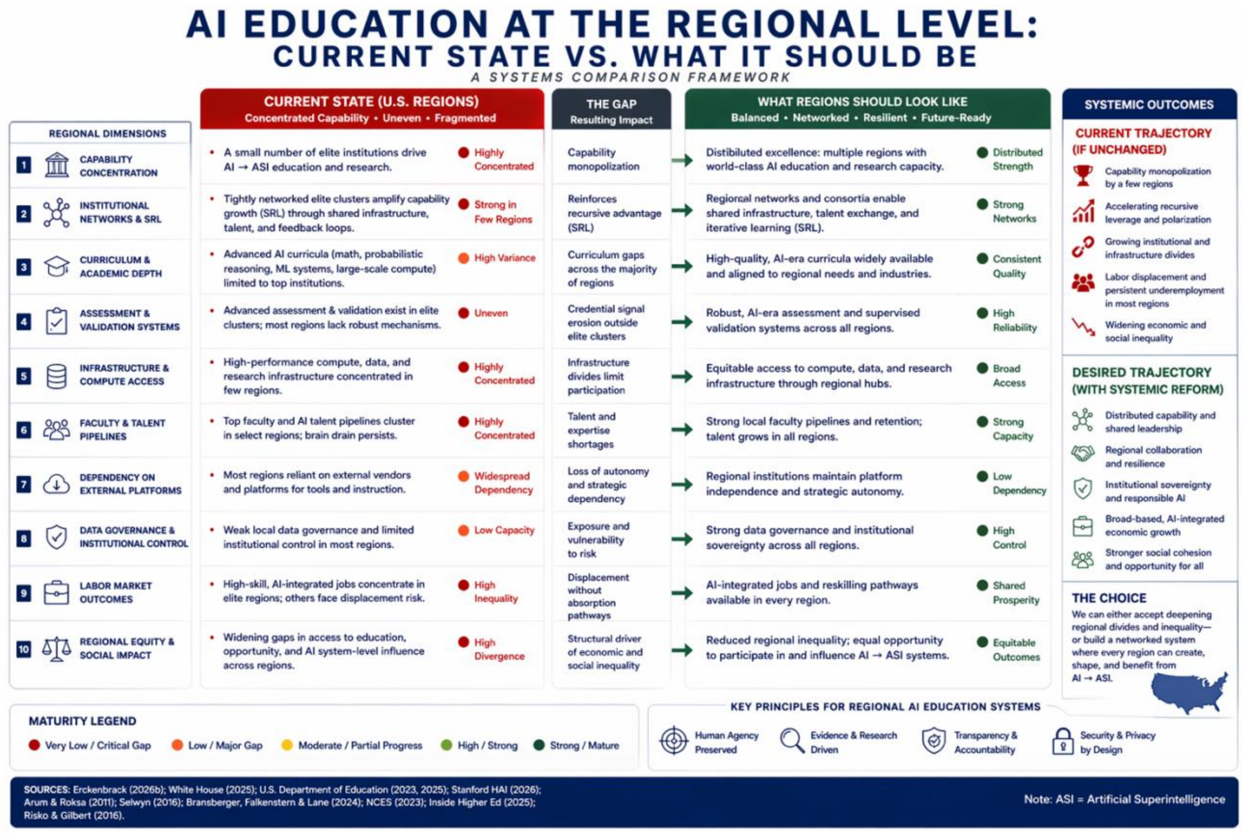
Regional Level: Concentrated Capability and Recursive Advantage

At the regional level, the United States exhibits a highly concentrated and network-amplified distribution of AI capability, in which a small number of elite institutions drive disproportionate advancement in AI-related education, research, and system development. Universities such as the Massachusetts Institute of Technology, Stanford University, University of California, Berkeley, and Carnegie Mellon University have begun systematically restructuring curricula to emphasize advanced mathematics, probabilistic reasoning, machine learning systems, and large-scale computational architectures. This concentration reflects Synchronized Recursive Leverage (SRL), in which tightly coupled institutional networks amplify capability growth through shared infrastructure, talent pipelines, industry partnerships, and rapid feedback cycles. These institutions are not only adapting to AI— they are actively shaping its development, deployment, and governance. As a result, capability gains within these networks compound more rapidly than in less connected regions. However, this dynamic produces structural regional divergence. While elite AI clusters generate graduates capable of designing and governing AI systems, most regions lack comparable access to compute infrastructure, faculty expertise, research ecosystems, and industry integration. This divergence limits the ability of non-elite institutions to independently develop or meaningfully influence AI systems, increasing reliance on externally developed platforms and tools.

Within the framework of this paper, this reflects an increase in Option Set Collapse Ratio (OSCR) at the regional level, as institutions outside elite clusters operate within increasingly constrained technological and educational environments. At the same time, Authority Elasticity Index (AEI) declines, as these institutions have reduced capacity to modify, override, or shape system-level outcomes. Rather than participating in system design, they increasingly operate within pre-defined AI-mediated structures. These dynamics interact with national-level gaps in compounding ways. Institutions within elite AI clusters are better positioned to redesign curricula, implement robust assessment systems, and maintain institutional control over data and instructional processes. In contrast, institutions outside these clusters face greater dependence on external platforms, limited governance capacity, and reduced visibility into how AI systems shape educational and operational decisions.

