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Left Before the Bell

A National Meta-Analysis of K-12 Education in the Age of Automation

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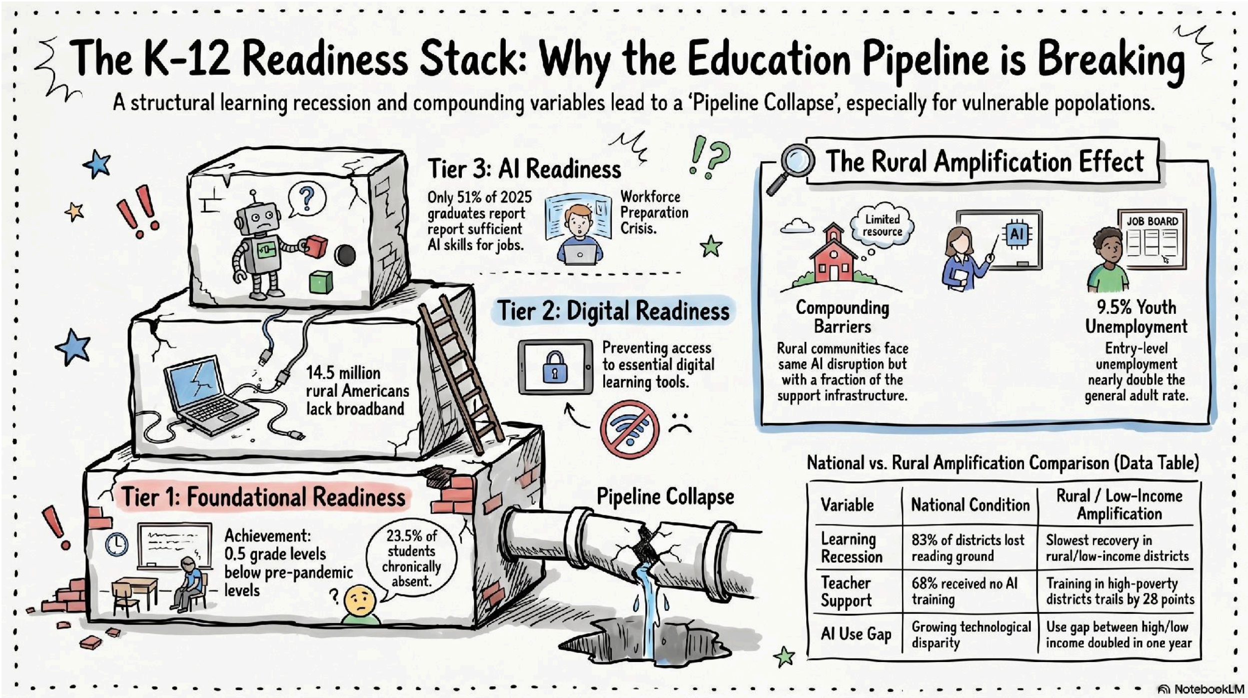

Figure 5. The Zip Code Gap: How Policy Fragmentation Shapes Student Readiness. OCF / NotebookLM, 2026

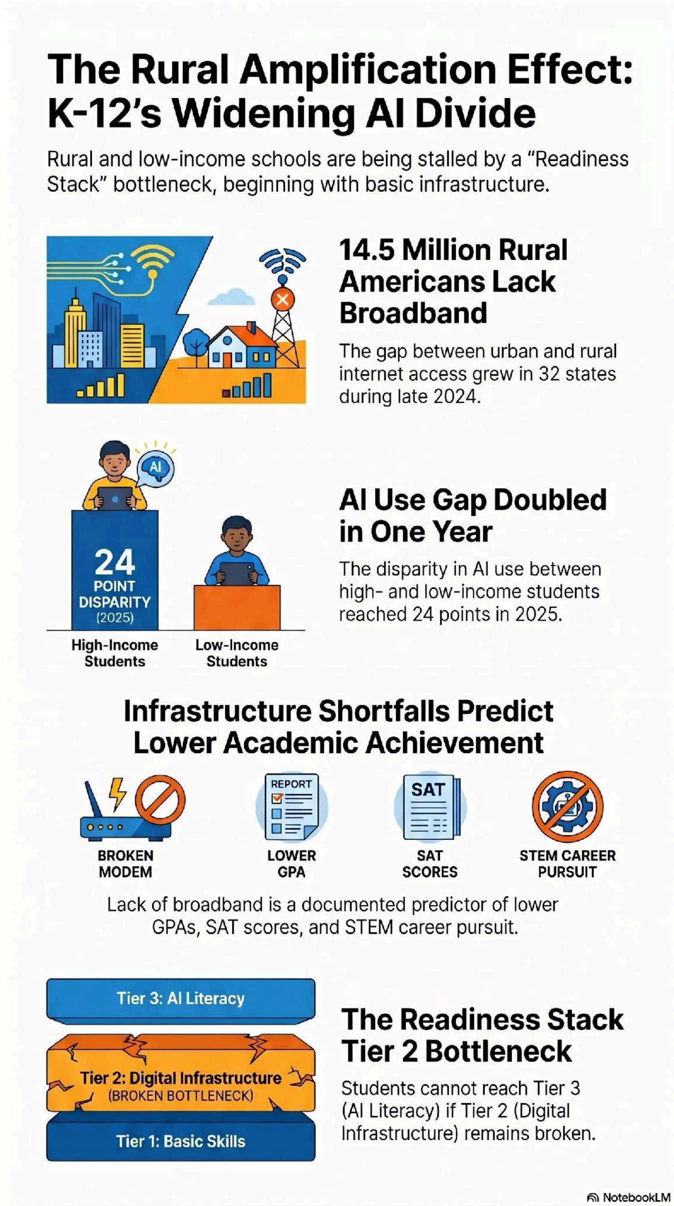

Figure 6. The Rural Amplification Effect: K-12's Widening AI Divide. OCF / NotebookLM, 2026

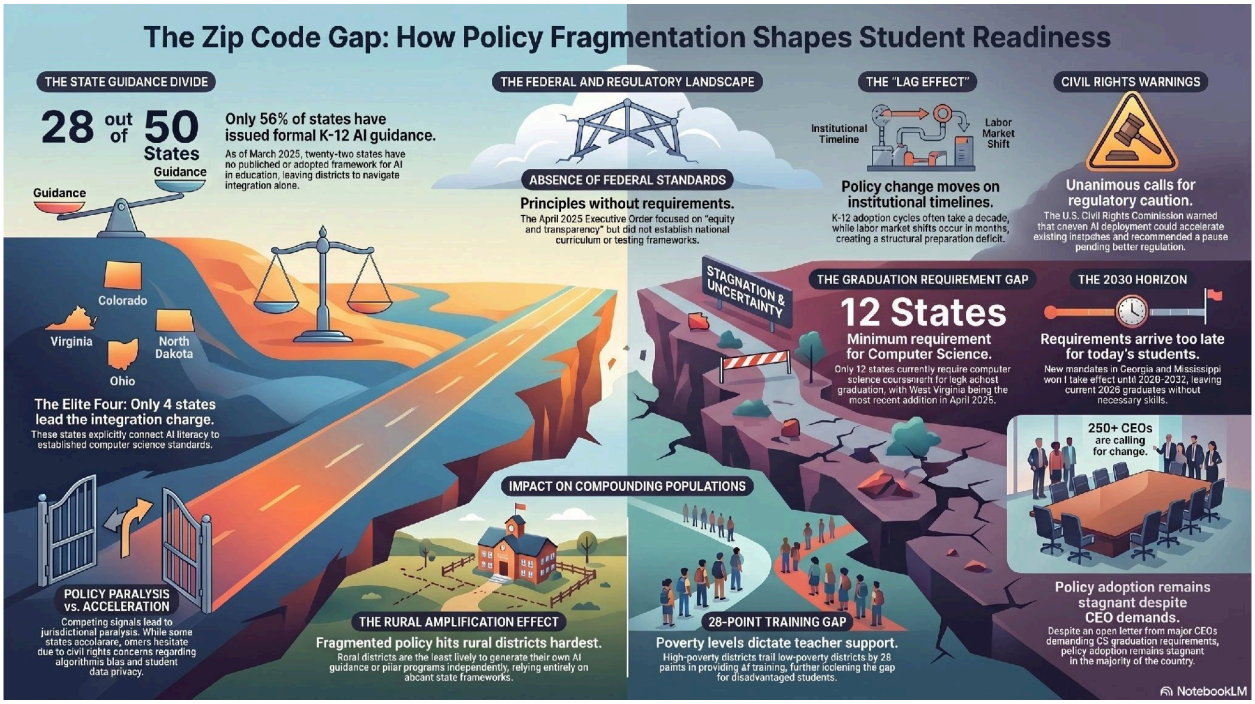

Figure 7. The K-12 Readiness Stack: Why the Education Pipeline Is Breaking. OCF / NotebookLM, 2026

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What This Paper Is. What It Is Not.

