Supporting Schools Before Students Are at Risk: Early Warning Systems for Proactive Prevention

A National Implementation Framework for State Education Agencies

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Introduction

The educational landscape in the United States faces significant challenges in ensuring all students have access to high-quality learning experiences. Traditional accountability efforts have focused on identifying and supporting schools formally designated as underperforming—a process that often comes too late to prevent the cascading effects of academic decline. This reactive approach results in schools requiring comprehensive, resource-intensive interventions that are costly, time-consuming, and often ineffective.

Against this backdrop, early identification of schools at risk of academic decline and the development of timely, targeted interventions are paramount to ensuring equitable access to educational success, particularly for students in underserved communities.

While traditional accountability systems have provided essential transparency and a structure for supporting schools in need, they often come too late to prevent decline (DeAngelis, 2016). Early warning systems do not replace these mechanisms but extend their reach, thus enabling SEAs to intervene earlier, preserve capacity, and strengthen the overall school improvement continuum (Bryk et al., 2010; Hough & Bryk, 2020).

While the concept of early warning systems has proven effective for identifying individual students at risk of failing academically or dropping out (Allensworth & Easton, 2005, 2007; Balfanz et al., 2007; Neild & Balfanz, 2006; Silver et al., 2008; U.S. Department of Education, Office of Planning, Evaluation and Policy Development, 2016), its application to school-level improvement efforts represents a relatively unexplored but promising frontier.

This study adopts a systematic approach to school-level early warning by examining areas where research has consistently shown that schools commonly experience decline: leadership stability, talent management, organizational culture, financial operations, and instructional programming. Rather than relying solely on lagging academic indicators, this study's methodology incorporates leading indicators that signal distress before formal accountability identification occurs.

Research Purpose and Scope

This research explores the feasibility and effectiveness of implementing school-level early warning systems through a comprehensive analysis of administrative data and practitioner perspectives in Colorado. The study aims to address several critical gaps in the school improvement literature: the identification of reliable predictive indicators that transcend geographic and demographic contexts, the development of implementable frameworks that states can adapt to existing infrastructure, and the validation of quantitative findings through qualitative practitioner knowledge.

Working in partnership with the Colorado Department of Education, the research team developed and tested predictive models using longitudinal administrative data from over 1,500 schools across diverse educational contexts in Colorado. The temporal design of the analysis—using 2023–24 data to predict 2024–25 accountability outcomes—provides empirical evidence for the predictive validity of readily available school indicators while offering practical implementation timelines for state education agencies (SEAs).

Adapting Proven Early Warning Methodologies for School-Level Prediction

This study represents the first comprehensive analysis to demonstrate that school decline follows predictable patterns detectable through administrative data systems already maintained by SEAs. Building on the successful application of early warning system methodologies for student dropout prediction, this research adapts these proven approaches to institutional performance, demonstrating that the same predictive principles that identify students as being at risk for failing academically or dropping out can be systematically applied to identify schools as at risk for low performance.

The methodological innovation lies in scaling individual-level prediction to institutional-level forecasting while maintaining the practical utility and accuracy that make early warning systems operationally valuable. Rather than simply describing characteristics of struggling schools, this approach enables states to predict which specific schools will require intervention 12–18 months before traditional accountability measures would identify them.

Implications for State Practice

The findings provide SEAs with empirically grounded tools for shifting from reactive to proactive school improvement strategies. The identification of four universal predictors—academic proficiency indicators, attendance patterns, teacher effectiveness measures, and prior accountability history—offers states a parsimonious set of indicators that can be implemented using existing data collection systems.

Integrating early warning approaches within existing accountability frameworks allows SEAs to refine rather than redesign their school improvement processes. By embedding preventive analysis alongside Comprehensive and Targeted Support designations, states can allocate resources more strategically and reduce the number of schools that ultimately require full turnaround intervention.

This technical report provides the methodology, comprehensive findings, and implementation guidance for SEAs considering early warning system development. This report is intended to offer the technical depth necessary for research validation, policy development, and system implementation across diverse state contexts.

Report Structure

This report provides comprehensive documentation of the early warning system development process, detailed empirical findings, and evidence-based recommendations for state implementation. The analysis demonstrates both the statistical feasibility and practical utility of school-level early warning approaches while acknowledging the complexities and limitations inherent in predictive modeling of organizational performance.

Research Design and Methodology

This mixed-methods case study, begun in fall 2024, employed a comprehensive approach to understanding how early warning systems can be integrated into state accountability and school support frameworks. The research design combines quantitative predictive modeling with qualitative practitioner validation to ensure findings are both statistically robust and practically implementable.