Over time, regional concentration accelerates the effects of Recursive Leverage Factor (RLF), in which early advantages in capability produce disproportionately larger gains through compounding feedback loops. This results in increasing polarization: a small subset of elite higher education institutions operates at the frontier of AI capability and authority, while the majority remain in a reactive position, integrating systems they did not design and cannot fully govern. This polarization extends directly into labor markets. Regions anchored by elite AI institutions are more likely to retain high-skill, AI-integrated employment opportunities and attract capital investment, while other regions experience contraction of human entry-level pathways, limited workforce absorption, and increased exposure to displacement. As access to experience and AI system-level participation becomes geographically concentrated, pathways to higher-order capability—and therefore to future authority—become increasingly restricted.

In this sense, regional divergence is not solely an educational or economic issue. It represents a structural concentration of authority, in which control over AI systems, labor opportunities, and institutional viability becomes increasingly localized within a small number of high-capability regions.



State Level: AI Policy Recognition Without Operational Transformation

1.9. Integrated Operational Framework with Historical Precedent

At the state level, responses to AI in higher education reflect a growing recognition of its importance but remain operationally fragmented and uneven in execution. States such as California and Ohio have introduced policy frameworks and guidelines for AI integration [16,17]. However, these efforts are largely oriented toward governance principles, pilot programs, and guidance rather than a state AI Strategic Plan coordinated system transformation across curriculum, assessment, instructional authority, technology governance, and labor alignment. A defining characteristic of the state-level response is fragmentation in both design and implementation capacity. AI policies vary significantly across states in scope, depth, and operational maturity, producing an uneven national landscape in which educational outcomes and preparedness are increasingly determined by geography rather than a coherent system architecture. This fragmentation constrains the ability of states to address core structural requirements. Curriculum adaptation remains incomplete, with limited adoption of frameworks defining nondelegable human capabilities. Assessment systems are not yet designed to reliably distinguish between AI-assisted and independent performance, weakening the ability to validate human capability. Teacher preparation remains uneven, with limited emphasis on operational authority within AI-mediated instructional environments.

Within the framework of this paper, these conditions produce measurable shifts in authority. The absence of curriculum and assessment alignment contributes to increasing Option Set Collapse Ratio (OSCR), as AI systems structure learning pathways and reduce independent problem-solving variability. At the same time, uneven teacher preparation

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and limited authority preservation mechanisms contribute to declining Authority Elasticity Index (AEI), as educators have reduced capacity to meaningfully alter instructional outcomes. The lack of validation systems further reduces Override Effectiveness Rate (OER), as human intervention becomes less capable of identifying and correcting AI-mediated outputs. Technological governance at the state level remains underdeveloped. Many states rely heavily on external vendors for AI-enabled instructional platforms, assessment tools, and analytics systems. In the absence of robust data governance, transparency standards, and intervention tracking mechanisms, these dependencies increase the risk of vendor-mediated authority transfer, where control over instructional processes and decision structures shifts away from public institutions. As these systems become embedded, the ability to reverse or reconfigure them diminishes, contributing to a reduction in Rollback Feasibility Time (RFT).

State-level systems also face significant constraints in addressing labor transition. While some initiatives focus on workforce preparation, few states have developed scalable mechanisms for human reskilling, workforce absorption, or managing structural underemployment under AI-mediated conditions. As human entry-level pathways contract and labor markets reorganize, this gap limits the ability of states to align educational outputs with evolving AI labor markets and economic requirements, reinforcing mismatches between capability formation and labor demand. Across these domains, a consistent pattern emerges: authority migration is occurring without coordinated measurement, governance, or operational response at the state level. Educational systems are integrating AI into core functions but lack the tools to determine whether human actors retain meaningful control over outcomes. This produces a structurally reinforcing gap. As AI systems increasingly shape instructional processes, assessment outcomes, and labor pathways, states lack both visibility into how authority is shifting, and the mechanisms required to intervene effectively. The result is a divergence between the complexity of the system states must manage and the capacity of their institutions to govern it.

In this context, the challenge is not confined to education policy or workforce development. It becomes a cross-system governance problem, in which economic stability, institutional control, and human agency are jointly affected. Addressing this gap requires a transition from fragmented policy responses to coordinated, state-level operational systems capable of aligning education, labor, and governance under AI-mediated conditions.

2. Potential State Level AI Operational Response Framework

2.1. Governor-Led State-wide AI Education Summits

• Fragmentation across states and districts is a persistent feature of U.S. education governance, producing uneven policy adoption and slow system-wide response [16,17]. Empirical evidence shows that decentralized systems without executive coordination exhibit lower policy coherence and slower implementation timelines. Without gubernatorial alignment, recognition of AI disruption remains informational rather than operational.