This paper is:

- A meta-analysis of national data on K-12 educational readiness, technology integration, and graduate preparedness in the context of AI-driven labor market change.
- Documentation of six compounding variables and their interaction: a pre-existing learning recession, chronic absenteeism, curriculum misalignment, policy fragmentation,

This paper is not:

- An indictment of teachers. The consistent finding in the literature is that where integration has failed, the cause is inadequate institutional support, not unwillingness or incompetence among educators.
- A policy prescription. The data documents conditions. What to do about them is a separate conversation this paper deliberately does not initiate.

teacher support gaps, and infrastructure disparity. • An honest account of where the data is strong, where it is thin, and what research gaps the field has not yet filled. • The first paper in a three-part series extending OCF's workforce readiness research upstream into the educational pipeline.	• An argument that AI in education is straightforwardly beneficial. The evidence on implementation quality, equity, and outcomes is mixed and honestly reported. • A complete picture. Longitudinal data on AI literacy outcomes does not yet exist. The field is moving faster than the research that should be guiding it.

Abstract

This paper presents a national meta-analysis of K-12 educational readiness in the context of accelerating technological change and AI-driven labor market disruption. Drawing on peer-reviewed literature, federal and state policy data, longitudinal learning assessments, and graduate employment surveys, this analysis examines six compounding variables: a learning recession that predates COVID-19 by nearly a decade, chronic absenteeism that has not returned to pre-pandemic levels, curriculum misalignment with emerging workforce demands, fragmented state and federal policy frameworks for technology integration, structural barriers to teacher professional development, and widening infrastructure disparities between urban, suburban, and rural school systems.

The central finding is not that any single variable is catastrophic in isolation. It is that these variables compound in the communities least equipped to absorb them: the same rural and low-income populations documented in OCF's prior workforce readiness research. As of spring 2024, the average U.S. student remained nearly half a grade level behind pre-pandemic achievement. The Harvard/Stanford Education Scorecard removed the word 'Recovery' from its title in 2025, signaling that the operative frame is no longer a temporary disruption but a structural learning recession beginning in 2013. Only 28 states had issued formal K-12 AI guidance as of March 2025. Only 12 states require computer science coursework for high school graduation. Only 51% of 2025 graduates reported sufficient AI skills for jobs applied to. Entry-level unemployment among young college graduates reached 9.5% by September 2025.

These are sequential outputs of the same upstream failure. This paper documents that failure without attribution to individual actors and without prescription. The data speaks.

Keywords: *K-12 education, workforce readiness, AI integration, curriculum relevance, COVID learning loss, chronic absenteeism, rural education, digital divide, teacher professional development, graduate employability, education policy, learning recession, ocf_schema_v1*

At a Glance

~0.5 grade levels Average student below pre-pandemic achievement in math and reading as of spring 2024	**23.5%** Students chronically absent in 2024-25, down from 28.5% peak but 8 points above pre-pandemic baseline	**28 of 50** States with formal K-12 AI guidance as of March 2025. Twenty-two states have none.	**68%** Teachers who received no AI training in 2024-25, despite 60% using AI tools for their work
83% Districts that lost ground in reading between 2015 and 2025. The recession predates COVID.	**51%** Graduates who reported sufficient AI skills for the jobs they applied to in 2025	**14.5M** Rural Americans without broadband access, a number growing relative to urban peers in 32 states	**9.5%** Entry-level youth graduate unemployment, September 2025. Nearly double the general adult rate.

> *Pipeline Note: These numbers are not independent findings. They are the upstream educational origin of the workforce outcomes documented in OCF's prior research series. The workers documented as underprepared in The Skills Gap Is Here were educated in the system documented here. The pipeline does not break at graduation. It starts breaking years earlier.*

I. Introduction

The American K-12 system was not designed for the labor market it is currently producing graduates into. This is not a controversial claim. It is a structural observation supported by convergent data from labor economists, education researchers, employer surveys, and longitudinal student assessment programs. The question this paper addresses is not whether a gap exists. That is established. The question is what variables produced the gap, how they interact, and where the compounding effects are most severe.

This analysis is the first paper in a three-part series extending OCF's prior workforce readiness research upstream into the educational pipeline. OCF's national workforce meta-analysis documented that 11.7% of U.S. jobs are automatable with current technology, that entry-level job postings declined 29% since 2024, and that access to training is the binding constraint on adaptation. That paper documented where workers arrive. This paper examines the conditions that shaped them before arrival.

Six variables structure this analysis. They are treated as compounding rather than independent because the evidence indicates they interact: the populations most affected by one are disproportionately affected by the others. Section II documents the methodology governing source selection, inclusion and exclusion criteria, the synthesis approach, and the confidence calibration used throughout. Sections III through VIII examine each variable. Section IX synthesizes their interaction.

The first variable is a learning recession that predates COVID-19. The Harvard/Stanford Education Scorecard, in its 2025 iteration, removed the word 'Recovery' from its title. Student achievement in reading began declining in 2013. COVID accelerated a trend already in motion rather than initiating one.

The second variable is chronic absenteeism. National chronic absenteeism rates nearly doubled between 2018 and 2022, from 15% to 28%, and have not returned to pre-pandemic levels. As of 2024-25, 23% of students are chronically absent. The American Enterprise Institute projects that pre-pandemic baselines may not be reached until 2029.

The third variable is curriculum misalignment. The gap between what K-12 students are taught, what is measured by standardized assessments, and what the labor market requires is well-documented and widening. Only 51% of 2025 graduates reported sufficient AI skills for jobs applied to.

The fourth variable is policy fragmentation. As of March 2025, only 28 of 50 states had issued any formal K-12 guidance on AI in education. Only 12 states require computer science coursework for high school graduation. No federal curriculum standard exists.

The fifth variable is the structural position of teachers. The literature consistently finds that teacher adoption of new instructional technology is constrained not by willingness but by inadequate institutional support, insufficient professional development, and the absence of curricular frameworks that make integration practical. The system failed to support them. That is the finding of the literature, and it is the framing of this paper.

The sixth variable is infrastructure disparity, with particular severity in rural and low-income communities. FCC data documents that 14.5 million rural Americans lack broadband access. The gap between urban and rural internet access grew in 32 states during the second half of 2024. The economic disparity in student AI use reached a 24-percentage-point gap between high- and low-income families in 2025.

> *The students entering the labor market documented in OCF's workforce research were educated in the system documented here. The pipeline does not break at graduation. It starts breaking years earlier.*

A note on standardized testing as a measurement instrument: this analysis uses standardized assessment data primarily because it constitutes the most comprehensive longitudinal dataset available and is methodologically consistent across time periods, enabling trend analysis not possible with other instruments. This does not constitute an endorsement of standardized testing as an adequate measure of the full range of skills students need. The literature documents a systematic misalignment between what standardized tests measure and what employers require, a misalignment addressed directly in the curriculum variable examined in Section V. Where this limitation affects interpretation, it is noted in the relevant section. The consequence is that this analysis likely understates the preparation gap: standardized assessments capture the skills that are easiest to test, not necessarily the skills that matter most in the labor market this analysis documents.

II. Methodology

A. Search Strategy and Source Identification

This analysis conducted a systematic search across seven categories of source type: (1) federal longitudinal datasets and government databases, including NAEP, FCC, USDA, and NCES; (2) peer-reviewed academic journals and systematic reviews; (3) major research organization publications, including RAND Corporation, American Enterprise Institute, Brookings Institution, and Urban Institute; (4) annual practitioner surveys with documented sampling methodology, including Gallup, Pew Research Center, and Cengage Group graduate employment surveys; (5) nonprofit and advocacy organization research with disclosed methodology, including Code.org, Center on Reinventing Public Education, and Education Commission of the States; (6) federal policy and commission documents; and (7) international comparative data from OECD and PISA. The search covered publications dated January 2013 through May 2026, encompassing the full period of the learning recession documented in the findings.

Search terms were organized around the six analytical variables structuring this analysis: learning loss and academic achievement decline, chronic absenteeism, curriculum alignment and workforce preparation, K-12 technology and AI policy, teacher professional development, and broadband infrastructure and rural access. Secondary terms targeted population-specific subsets: rural students, low-income populations, and Tribal land communities.

B. Inclusion and Exclusion Criteria

Inclusion criteria required: (1) empirical grounding, including original data collection, secondary analysis of federal datasets, or systematic review of peer-reviewed literature; (2) a documented publication date within the search window; (3) U.S. population focus or direct U.S. comparability for international sources; and (4) transparent methodology or data provenance. Sources meeting these criteria were evaluated for methodological quality using a three-tier classification: federal or longitudinal datasets with large samples (Tier A), peer-reviewed studies and research organization reports with documented methods (Tier B), and practitioner surveys and advocacy organization data with disclosed sampling (Tier C). All three tiers are represented in this analysis, and findings relying primarily on Tier C sources carry lower confidence values in the Model Reference Appendix.

Exclusion criteria eliminated: opinion or commentary without empirical support; sources without a clear publication date; single-school or single-district case studies without generalizability evidence; and sources whose methodology could not be independently assessed. Approximately 80 sources were identified in the initial search. Following exclusion review, 35 primary sources are cited in this analysis, covering a combined research population exceeding 40 million students, 300,000 teachers, and 8,000 school districts.

C. Synthesis Approach

This analysis follows a narrative synthesis framework. Each of the six analytical variables is examined across all included sources bearing on that variable. Convergence is assessed on three dimensions: direction of finding, effect magnitude, and methodological independence of sources. A finding classified as high-confidence (0.90 and above in the Model Reference Appendix) requires convergent direction across at least two methodologically independent Tier A or B sources. A finding classified as moderate-confidence (0.75 to 0.89) reflects convergent direction with some reliance on Tier B or single-Tier-A sourcing. Findings below 0.75 confidence carry explanatory notes in the appendix.

Where sources diverge, divergence is documented and attributed where possible. The primary sources of divergence in this corpus are geographic: findings that hold at the national level frequently show different patterns across urban, suburban, and rural sub-populations. The Rural Amplification Effect documented in Section IX describes the systematic pattern of rural divergence from national averages across all six variables. Divergence that is not attributable to geographic sub-population differences is noted within the relevant section.

D. Limitations

Three limitations constrain the confidence of specific findings and are disclosed here rather than distributed across sections. First, AI literacy and AI-in-education research is less than five years old for most of the questions this analysis addresses. The evidence base is growing but is not yet mature, and effect sizes documented in 2025 surveys should be expected to shift as the field matures. Second, the AI use disparity finding (F006) and several infrastructure disparity findings rely on survey data from single organizations, which carry inherent response and sampling bias risks; however, these findings are directionally consistent with federal access data, which is why they are included with moderate rather than high confidence. Third, this analysis covers the educational preparation inputs to workforce readiness, not the long-term labor market outcomes for current K-12 cohorts, as those students have not yet entered the workforce in sufficient numbers to generate follow-up data. The causal chain from educational preparation to workforce outcomes is documented through existing graduate cohorts and is a structural inference about current students, not a tracked longitudinal finding.

III. The Learning Recession: A Decline That Predates COVID

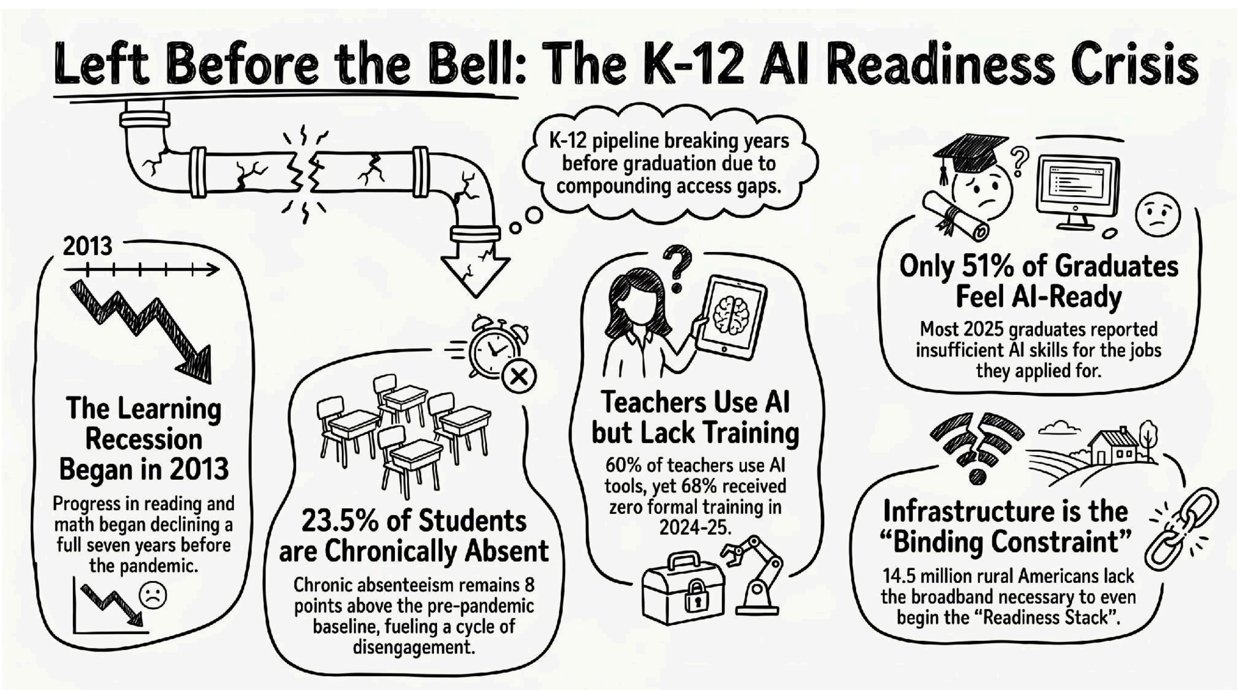

Figure 3. Left Before the Bell: The K-12 AI Readiness Crisis. OCF / NotebookLM, 2026

Three independent longitudinal data systems converge on the same finding with high confidence. The Harvard/Stanford Education Scorecard (covering 8,719 districts and 35 million students across 43 states), the National Assessment of Educational Progress (covering 4th and 8th graders nationally), and OECD PISA (covering 15-year-olds across member nations) each document a pattern of declining U.S. student achievement that precedes the COVID-19 pandemic. The Harvard/Stanford research team made this explicit in 2025 by removing the word 'Recovery' from their report title, citing direct evidence that U.S. student progress in reading and math began declining in 2013. COVID accelerated and deepened a trajectory already in motion. The meta-analytic significance of this convergence is that no single dataset, sampling approach, or research team can account for agreement across all three: the finding is robust to methodological variation.

This reframing matters for this analysis. It means the educational preparation gap documented in the following sections is not primarily an artifact of pandemic disruption that will resolve as the disruption recedes. It is structural. It predates the disruption. The disruption made it worse.