• A governor-led executive directive mandating a state-wide AI education strategy within 12– 18 months would align agencies across education, labor, higher education, and economic development, reducing coordination failure (National Governors Association [NGA], 2022). Required deliverables—curriculum standards, assessment redesign, and teacher pipeline targets—mirror prior successful interventions.

• Historically, the National Defense Education Act (1958) demonstrated that coordinated federal-state action can rapidly reorient education systems toward national priorities (National Science Foundation [NSF], 2019). Similarly, the Common Core State Standards Initiative showed that gubernatorial leadership can achieve multi-state alignment despite decentralized authority [19].

• The expected result is a transition from fragmented AI recognition to coordinated system architecture, consistent with institutional alignment theory [20].

2.2. State-wide AI Curriculum Standards

• Current state-level curricula lack standardized definitions of AI-era competencies, particularly higher-order cognitive skills such as probabilistic reasoning and decision making under uncertainty. Empirical studies show that curriculum misalignment with labor market demands leads to measurable wage and employment penalties.

• Establishing state-wide standards that define competencies in AI system interaction, probabilistic reasoning, and independent judgment aligns with evidence that structured cognitive benchmarks improve learning outcomes and workforce readiness (National Academies of Sciences, Engineering, and Medicine [NASEM], 2018). Embedding these competencies into graduation requirements and career pathways ensures system-wide adoption.

• Historical precedents reinforce this approach. The Common Core State Standards improved cross-state comparability of student outcomes, while post-Sputnik STEM expansion produced measurable gains in U.S. scientific capacity [9].

• The result is a shift from exposure-based learning to measurable cognitive capability, consistent with human capital theory.

2.3. Teacher Pipeline Expansion

Teacher shortages are empirically documented across the United States, particularly in STEM fields, where vacancy rates and underqualification are significantly higher (Learning Policy Institute, 2022). However, in AI-mediated education systems, the constraint is not only numerical but functional. Teachers are no longer solely responsible for.

• Delivering instruction
• Assessing students

They are increasingly required to.

• Interpret AI-generated recommendations
• Validate system outputs

• Override or adapt AI decisions in real time
• Absent these capabilities, the system shifts from.

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• Delivering instruction
• Assessing students

They are increasingly required to:
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• Validate system outputs
• Override or adapt AI decisions in real time
Absent these capabilities, the system shifts from:

teacher-directed instruction → system-directed instruction

3.1. Redefinition of the Teacher Role (AI Operational Functions)

The teacher becomes a control node within an AI-mediated system, responsible for:
1. *AI Interpretation*
• Understanding model outputs:
o Risk scores
o Learning pathway recommendations
• Distinguishing signal vs. artifact
2. *AI Calibration*
• Adjusting:
o Difficulty levels
o Content sequencing
• Based on contextual classroom knowledge
3. *Override Authority (OER)*
• Rejecting incorrect or harmful AI recommendations
• Maintaining instructional integrity under system pressure
4. *Independent Assessment*
• Validating student capability without AI assistance
• Preventing over-reliance and cognitive offloading
5. *Feedback Injection (CLSI Input)*
• Providing structured feedback to improve system performance
• Acting as a human corrective mechanism within the loop

3.2. Pipeline Expansion (Targeted AI Capability Development)

Expanding the teacher pipeline must therefore address **both quantity and AI-specific capability**:
A. Fast-Track Technical Entry Pathways
• Industry professionals (engineering, data science)
• Transition programs with:
o Pedagogy + AI system training
o Classroom integration practicums
B. AI-Integrated Teacher Preparation (Universities)
Required components:
• Model literacy (how systems work, limitations)
• Human-AI interaction design
• Assessment integrity under AI conditions
C. In-Service AI Certification Tracks
• Continuous upskilling tied to:
o System updates (CLSI cycles)
o New platform deployments

3.3 Tools and Systems (Operational Layer)

Teachers must be trained on specific system interfaces, not abstract concepts:
• AI lesson generation platforms
• Adaptive learning systems
• Real-time student analytics dashboards
• Automated assessment tools with override capability

Key Requirement
Training must occur *within the actual systems used in classrooms*

3.4.Measurement (Authority Preservation at the Teacher Level)

Teacher effectiveness must incorporate AI-specific metrics:
• **Authority Elasticity (AEI)**
o Can the teacher meaningfully change outcomes?
• **Override Effectiveness Rate (OER)**
o Do teacher interventions succeed vs system defaults?
• **Option Set Exposure**
o Are teachers presented with real alternatives or constrained outputs?