A. Achievement Data

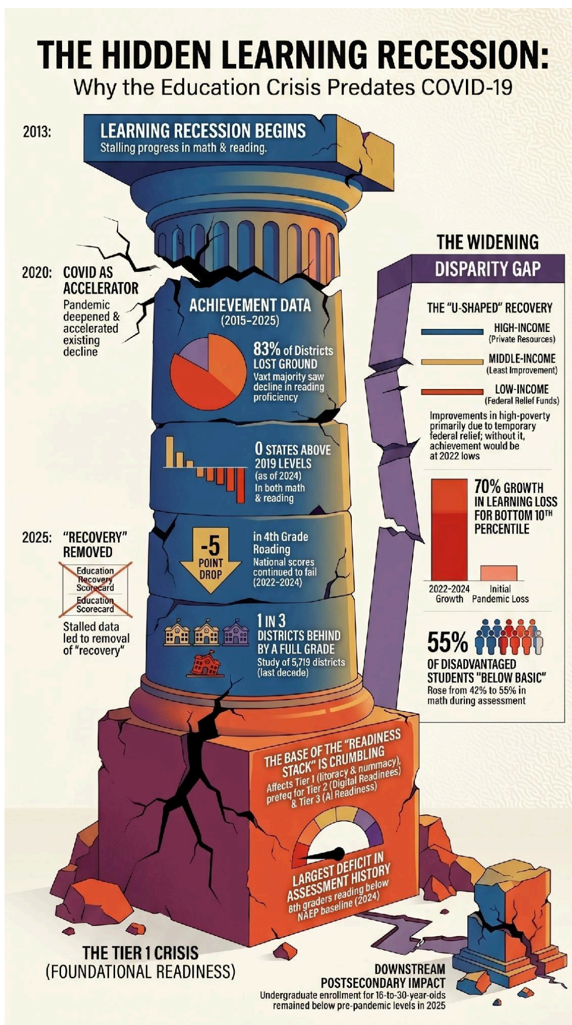

Figure 1. The Hidden Learning Recession: Why the Education Crisis Predates COVID-19. OCF / NotebookLM, 2026

The 2024 National Assessment of Educational Progress assessed representative samples of fourth- and eighth-grade students across 43 states.

−5 pts	Average 4th-grade reading score decline from 2019 to 2024. Scores continued to fall between 2022 and 2024 after historic pandemic-era drops.

0 states	Number of states that scored above 2019 levels in both math and reading. No jurisdiction improved in both subjects.

1 in 3	Districts that fell behind by a full grade level in reading between 2015 and 2025, per Harvard/Stanford Education Scorecard covering 8,719 districts.

The Harvard/Stanford Education Scorecard, drawing on NAEP combined with state assessment data from 35 million students across 8,719 districts in 43 states, provides the most granular picture available. Its 2025 findings establish that recovery from the COVID disruption is partial, uneven, and distributed in ways that reflect and amplify existing inequalities.

The recovery pattern is U-shaped: the highest-income and lowest-income districts have seen the most improvement, while middle-income districts have seen the least. The researchers attribute high-poverty district improvement primarily to federal pandemic relief funding, and note explicitly that without that relief, the average high-poverty district would have remained at its 2022 achievement level. The improvements documented in high-poverty districts are funding-dependent, not structural.

A critical structural risk follows directly from the funding-dependent nature of high-poverty district recovery. The federal Elementary and Secondary School Emergency Relief (ESSER) funds that drove those gains exhausted their legal obligational runways in 2026. Architectural modeling by Harvard CEPR indicates that without continued federal intervention, high-poverty districts face an immediate structural regression toward their 2022 degraded baseline. The U-shaped recovery, which is already dependent on the temporary infusion of federal emergency funds at one end, is therefore time-limited. The recovery data that produced moderate optimism in 2025 reporting reflects conditions that are structurally scheduled to reverse.

The 2025 to 2026 reading data introduces a notable state-level divergence that the aggregate national figures mask. Reading improvement is measurably present only in states that implemented comprehensive, mandatory Science of Reading statutory overhauls: Mississippi, Louisiana, Tennessee, and Maryland show statistically significant improvement in early literacy. States that delayed or avoided these systemic mandates, including California, Massachusetts, and South Dakota, show zero statistical improvement, continuing a decade-long slide that has placed 8th-grade reading scores at their lowest national point since 1990. This state-level divergence is the strongest current evidence that targeted structural intervention can bend the reading recession trajectory, and the strongest current evidence that absence of such intervention produces continued decline regardless of other school quality variables.

B. The Disparity Widening

The 2024 NAEP data reveals a troubling pattern at the lower end of the achievement distribution. American Enterprise Institute analysis found that pandemic learning loss for students in the bottom 10th percentile grew 70% larger between 2022 and 2024. For students in the bottom 25th percentile, losses grew 25% larger over the same period. The percentage of economically disadvantaged students scoring below basic in math rose from 42% to 55%.

> *The students who were furthest behind going into the pandemic are now further behind than they were coming out of it. The learning recession is not evenly distributed. It is concentrated precisely where the infrastructure to respond to it is thinnest.*

The percentage of 8th graders reading below the NAEP baseline is the largest in assessment history. Undergraduate enrollment among 18-to-20-year-olds remained below pre-pandemic levels in 2025. These are downstream markers: students who are less prepared at the K-12 level enter postsecondary education at lower rates or arrive requiring remediation. The PISA assessment found an 18-point decline in U.S. 15-year-old math scores from 2018 to 2022, one of the largest drops among OECD member nations.

IV. Chronic Absenteeism: The Compounding Variable

Chronic absenteeism, defined as missing at least 10% of the school year or roughly 18 days, is treated in this analysis as a distinct variable rather than a sub-component of COVID learning loss. Four independent data sources, drawing on different methodologies and populations, converge on the same finding: absenteeism surged to nearly double its pre-pandemic rate during the pandemic and has not recovered. The AEI Return to Learn Tracker (41 states, longitudinal), RAND American School District Panel (nationally representative district sample), Harvard/Stanford Education Scorecard (8,719 districts), and NCES administrative data report absenteeism findings in the same direction across different measurement approaches. This cross-source agreement, combined with documented causal mechanisms linking absence to both mental health deterioration and academic performance decline, produces the highest convergence confidence of any variable in this analysis.

A. The Scale of the Problem

15%	National chronic absenteeism rate in 2018-19, pre-pandemic baseline already characterized by the U.S. Department of Education as a national crisis.

28.5%	National chronic absenteeism rate at peak in 2021-22, nearly double the pre-pandemic baseline. An additional 6.5 million students became chronically absent.

94.7%	Percentage of U.S. students in 2024 attending a district with absenteeism above its own 2019 level. No state was below its 2019 72nd percentile rate.

AEI research projects that if the pace of absenteeism improvement continues decelerating at its current rate, the country could stall above 20% chronic absenteeism indefinitely. The projected earliest return to pre-pandemic baseline, assuming the current deceleration rate holds, is 2029. Acceleration of improvement is not guaranteed.

B. The Achievement Connection

The relationship between chronic absenteeism and academic performance is now well-documented. AEI research estimates that rising absenteeism may account for approximately 8% of total pandemic-era learning loss. A separate NCES analysis, drawing on student self-reports correlated with NAEP performance, estimates that absenteeism may explain between 16% and 27% of the decline in NAEP math scores. The divergence in estimates reflects methodological differences. Both point in the same direction.

A 2026 UCL/Glasgow birth cohort study using longitudinal pre-pandemic data established a bidirectional relationship: students in the highest quartile of absences showed odds ratios of 2.2 for later mental health problems at age 7, 1.5 at age 11, and 1.9 at age 14. Persistent absence above 10% of the school year was associated with approximately double the odds of mental health problems across all measured ages. Absence causes mental health deterioration. Mental health deterioration causes further absence. Schools managing elevated chronic absenteeism are managing a reinforcing cycle, not a static problem.

C. Mental Health as a Driver

A Youth Trust Survey of 500,000 students found that 48% reported depression, anxiety, and stress are making it difficult to do well in school, up from 39% in 2020. Mental Health America analysis of school-based health center data identifies anxiety, depression, and mental health as the top health-related drivers of absenteeism. These findings are consistent with the post-pandemic trajectory: school closures increased social isolation, anxiety, and depression among students. The Healthy Minds Study found severe college student depression dropped from 23% to 18% between 2022 and 2025, a meaningful improvement that still leaves 18% of the population at that severity level.

> *Schools managing elevated chronic absenteeism are managing a reinforcing cycle. Absence causes mental health deterioration. Mental health deterioration causes further absence. The mechanism is documented at each link.*

The 2025 to 2026 AEI attendance data introduces a finding that complicates the national absenteeism trajectory: the aggregated improvement in the overall rate masks a sharp generational divergence by grade level. In districts implementing intensive early-childhood interventions, including attendance agents and home visit programs, 1st-grade chronic absenteeism declined by 12.6% and 5th-grade absenteeism declined by 11.8%. In the exact same districts, using identical intervention protocols, 12th-grade chronic absenteeism increased by 0.8%, permanently stabilizing at 32.1%. The intervention mechanism that works on young children through parental alignment does not transfer to older students who have reached independent age in an environment of low credential accountability and who are actively decoupling from the physical institution. Elementary-level interventions are producing measurable results; high school is a separate and currently worsening problem.

The practical classroom consequence of the stabilized absenteeism rate deserves direct documentation. In a representative elementary school of 500 students, the pre-pandemic baseline of 15% chronic absenteeism produced approximately 45 chronically absent students distributed across the building. At the current 2026 stabilized rate, that same building contains between 88 and 113 chronically absent students, rising to 139 in high schools. This concentration creates a structural instructional headwind independent of teacher quality or curriculum content: teachers are trapped in a continuous cycle of re-teaching foundational concepts to rotating cohorts of returning absentees, which reduces instructional velocity for the entire student body, including students with complete attendance records.

RAND data from 2024-25 finds that in roughly half of urban districts, more than 30% of students are chronically absent, a far higher share than in rural or suburban districts. About 9% of rural schools and 7% of suburban schools report that level. This is notable because most other variables in this analysis show rural students at greater disadvantage. The geographic distribution of educational preparation gaps is not uniform across variables, and this analysis treats each on its own evidence.

V. Curriculum Misalignment: What Is Taught vs. What Is Needed

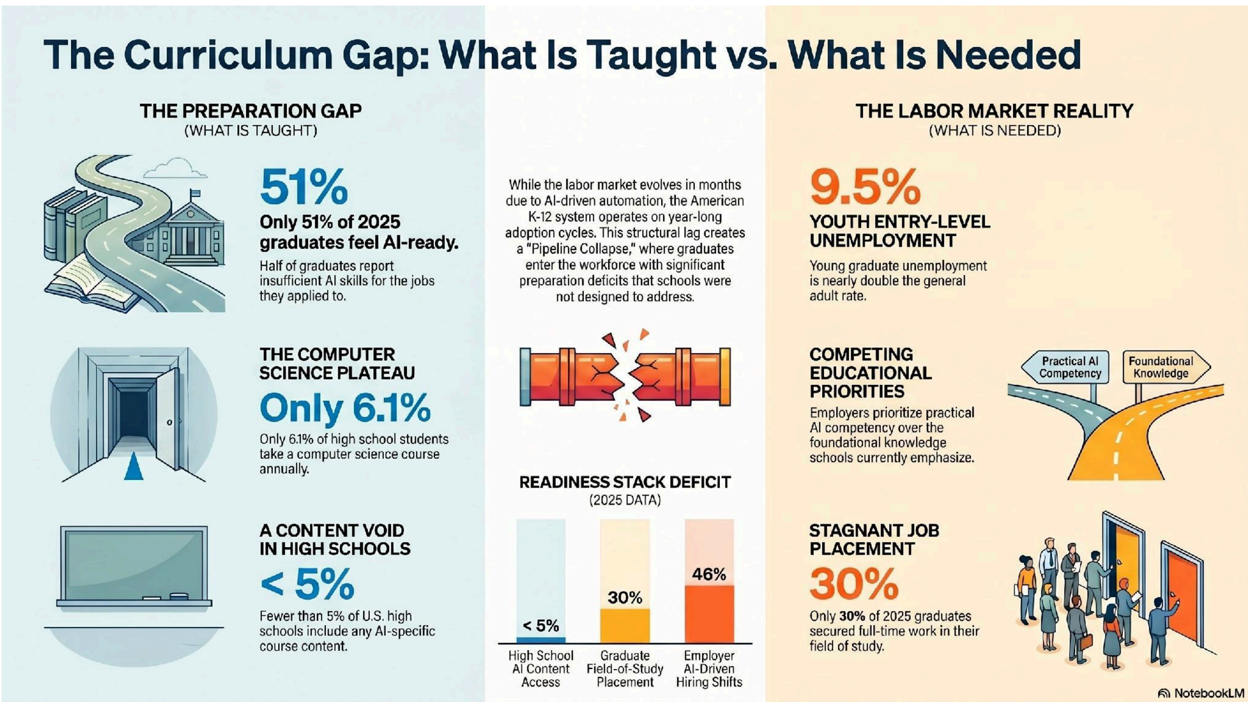

Figure 2. The Curriculum Gap: What Is Taught vs. What Is Needed. OCF / NotebookLM, 2026

The preparation gap is documented from four independent measurement directions: employer-side surveys, graduate-side outcome data, curriculum content audits, and international comparisons. The convergence across these methodologically distinct approaches strengthens confidence above what any single source would support. Employer surveys (Cengage 2025, OECD Skills 2025) identify specific skills graduates lack. Graduate employment data (IntuitionLabs 2025, Urban Institute 2025) quantify downstream labor market outcomes. Curriculum audits (Code.org/CSforAll 2025) document what is and is not being taught. International comparisons (OECD PISA 2022) establish relative performance decline. No single source could establish the full picture; the four-direction convergence is what distinguishes a documented structural gap from a data artifact.

A. The Graduate Outcome Data

The Cengage Group 2025 Graduate Employability Report, in its fifth year and drawing on surveys of employers, recent graduates, and educators, provides direct measurement of the preparation gap:

- Only 51% of 2025 graduates reported they had sufficient AI skills for the jobs they applied to.
- Only 30% of 2025 graduates secured full-time work in their field of study.
- 76% of employers reported hiring the same or fewer entry-level workers compared to the prior year, up from 69%, with AI cited as a driver by 46% of those employers.
- The report identifies a fundamental misalignment: educators emphasize soft skills and foundational knowledge. Employers want practical, job-specific skills and demonstrated AI competency. These are not complementary priorities. They are, currently, competing ones.

IntuitionLabs analysis found that entry-level unemployment among young college graduates ages 20 to 24 reached 9.5% by September 2025, nearly double the general adult rate and approaching the pandemic-era peak of 10.9% reached in early 2020. This is the downstream labor market expression of the upstream educational preparation gap.

B. The Computer Science and AI Literacy Gap

The Code.org and CSforAll 2025 State of AI and CS Education report documents the scope of the content gap directly:

- Fewer than 5% of U.S. high schools include any AI-specific content in any course.
- Only 60% of high school students had access to any computer science courses in 2024-25.
- Only 6.1% of high school students take any computer science course in a given year.
- Access to computer science has plateaued nationally except in states with graduation requirements.
- Only 32.5% of young women take high school computer science courses, compared to 67.5% of young men.

The 2025 report warns explicitly that decoupling AI literacy from foundational computer science instruction risks building AI education on uneven foundations. States introducing AI-specific guidance without grounding it in computer science curriculum create conditions for superficial exposure rather than substantive competency.