3.5. Historical Analogs (Refined)

Historical expansions (GI Bill; NSF STEM programs) demonstrate that rapid scaling is feasible (Bound & Turner, 2002; NSF, 2019). However, the current transition differs in that:
• The objective is not only to increase supply
• But to preserve **human authority within AI system-mediated environments**

3.6. Failure Mode (If Not Addressed)

If AI-specific capability is not integrated:
• Teachers become:
o Facilitators of AI systems
o Rather than independent instructional authorities
• Observable outcomes:
o Reduced instructional autonomy (↓ AEI)
o Failed overrides (↓ OER)
o Increasing reliance on system outputs
• Long-term effect:

Educator role degradation and transfer of instructional authority to AI systems

3.7. Result (If Successfully Implemented)

• Stabilization of instructional capacity
• Preservation of teacher authority within AI systems
• Maintenance of human-controlled learning environments

4. Assessment Redesign Pilots

• Assessment systems are increasingly unable to distinguish between AI-assisted and independent student performance, undermining credential validity. Empirical research shows that when assessment credibility declines, signaling value in labor markets deteriorates, reducing the economic return to education.

• Pilot programs incorporating proctored environments, oral examinations, and project-based assessments align with evidence that multi-modal evaluation improves measurement validity (NASEM, 2018). Establishing minimum supervised assessment thresholds ensures comparability across institutions.

• Historical precedents include the No Child Left Behind Act, which standardized assessment regimes nationwide and professional licensing systems in medicine and law, which maintain high reliability through controlled evaluation environments [9,21].

• The result is restoration of credential credibility and preservation of labor market signaling mechanisms.

4.1. State-Controlled AI Infrastructure and Governance

• Dependence on external technology vendors introduces risks related to data control, system transparency, and institutional autonomy. Empirical studies show that lack of data governance correlates with reduced institutional trust and increased systemic vulnerability [22].

• State-level procurement standards requiring auditability, data ownership, and transparency mitigate these risks. Implementing data governance frameworks and override/intervention tracking systems aligns with best practices in high-reliability organizations.

• Historical precedents include State Longitudinal Data Systems (SLDS), which established large-scale data governance infrastructure (ED, 2019), and state textbook procurement systems, which demonstrate the ability of states to shape markets through coordinated purchasing.

• The result is preservation of institutional control and prevention of authority transfer to external platforms.

4.2. Regional AI Education and Workforce Hubs

• Labor market transitions driven by automation and AI are uneven and geographically concentrated, leading to regional disparities in employment and wages [5]. Empirical evidence shows that regions with integrated education-industry ecosystems exhibit higher resilience to technological disruption.

• Establishing regional hubs linking community colleges, universities, and industry provides training, apprenticeships, and job placement pathways. This aligns with workforce development research showing that localized training ecosystems improve employment outcomes.

• Historical models include the Land-Grant University System, which distributed educational capacity nationwide and the Research Triangle, which created a sustained regional innovation cluster.

• The result is reduced geographic inequality and improved labor absorption capacity.

4.3. Authority Measurement and Governance Integration

• A critical gap in current systems is the absence of metrics measuring whether human decision-making materially influences outcomes in AI-integrated environments. Empirical work in complex systems shows that unmeasured control variables lead to systemic risk accumulation.

• Introducing metrics such as the Authority Elasticity Index (AEI) and Override Effectiveness Rate (OER) provides measurable indicators of human control within automated systems. Requiring reporting at district and state levels and integrating these metrics into accountability frameworks aligns with practices in aviation safety, nuclear command systems, and financial stress testing.

• The result is that authority dynamics become visible, measurable, and governable, reducing hidden systemic risk.