C. The Curriculum Development Lag

Curriculum revision in K-12 public education moves on institutional timelines. State adoption cycles, textbook procurement schedules, teacher certification requirements, and standardized testing alignment create a system that can require years, sometimes a decade, to incorporate new content at scale. The labor market, particularly in technology-adjacent fields, moves on market timelines measured in months.

The result is a structural lag that is not attributable to any individual decision or actor. It is an emergent property of how public K-12 curriculum development works. The OECD Skills Outlook 2025 identifies the same pattern at the international level: curricula must ensure proficiency in core 21st-century skills, but funding formulas and adoption processes have not kept pace with the evolving definition of those skills.

> *Curriculum decisions reflect established practice, assessment infrastructure, and institutional inertia. The lag is predictable. The question is whether the current rate of labor market change has made that lag consequential in ways it was not previously.*

VI. Policy Fragmentation: A Student's Preparation Depends on Their Zip Code

The absence of a coherent national framework for technology integration in K-12 education is not a neutral condition. Three independent data sources document the same pattern of policy fragmentation across different methodological approaches: the Education Commission of the States (state-by-state policy inventory, March 2025), Code.org and CSforAll (graduation requirement tracking, April 2025), and Ballotpedia (legislative activity tracker). All three converge on a finding of significant state-level variation in the presence, scope, and enforceability of AI and computer science education guidance. Their agreement across different tracking methodologies establishes that the fragmentation is a documented structural feature of the policy landscape, not an artifact of any single source's categorization approach. Its costs fall disproportionately on students in states, districts, and schools that lack the resources or institutional capacity to fill the gap without guidance.

A. The State Guidance Landscape

28 / 50	States with published or adopted K-12 AI guidance as of March 2025. Twenty-two states have no formal framework.

12 states	States requiring any computer science coursework for high school graduation as of April 2025. West Virginia became the twelfth in April 2025.

4 states	States that explicitly connect AI literacy to computer science standards: Colorado, Virginia, North Dakota, and Ohio.

The Education Commission of the States documented that as a majority of states have now issued some form of guidance, policy attention is shifting from whether to provide guidance to how to integrate AI into specific instructional functions. This represents progress. It also means the 22 states that have issued nothing remain at square one.

B. The Federal Picture

The April 2025 Executive Order on Advancing AI Education reinforced principles including equity, transparency, and human oversight of automated systems in educational contexts. It did not establish curriculum standards, graduation requirements, or testing frameworks.

The U.S. Civil Rights Commission's November 2024 report on AI in education documented civil rights concerns regarding AI deployment in K-12 settings, including algorithmic bias in student assessment, data privacy in small communities, and the acceleration of existing inequities through uneven AI tool deployment. The National Education Policy Center, cited in that report, recommended a pause on AI in education pending appropriate regulatory frameworks. The report was adopted unanimously by the Commission.

These competing signals produce paralysis in some jurisdictions and inadequately resourced acceleration in others. The students who bear the cost of policy incoherence are disproportionately the same students already facing the greatest preparation gaps.

C. The Graduation Requirement Trajectory

Legislative activity in 2025-26 suggests the landscape is shifting. Georgia passed legislation making computer science including AI a high school graduation requirement beginning in 2031-32. Mississippi passed legislation requiring CS credit with AI instruction beginning with the class of 2029-30. More than 250 CEOs signed an open letter in May 2025 calling for CS graduation requirements in all states.

> *The characteristic pattern of educational policy change: the students who needed it graduate before the policy reaches them. Georgia's 2031 requirement does not help the student who graduated in 2026.*

VII. Teacher Support Structures: The System Failed to Prepare Educators

The literature on K-12 technology integration is consistent on one point across three independent systematic reviews and two large-scale national surveys: teachers are not the primary obstacle to AI integration in American classrooms. A 2025 Frontiers in Education systematic review (23 peer-reviewed studies), an MDPI Computers systematic review (43 empirical studies), and a 2026 systematic review of GenAI in teacher education converge on an identical conclusion: teacher willingness and technical curiosity are not the limiting variable. The limiting variable is institutional support structure. This meta-analytic finding, derived from convergent review of over 60 independent empirical studies, is the strongest single finding in the literature on the teacher variable. Large-scale national survey data from RAND (nationally representative, 2025) and Gallup (2025) corroborate the pattern at the population level: adoption is high, training is absent.

A. Adoption Without Training

The gap between teacher AI use and teacher AI training is one of the clearest findings in the 2024-25 data:

- 60% of teachers used an AI tool for their work in the 2024-25 school year.
- 68% of those teachers received no AI training during that same school year.
- Roughly half of teachers who use AI tools taught themselves how to use them.
- Only 19% of teachers work in schools with any formal AI policy.

RAND's comprehensive 2025 survey found that while 53% of ELA, math, and science teachers used AI for school in 2025, an increase of more than 15 percentage points from the prior year, only 35% of district leaders report providing students with any training on AI use. Over 80% of students report that teachers did not explicitly teach them how to use AI for schoolwork. Only 45% of principals report having any school or district policy on AI use.

The pattern this data describes is not resistance. It is adoption without infrastructure. Teachers are using AI tools at significant and increasing rates. They are doing so without training, without policy guidance, and without curricular frameworks that integrate AI use into existing instructional practice.

B. The Training Gap by Poverty Level

RAND's American School District Panel data from fall 2024 documents a training disparity that mirrors the preparation gap documented elsewhere: 67% of low-poverty districts reported providing teacher training on AI use, compared to 42% of middle-poverty districts and 39% of high-poverty districts. The districts serving the students most in need of effective AI integration are the least likely to have provided their teachers with training to deliver it.

C. What the Research Says About Effective Professional Development

A 2025 Frontiers in Education systematic review of 23 peer-reviewed studies identified the characteristics that distinguish effective professional development from ineffective: collaborative learning environments, hands-on digital training, ongoing mentorship, and sustained institutional support. Programs aligned with teachers' specific classroom needs produce meaningfully greater implementation rates than general technology training or one-time sessions.

The MDPI systematic review of 43 empirical studies on teacher AI professional development needs found that technical training alone is insufficient across all study populations and contexts. Successful integration requires pedagogical knowledge, organizational support structures, and continuous rather than episodic professional development.

A 2026 systematic review of GenAI integration in teacher education programs found that initial teacher education programs have not yet systematically embedded AI literacy in their curricula. Teachers graduate from preparation programs without foundational AI competency. In-service professional development is being asked to compensate for a gap in pre-service preparation that the pre-service system itself has not yet addressed.

> *Teachers are curious and often optimistic about AI but systemic shortcomings in training, curriculum, and infrastructure prevent sustained pedagogical use. A readiness gap exists. Not a willingness gap.*

VIII. Infrastructure and Rural Disparity: The Rural Amplification Effect in Education

Six independent data sources, spanning federal administrative data, nationally representative surveys, and academic research, document the same pattern of rural infrastructure disadvantage with remarkable consistency. FCC broadband deployment data, USDA rural connectivity surveys, Pew Research Center household surveys, Ookla network performance analysis, NCES rural student connectivity data, and Michigan State University longitudinal research on broadband and student performance each approach the infrastructure gap from different methodological angles and converge on the same directional finding. The breadth of source agreement, spanning government, commercial, survey, and academic sources, is what allows this variable to be characterized as documented rather than inferred. The prior OCF workforce readiness series established the Rural Amplification Effect in the labor market context; this analysis extends the same finding upstream into K-12 education using the same multi-source convergence approach.

A. The Broadband Baseline

14.5M	Rural Americans without broadband access, per FCC data. Rural schools cannot offer equivalent online resources to urban counterparts.

22.3%	Rural Americans lacking terrestrial broadband coverage vs. 1.5% in urban areas, per USDA data.

32 states	States where the gap between urban and rural internet access grew in the second half of 2024, despite overall broadband availability increases.

The broadband gap is not closing. Ookla's 2024 analysis found that in 32 states, the differential between urban and rural internet access expanded even as overall availability increased. Infrastructure investment is reaching urban and suburban areas faster than rural ones. This is not a temporary condition. It is a widening one.

Michigan State University research on rural K-12 students found that students without home broadband scored lower on digital skills assessments, completed less homework, had lower GPAs, performed worse on the SAT and PSAT, and were less likely to pursue STEM careers or four-year college degrees. Absence of broadband is not a minor inconvenience in the current educational environment. It is a documented predictor of reduced academic performance across multiple dimensions.

B. The AI Use Disparity

Center on Reinventing Public Education data found that the gap between high-income and low-income family teen AI use reached 24 percentage points in 2025, double the 12-point gap documented in 2024. Nearly half of teens from highest-income families used AI for school. Only 19% of teens from lowest-income families did the same. The compounding velocity of this gap, doubling in a single year, suggests that absent structural intervention, AI literacy will track income stratification closely.

C. The Connection to Prior OCF Research

The geographic disparity documented here is continuous with OCF's workforce readiness series. The Skills Gap Is Here documented that rural communities receive approximately 7% of AI workforce development funding while comprising approximately 20% of the U.S. population. Already Left Behind documented the same Rural Amplification Effect in the Midwest. Growing. And Not Ready. documented it in South Dakota specifically.

What this paper adds is the upstream educational dimension: the workers who will arrive at a rural labor market already underinvested in AI workforce development are being educated in schools with less broadband, less computer science access, less teacher training, and less policy guidance than their urban and suburban counterparts. The preparation deficit is not acquired in the workforce. It begins in the classroom, compounds through K-12, and arrives in the labor market already accumulated.

> *The Rural Amplification Effect does not begin at the workforce entry point. It begins in the classroom. The preparation deficit is fully formed before graduation.*

IX. Synthesis: The Readiness Stack and Compounding Populations

The six variables documented in Sections III through VIII do not operate independently. They interact, and their interaction is not additive but multiplicative: the populations most affected by one variable are systematically the same populations most affected by the others. The methodology in Section II documented the convergence framework used to assess each variable individually. This section synthesizes across variables, examining where the evidence from independent sources converges on a common population-level pattern.

OCF's analytical framework organizes these compounding variables into a three-tier structure called the Readiness Stack. Tier 1, Foundational Readiness, encompasses the literacy, numeracy, and attendance baselines that learning recession and chronic absenteeism data measure. Tier 2, Digital Readiness, encompasses device access, broadband availability, and basic technology fluency that infrastructure data documents. Tier 3, AI Readiness, encompasses computational thinking, AI literacy, and practical skills that curriculum alignment and policy data show are widely absent. A student who has not cleared Tier 1 cannot access Tier 2. A student who has not cleared Tier 2 cannot access Tier 3. The compounding documented in this paper follows the structure of the stack.

The interaction between variables follows a documented directional sequence. Infrastructure deficits (Variable 5) create the conditions for learning stagnation and absenteeism (Variable 1), which produce the classroom-level academic deficits that policy frameworks would need to address. The absence of coherent policy frameworks (Variable 3) ensures that teacher training infrastructure is not deployed where it is most needed (Variable 4). Together, Variables 1 through 4 produce the credential-to-competency gap that manifests as the graduate employment and youth unemployment outcomes documented in the workforce data (Variable 2). The chain is not theoretical. Each link in it is independently documented in the source corpus.

The core structural tension of the system is expressible as a simple relationship:

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Systemic Friction = Delta(Macroeconomic Automation Velocity) -
Delta(Institutional Adaptation Velocity)
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The macroeconomic environment is changing at accelerating speed, driven by the deployment of automated workflows and the resulting contraction of entry-level labor market roles. The institutional counter-response is linear, fragmented, and weighted down by a stabilized 23% absenteeism rate and a learning recession that predates the pandemic by seven years. The direction of the friction vector is not ambiguous: institutional adaptation velocity is lower than macroeconomic automation velocity by a margin that is widening, not closing. The data does not describe a system in recovery. It describes a system undergoing permanent, stratified decoupling.

The learning recession that predates COVID established a Tier 1 baseline deficit. The COVID disruption deepened it and disrupted the school-based routines that had been compensating for it. Chronic absenteeism has prevented full re-engagement and continues to compound learning loss years after schools reopened. Students returning to classrooms with inadequate broadband, no computer science offerings, teachers without AI training, and no state AI guidance are returning to an environment not equipped to close the gap at any tier.

Variable	National Condition	Rural / Low-Income Amplification
Learning recession (Tier 1)	83% of districts lost reading ground 2015-2025	Slowest recovery in rural and low-income districts
Chronic absenteeism (Tier 1)	23.5% nationally vs. 15% pre-pandemic	High-poverty urban worst; rural elevated above 2019 baseline

Variable	National Condition	Rural / Low-Income Amplification
Curriculum misalignment (Tier 3)	51% of graduates lack sufficient AI skills	Rural schools less likely to offer CS; small schools cannot sustain specialized courses
Policy fragmentation (all tiers)	22 states with no AI guidance; 12 with CS graduation requirements	Rural districts least likely to generate guidance or pilot programs independently
Teacher support (all tiers)	68% received no AI training in 2024-25	High-poverty districts trail low-poverty districts in training by 28 points
Infrastructure disparity (Tier 2)	14.5M rural Americans without broadband	AI use gap doubled to 24 points between high- and low-income students in a single year

Table 1. Summary of variable conditions and rural / low-income amplification. Sources documented in individual sections above.

The populations for whom all six variables compound simultaneously are the same populations documented as most vulnerable in OCF's workforce research: rural students, low-income students, students on Tribal lands, and students in small schools in under-resourced districts. These are not different problems. They are the same structural disadvantage expressed at different points in the pipeline.

The graduate employment data, 51% of 2025 graduates with sufficient AI skills, 30% securing field-appropriate employment, 9.5% entry-level unemployment among young college graduates, represents the downstream expression of the upstream conditions documented here. What OCF terms Pipeline Collapse in the labor market context begins in the educational preparation context documented in this paper. The elimination of entry-level work as an informal second education system removes the safety net that had historically compensated for preparation gaps. As that tier of the labor market contracts, the preparation burden falls back on the educational system at the precise moment the educational system has accumulated significant preparation deficits.

The consistent finding across both this analysis and OCF's workforce readiness research is that Access as the Binding Constraint holds at every tier: it is not student motivation, worker willingness, or individual capacity that determines outcomes. It is access to quality infrastructure. In K-12 education, access means broadband, qualified teachers, current curriculum, and policy frameworks. Where access is absent, outcomes reflect that absence reliably.

> *Access as the Binding Constraint holds at every tier. It is not student motivation or individual capacity that determines outcomes. It is access to quality infrastructure. Where access is absent, outcomes reflect that absence reliably.*

Implications

For Funders

The data in this paper identifies specific points in the preparation pipeline where investment produces measurable outcomes. Broadband infrastructure investments have demonstrated educational performance correlations in rural settings. Teacher professional development programs with collaborative learning structures, contextual relevance, and ongoing mentorship produce higher implementation rates than one-time training events. The federal pandemic relief funding that drove high-poverty district academic recovery represents a natural experiment in access-based intervention: where the funding existed, outcomes improved. Where it was absent, they did not. Funders seeking to close the preparation gap have an evidence base for intervention design. The constraint is access infrastructure, not student or teacher capacity.

For State Education Boards and Policymakers

Twenty-two states have no formal K-12 AI guidance. Thirty-eight states do not require computer science for high school graduation. Four states connect AI literacy to computer science standards. The legislative trajectory suggests that requirements are coming, but the timeline means current students graduate before most new requirements reach them. State boards that are still developing guidance frameworks have a substantial body of implementation evidence from the 28 states that have issued guidance and the 12 that have enacted CS graduation requirements. The consistent finding in that evidence is that access to quality computer science instruction has plateaued except in states with graduation requirements. Standards produce access. Access produces outcomes.