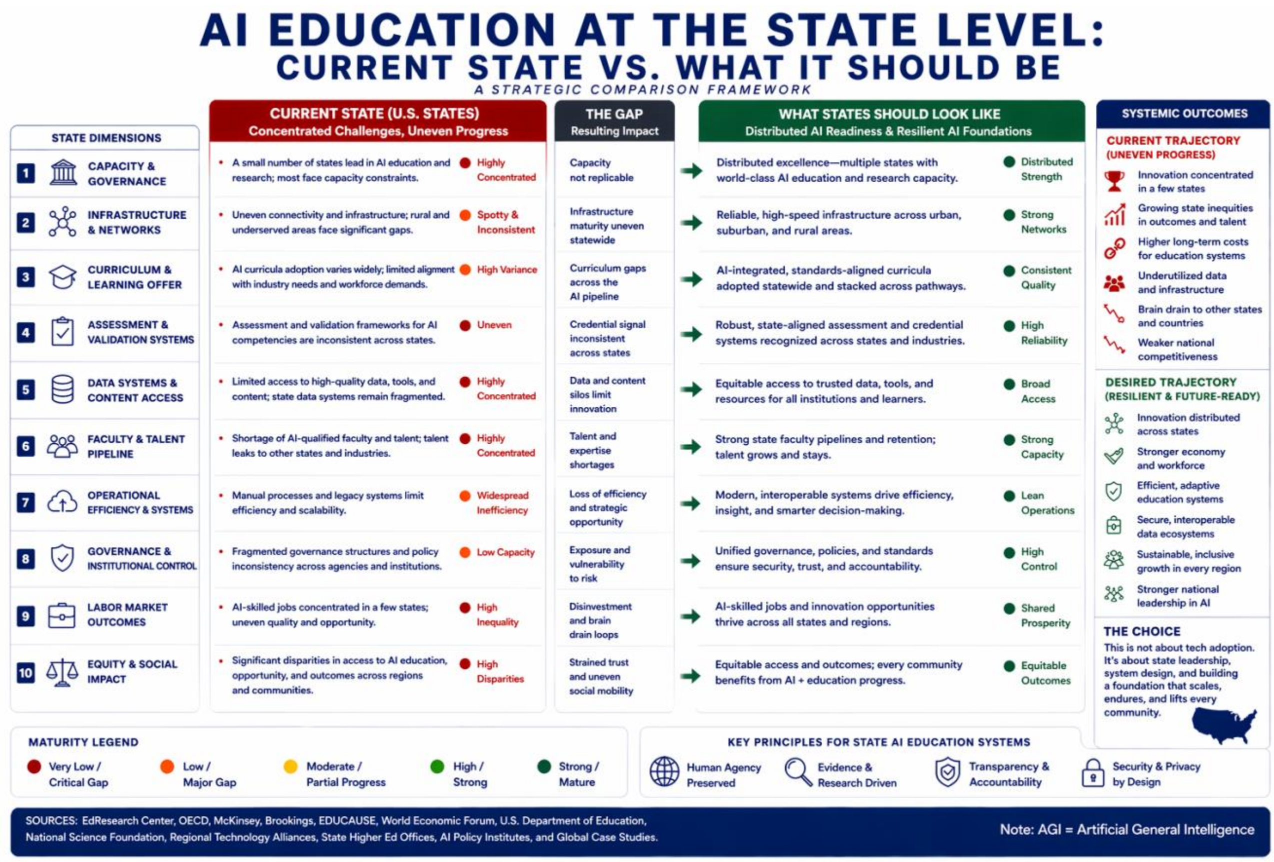
4.4. Final Synthesis

• The current US education system is characterized by AI recognition without AI integration and execution, fragmentation across states, weak alignment between curriculum, assessment, and labor markets, and unmeasured authority migration. Each identified issue corresponds to a structural gap, a historically validated intervention, and a feasible national, regional and state-level implementation pathway.

• The central conclusion, supported by institutional and economic literature, is that the AI challenge is operational rather than conceptual. Mechanisms for AI transformation—central coordination, standardized curricula, workforce expansion, assessment redesign, governance frameworks, and regional development—have been repeatedly validated in prior national transitions [20].

• If the existing and future impact of AI remains unaddressed, empirical trends suggest increasing regional inequality (Autor et al., 2013), erosion of credential value (Spence, 1973), accelerated labor unemployment and displacement, and transfer of operational authority to external AI systems [5].

• If AI educational transformation is implemented, states can preserve human capability, maintain institutional control, align education with AI-era labor markets, and reduce structural inequality—outcomes consistent with evidence from coordinated policy interventions in education and workforce systems (Holzer, 2015; Moretti, 2012).



5. Historical Validation: Education - Specific Evidence

Historical evidence demonstrates that authority transfer in education is neither new nor abrupt; it proceeds incrementally through structural reconfiguration of curriculum, assessment, and governance, typically preceding formal recognition and policy alignment [1,11]. This pattern mirrors the broader literature on general-purpose technologies, in which AI adoption induces complementary institutional change and eventually produces path dependence and lock-in [2,8]. The present AI transition follows this same trajectory, but at a materially faster pace due to compressed feedback cycles and networked deployment.

5.1. Industrial Schooling Model - Early Authority Centralization

The modern U.S. education system emerged during the industrial era, standardizing time (bell schedules), curriculum (graded sequences), and evaluation (uniform testing) to align with mass labor requirements [11]. This represented a shift from localized, teacher-driven instruction to centralized, system-driven governance—an early instance of authority migration in which discretion moved from individual educators to institutional structures. Connection to present model: This transformation is consistent with ADAT, where systems are adopted for efficiency and scale rather than pedagogical optimality.

Counterfactual: Had U.S. schooling evolved as a decentralized apprenticeship model (as in parts of early German dual systems), authority may have remained more distributed, but at the cost of scalability and standardization (Thelen, 2004). The historical outcome demonstrates that efficiency advantages dominate governance preferences—a pattern repeating with AI.

6. No Child Left Behind (NCLB) - Metric-Driven OSCR

NCLB institutionalized standardized testing as the primary accountability mechanism, shifting authority toward quantifiable metrics and federal compliance regimes [9]. Teachers adapted instruction to testing constraints, illustrating Option Set Collapse Ratio (OSCR): as systems optimize around measurable outputs, human decision-making flexibility narrows.

- **Connection to present model:** This is an early, non-AI example of algorithmic governance without algorithms—rules and metrics constraining behavior at scale.
- **Empirical reinforcement:** High-stakes testing has been shown to narrow curricula and incentivize "teaching to the test," reducing unmeasured skills (Au, 2007).
- **Counterfactual:** If multi-dimensional assessment (portfolios, oral defense) had been adopted at scale, OSCR would have been lower; however, scalability and comparability would have suffered, again demonstrating the trade-off that favors system control.