For Rural Intermediaries and School Districts

The Rural Amplification Effect in education is structurally identical to the pattern OCF documented in workforce readiness: same exposure, fraction of the support infrastructure. Rural districts face the Readiness Stack from a position of Tier 2 deficits that urban and suburban districts have largely resolved. Broadband coverage, device access, and teacher recruitment pipelines are preconditions for Tier 3 development. Intermediary organizations operating in rural and Tribal contexts have an evidence base for sequenced intervention: Tier 1 and Tier 2 infrastructure gaps must be addressed before Tier 3 curriculum integration is practically achievable. Attempting to introduce AI literacy programming into classrooms without broadband and without trained teachers produces the pattern the current data documents: adoption without infrastructure, exposure without competency.

What the Research Agrees On

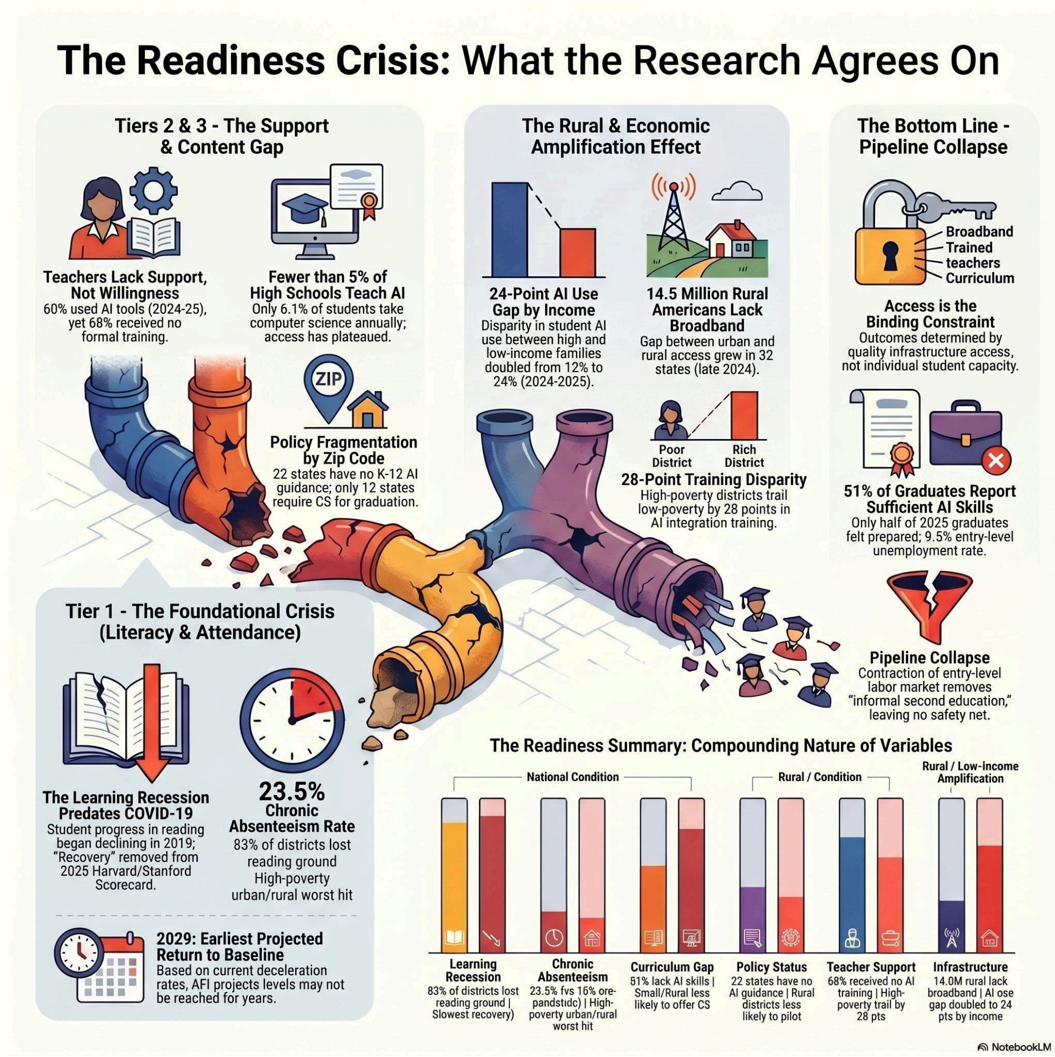

Figure 4. The Readiness Crisis: What the Research Agrees On. OCF / NotebookLM, 2026

The following conclusions are drawn from multiple independent sources across different methodologies. They represent the settled findings of the current corpus, not contested interpretations.

1. The learning recession predates COVID-19.

The Harvard/Stanford Education Scorecard explicitly documents that student progress in reading began declining in 2013. NAEP trend data corroborates this. COVID accelerated a pre-existing trajectory. Framing the problem as pandemic recovery understates the scope of the structural challenge.

2. Chronic absenteeism has not recovered to pre-pandemic levels and may not.

AEI's Return to Learn Tracker, covering 41 states longitudinally, projects that pre-pandemic absenteeism baselines may not be reached until 2029 and potentially not at all if deceleration continues. RAND and Harvard Scorecard data confirm this independently. 94.7% of U.S. students attend a district with absenteeism above its 2019 level.

3. Teacher adoption is constrained by support gaps, not willingness.

Three independent systematic reviews, covering 23, 43, and a broader 2026 corpus of empirical studies, converge on the finding that teachers are curious and often positive about AI but that technical training alone is insufficient and institutional support structures are the binding variable. RAND survey data confirms the pattern at national scale.

4. Rural and low-income students face compounding barriers at every tier.

Federal data from FCC, USDA, and NCES, combined with Pew broadband surveys, Ookla access analyses, and RAND poverty-stratified training data, establish consistent patterns at every level of the Readiness Stack. The Rural Amplification Effect is documented in this paper's data as it was in OCF's workforce research.

5. Graduate AI skill deficits are measurable and documented at significant scale.

The Cengage 2025 Graduate Employability Report, in its fifth year with consistent methodology, finds 51% of graduates reporting sufficient AI skills. This figure, combined with the 9.5% entry-level youth graduate unemployment rate and the Code.org finding that fewer than 5% of high schools include any AI content, constitutes a coherent cross-source pattern rather than a single-source finding.

6. Access to quality instruction, not student motivation, is the binding constraint.

This finding holds across the workforce readiness series and the education data in this paper. Federal pandemic relief data demonstrates it directly: where funding provided access to additional instructional resources, high-poverty districts improved. The mechanism is access, not capacity.

The Bottom Line

The Harvard/Stanford Education Scorecard removed the word 'Recovery' from its title. That is the finding, stated by the researchers who have spent five years looking at the district-level data across 35 million students. The problem is not recovering from a disruption. The problem predates the disruption, was worsened by it, and has not structurally improved enough to warrant a recovery frame. The work ahead is not restoration. It is something more fundamental.

Six variables compound in the populations that are least equipped to absorb them. Rural students, low-income students, students on Tribal lands, students in small schools in under-resourced districts. The Readiness Stack cannot be climbed from a position of Tier 2 deficits. Access to Tier 3 AI literacy requires Tier 2 digital infrastructure. Tier 2 digital infrastructure requires broadband. Broadband access is widening relative to urban peers in 32 states. The compounding is not theoretical. It is measured.

Teachers are using AI tools without training, without policy frameworks, without curricular structures that make integration practical rather than additional. They are doing this because they are professionals attempting to serve students in a rapidly changing environment. The failure to prepare and support them is a system failure, not a personnel failure. The distinction matters for where solutions must be directed.

The graduate employment data is not an aberration. Fifty-one percent of 2025 graduates with sufficient AI skills for the jobs they applied to is the downstream output of an upstream preparation system that has not adapted. Entry-level youth unemployment at 9.5% is the labor market expression of the educational conditions documented in this paper. These numbers will continue to reflect those conditions until the conditions change.

This paper is the first in a three-part series. The Midwest regional and South Dakota analyses that follow apply the same framework at decreasing geographic scales, consistent with the methodology of the workforce readiness trilogy. The findings will not improve as the geography narrows. The Rural Amplification Effect ensures they will not.

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Model Reference Appendix

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