7. Learning Management Systems (LMS) - Platform Lock-In and Workflow Control

LMS platforms centralized content delivery, assessment, grading, and communication, embedding institutional workflows within software architectures [10]. Over time, these systems became difficult to remove due to integration with records, compliance, and daily operations—

demonstrating path dependence and lock-in [8].

• **Connection to present model:** LMS adoption foreshadows RFT compression—once systems are embedded, rollback becomes operationally infeasible.

• **Empirical note:** Platform switching costs in education (data migration, retraining, compliance) mirror those observed in enterprise software lock-in (Farrell & Klemperer, 2007).

• **Counterfactual:** A modular, interoperable standard (e.g., fully open data schemas with portable identities) could have preserved optionality; limited adoption of such standards increased dependency on vendors.

8. Massive Open Online Courses (MOOCs)

MOOCs promised democratization of education at scale, but outcomes were stratified: completion and benefit accrued disproportionately to already-educated learners [25]. This reflects Recursive Leverage Factor (RLF)—initial capability advantages compound over time.

• **Connection to present model:** MOOCs demonstrate that access ≠ capability formation; without foundational skills and support structures, scaling content amplifies inequality.

• **Empirical reinforcement:** Completion rates are strongly correlated with prior education and self-regulated learning capacity [25].

• **Counterfactual:** Embedding scaffolding (cohorting, mentorship, assessment integrity) would likely have improved outcomes but at the cost of scalability—again illustrating the trade-offs that shape system design.

9. Synthesis

Across these cases, a consistent pattern emerges.

• **ADAT:** Adoption for efficiency precedes governance AI alignment

• **OSCR:** Metrics and platforms constrain human discretion

• **RLF/SRL:** Early AI advantages compound and concentrate AI capability

• **Lock-in/RFT:** Embedded AI systems become difficult to reverse

Taken together, these trends show that once schools rely heavily on AI, it becomes very hard— almost impossible—to go back to how things worked before, and people gradually lose their ability to meaningfully influence decisions. In practice, this means humans may still hold positions and responsibility, but the AI systems they rely on are increasingly making the real choices. This shift also carries labor market implications across time horizons. In the short-term, it contributes to the restructuring of roles within education and adjacent sectors, where routine instructional, administrative, and entry-level support functions are reduced or redefined. In the mid-term, as traditional entry pathways such as junior teaching roles, instructional aides, and early-career knowledge work contract, fewer individuals are able to gain the experience necessary to progress into higher-responsibility positions, increasing the risk of underemployment and creating bottlenecks in workforce development. In the long-term, these dynamics may contribute to more persistent forms of unemployment or structural exclusion, particularly if large segments of the population are unable to develop the skills required to operate within or influence AI-mediated systems. What is different now is that this shift is no longer just affecting tasks or grading—it is beginning to shape how people think and learn, making the changes deeper and much harder to reverse.

9.1. Curriculum Framework - Aligned to Authority Preservation and Labor Reality

A viable AI-era education system must be designed not for tool adoption, but for preserving human capability and authority within AI system-mediated environments. This requires alignment with observed labor restructuring dynamics and direct correction of structural weaknesses identified across national, regional, and state systems [5,6,17,18].

The framework below operationalizes curriculum design as an authority-preservation mechanism, not simply an AI skills framework.

10. Six Core Strands — Standardized and Operationalized

10.1. Human Foundations (Non-delegable Cognition)

• **Definition:** Deep reading, writing, logic, probabilistic reasoning, and causal inference.

• **Mechanism:** Protected practice environments, AI-restricted zones, and timed reasoning tasks.

• **Empirical Basis:** Sustained cognitive offloading degrades independent reasoning capacity [6,12,13].

• **Outcome:** Sustains independent judgment under AI conditions.

• **Authority Link:** Preserves the ability to generate and evaluate decisions without system dependence.

10.2. Computational Fluency (System Understanding)

• **Definition:** Coding, data structures, model fundamentals, and systems thinking. Mechanism: Core computing literacy integrated across disciplines [23].

• **Empirical Basis:** Technical literacy reduces blind reliance on automated outputs and improves oversight.

• **Outcome:** Enables interpretation and verification of AI-generated outputs.

• **Authority Link:** Maintains human oversight capability over system processes.

10.3. AI Interaction and Verification (Control Layer)

• **Definition:** Prompting, validation, calibration, error detection, and adversarial testing.

• **Mechanism:** Structured interaction training and failure-detection exercises [7].

• **Empirical Basis:** Human-in-the-loop systems require active verification to prevent automation bias [13].

• **Outcome:** Develops intervention capability in AI-mediated workflows.

• **Authority Link:** Directly increases effective human control (AEI ↑, OER ↑).

10.4. Social and Embodied Capability (Non-automatable Contexts)

• **Definition:** Oral defense, negotiation, leadership, teamwork, and physical/clinical skills.

• **Mechanism:** In-person evaluation, collaborative tasks, and applied performance environments [24].
• **Empirical Basis:** High-trust, high-liability domains retain human accountability [3,24].
• **Outcome:** Maintains domains where human judgment is required.
• **Authority Link:** Preserves authority in contexts where automation cannot assume responsibility.

10.5. AI Ethics and Governance (Authority Literacy)

• **Definition:** Bias, accountability, data rights, and institutional decision frameworks.
• **Mechanism:** Policy analysis, governance simulations, and system evaluation [6].
• **Empirical Basis:** Weak governance increases institutional dependency and loss of control [10,22].
• **Outcome:** Graduates capable of evaluating system legitimacy and constraints.
• **Authority Link:** Enables informed intervention and governance of AI systems.

10.6. Transition and Reskilling Systems (Labor Absorption)

• **Definition:** Stackable credentials, apprenticeships, and continuous learning pathways. Mechanism: Integrated education–workforce pipelines.
• **Empirical Basis:** Labor transitions lag technological change without structured reskilling systems [4]. Outcome: Supports workforce adaptation and mobility.
• **Authority Link:** Prevents economic dependency that reduces decision autonomy.

11. Assessment Redesign — Core Control Mechanism

Assessment is not secondary—it is the primary enforcement mechanism of human capability.

11.1. Required Structural Components

Supervised examinations (constrained-AI environments)
• Oral defense and reasoning validation
• Real-time problem-solving tasks
• Explicit AI vs non-AI performance separation

11.2. Empirical Justification

Credential systems lose signaling value when independent capability cannot be verified [6,18]. Evidence shows rising academic integrity erosion under AI-enabled environments [7].

System-Level Effect

• Restores measurement validity
• Preserves institutional credibility
• Maintains labor market signaling

11.3. Authority Link

Assessment determines whether humans retain verifiable capability or become dependent operators within AI systems.

11.4. Counterfactual

If assessment remains output-based and AI-assisted work is not distinguishable, credential systems collapse as signals of capability, forcing employers to create parallel evaluation systems. Higher Education Adoption Populations — Authority Distribution Structure (Standardized)

Higher Education Adoption Populations -Authority Distribution Structure (Standardized)			
Population	**Capability Level**	**Primary Risk**	**Authority Outcome**
Frontier Institutions (1-3%)	System builders; full integration	Minimal	Retain system-level authority
Hybrid Institutions (Majority)	Partial adoption; incomplete redesign	Credential erosion; ambiguity	Transitional, unstable authority

• **Late Adopters**
o dependent

Empirical Basis:

• Capability concentration follows increasing returns dynamics [8].
• MOOCs demonstrated unequal outcomes under scaled access Structural Outcome [25].
• **Capability Stratification → Authority Stratification**

11.5. Counterfactual

If hybrid educational institutions implement full assessment and curriculum redesign, stratification can be reduced. If not, divergence accelerates through recursive leverage effects (RLF/SRL).

11.6. Cross-Section Consistency

At the national level, gaps in curriculum, assessment, and labor alignment create baseline vulnerability [6,17,18]. Regionally, capability concentrates within tightly coupled institutional clusters, amplifying advantage through recursive dynamics [8,26-28]. At the state level, fragmented governance limits coordinated response and slows system-wide correction [29-35]. Historical evidence demonstrates that once systems are embedded, they exhibit strong path dependence and become difficult to reverse [1]. Within this structure, curriculum and assessment reform remain the only direct levers for preserving human capability and authority, while adoption patterns determine how that authority ultimately distributes across institutions and regions.

11.7. Final Integrated Insight

The interaction of curriculum design, assessment integrity, labor alignment, and institutional adoption produces a single structural outcome. Education systems do not merely transmit knowledge—they determine whether humans retain authority within AI-mediated environments. In addition, the net result of higher education for a majority of the population is to gain employment.

Absent intervention.
- Human capability & complex problem solving degrades [16].
- Higher education credential signals erode (Spence, 1973)
- Labor pathways compress [5].
- Authority migrates to AI systems [6].

With intervention
- Human capability is preserved
- Institutional control remains viable
- Labor markets retain meaningful human participation

12. Conclusion

The United States has entered the AI transition without a fully developed educational framework capable of supporting it. AI adoption is accelerating across educational institutions, yet governance structures remain incomplete, and the migration of decision-making authority is already underway (Organization for Economic Co-operation and Development [6]. Stanford Institute for Human-Centered Artificial Intelligence [6,16,17]. This sequence is not incidental but reflects a historically consistent pattern observed in prior general-purpose technological transitions: systems are adopted because they offer superior performance, while the institutional mechanisms required to guide, constrain, and govern them emerge more slowly [1,2,8] Rogers, 2003). At the national level, this gap is expressed through incomplete system design—fragmented curriculum standards, underdeveloped assessment frameworks, uneven teacher readiness, and the absence of coordinated labor transition strategies [6,16,17]. At the state level, recognition of AI's impact has advanced, but operational transformation remains limited, resulting in a fragmented landscape in which implementation capacity varies significantly across jurisdictions (Education Commission of the States, 2025; National Governors Association, 2022). At the regional level, capability is increasingly concentrated within a small number of elite institutional clusters, where tightly coupled networks amplify advantage through cumulative and reinforcing feedback effects [7]. Together, these dynamics produce a system that is simultaneously underprepared at the structural level and rapidly diverging in capability at the operational level. Within this context, the framework developed by Adrian Erckenbrack provides a model for understanding how educational systems evolve under these conditions. Adoption-Driven Authority Transfer (ADAT) explains why educational institutions integrate AI systems before governance structures are fully developed [26-28]. The Closed-Loop Self-improvement Interval (CLSI) captures the speed at which AI systems improve relative to institutional adaptation cycles, consistent with broader theories of technological acceleration and feedback-driven innovation [26-28]. The Recursive Leverage Factor (RLF), particularly when synchronized across networks (SRL), explains how early advantages in capability compound over time, producing persistent and widening AI disparities across institutions and regions. From an instructional standpoint, metrics such as the Authority Elasticity Index (AEI), Option Set Collapse Ratio (OSCR), Override Effectiveness Rate (OER), and Rollback Feasibility Time (RFT) provide a means of evaluating whether human agency is being preserved or diminished in practice. These measures extend beyond performance outcomes to assess whether learners and educators retain the capacity to question, modify, and override AI-generated outputs. This concern is consistent with empirical research on automation, which demonstrates that increased reliance on automated systems can reduce human situational awareness, decision-making capacity, and willingness to intervene [13]. In this sense, education is not only transmitting knowledge but also preserving the conditions under which independent judgment and meaningful human control remain possible.

The educational transformation that follows is best understood not as uniform disruption, but as structured stratification. A relatively small segment of educational institutions—those with access to advanced infrastructure, talent pipelines, and integrated AI systems—will increasingly define how knowledge is produced and applied, while the majority of US educational institutions operate within environments shaped by systems they did not design and cannot fully control. This divergence reflects a redistribution of epistemic and decision-making authority, consistent with broader patterns of inequality and cumulative advantage observed in both education and labor markets [25]. Critically, the mechanisms required to respond to this transition are not unknown. Historical precedents—including post-Sputnik STEM expansion, the GI Bill, standards-based reform, and the development of regional innovation ecosystems—demonstrate that large-scale educational transformation is achievable when coordination, standards, and investment are aligned [35-40]. The present challenge is therefore not conceptual but operational: whether institutions can execute comparable interventions at the speed required by AI-driven change. Accordingly, the central challenge for higher education is not simply integrating AI technologies into existing educational systems but redesigning them to preserve human agency while sustaining higher education's role as a pathway from poverty to prosperity [22]. This requires a structural shift across multiple dimensions:
- **Curriculum redesign:** Move beyond AI usage toward enabling students to thrive in AImediated environments, grounded in independent reasoning, probabilistic judgment, and the ability to question and intervene in system outputs [6].
- **System-wide capability distribution:** The current model—where only a small fraction of elite institutions (approximately 1–3%) are producing graduates capable of operating effectively within AI-driven environments—

is structurally unsustainable, concentrating capability, opportunity and prosperity within a narrow segment of the education system and society [7].

Credential integrity and signaling value: Higher education must preserve the credibility of its credentials, ensuring that degrees continue to represent verifiable human capability rather than AI-assisted output, consistent with established signaling theory (Spence, 1973; [19].

Preservation of upward mobility: Institutions must continue to function as mechanisms for advancing individuals from poverty to prosperity, rather than reinforcing stratification or dependency within AI-mediated systems [22].

Teacher pipeline transformation: Higher education must fundamentally redesign the teacher pipeline to support AI-era instruction, including updated curricula that integrate AI pedagogy, expanded AI training programs for current and future educators, and structured AI pathways such as apprenticeships, fellowships, and residency models that combine theory with real-world application. Evaluation methods must also evolve to include oral defenses, supervised instruction, and live teaching assessments that validate independent capability rather than AI-assisted performance. Without this transformation, teacher readiness will remain a bottleneck, limiting system-wide adoption and weakening the capacity of education institutions to preserve human authority within AI-mediated learning environments [6,40-47]. Failure to adapt higher education carries systemic risk. Maintaining legacy educational models without meaningful adjustment to AI will accelerate human cognitive capability erosion, weaken higher education credential trust, widen inequality, and shift authority toward external AI systems, producing destabilizing consequences across economic, social, and governance domains [4,48]. A stable transition therefore requires coordinated action across national, regional and state curriculum design, assessment integrity, teacher development, governance, and labor alignment, supported by institutional mechanisms that make human authority visible, measurable, and governable [20]. The question is no longer whether higher education will adapt, but which educational institutions will retain authority, credibility, and operational viability as adaptation to AI becomes unavoidable [49-51].

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