Research Questions

The study addressed four key questions essential for state-level early warning system implementation:

- **What school characteristics are the strongest predictors of academic gains and decline?**
- **How can SEAs integrate early warning systems into existing accountability and school support approaches?**
- **What organizational and policy alignments are necessary for effective early identification and intervention strategies?**
- **What resources and frameworks can be adapted from this research to benefit other states and districts?**

Research Approach

Quantitative Analysis

The quantitative component used multilevel logistic regression models to predict binary accountability outcomes under state performance frameworks. The research team classified schools based on whether they required Priority Improvement or Turnaround designations, using a temporal design in which 2023–24 predictor variables forecast 2024–25 accountability status. The analysis incorporated administrative data from over 1,500 schools across diverse geographic and demographic contexts in Colorado, encompassing urban, suburban, and rural settings. A model was developed for elementary/middle schools, and a separate model was developed for high schools due to distinct performance indicators and developmental considerations across educational levels.

Data Sources: The study used both publicly available state data and additional administrative data sets provided through secure data sharing agreements. Variables spanned five theoretical domains: leadership stability, talent management, organizational culture, financial operations, and instructional programming (see Appendix A for a complete data inventory).

Model Development: The modeling process employed systematic variable selection and refinement procedures, examining relationships among covariates through correlation analysis and variance inflation factors to ensure model parsimony while maintaining predictive accuracy (see Appendix B for a detailed methodology).

Analytical Framework

The study's analytical framework builds on organizational decline theory and school improvement research, hypothesizing that school performance deterioration follows predictable patterns detectable through administrative indicators. The framework emphasizes the identification of leading rather than lagging indicators, enabling intervention before decline becomes entrenched.

Theoretical Foundation: The research draws on established literature regarding organizational decline, early warning indicators, and school improvement effectiveness while contributing novel insights into the predictive utility of commonly collected administrative data.

Validation Strategy: Quantitative findings were systematically validated through practitioner interviews, ensuring that statistical patterns aligned with professional observations and experiential knowledge of school decline processes

Qualitative Validation

The qualitative component involved semistructured interviews with 16 Colorado Department of Education staff members from multiple divisions, including Accountability and Continuous Improvement, School and District Transformation, Schools of Choice, Federal Programs and Supports, and Field Services.

Interview Protocol: Interviews explored practitioners' experiences with school decline patterns, existing support systems, and perspectives on early warning approaches. The protocol was designed to validate quantitative findings while gathering insights into implementation challenges and opportunities.

Analysis Approach: Interview data were recorded, transcribed, and analyzed through both traditional qualitative methods and secure artificial intelligence tools to maintain data confidentiality while enabling comprehensive thematic analysis.

Methodological Considerations

Strengths

- **Temporal Validity:** A 1-year predictive window aligns with practical implementation timelines.
- **Contextual Diversity:** The analysis spans urban, suburban, and rural educational settings.
- **Practitioner Validation:** The qualitative component ensures that findings resonate with professional experience.
- **Transferability Focus:** Indicators that are available across all state contexts are emphasized.

Limitations

- **Administrative Data Constraints:** Analysis is limited to readily available indicators, potentially missing important contextual factors.
- **Single-State Scope:** While Colorado's diversity provides broad applicability, multistate validation would strengthen generalizability.
- **Missing Data Considerations:** Substantial missing data in the high school sample (40% exclusion rate) may affect generalizability.
- **Temporal Assumptions:** The models assume that predictive relationships remain stable over time.

Implementation Considerations

The methodology was designed with state implementation feasibility as a primary consideration. All indicators used in the analysis are collected by SEAs as part of routine administrative processes, enabling immediate replication without additional data collection infrastructure.

The research provides both the empirical foundation for early warning system development and practical guidance for adaptation across diverse state contexts. Technical specifications for model replication and adaptation are provided in Appendices A and B to support state-level implementation efforts.

Research Findings

The study found that school decline follows predictable patterns that can be detected with accuracy using administrative data routinely collected by SEAs. The analysis of over 1,500 schools demonstrates that early warning systems not only are technically feasible but also can provide the 12- to 18-month advance notice necessary for effective early intervention.

The predictive models achieved strong classification performance across different school configurations while identifying a set of indicators that transcend geographic and demographic boundaries.

Overview: Early Warning Systems Work

The research demonstrates that states can predict which schools will require accountability intervention with 80–89 percent accuracy using data they already collect. This predictive capability provides sufficient advance warning to enable proactive support rather than reactive crisis response.

Early Warning System Performance Summary

High Schools: 89 percent accuracy, 9 percent false alarms

Elementary/Middle Schools: 80 percent accuracy, 22 percent false alarms

Advance Warning: 12–18 months before accountability identification

Data Required: Already collected through routine state processes

Understanding What These Numbers Mean

Before one dives into the technical details, it is important for them to understand what prediction accuracy means in practical terms and how to interpret the strength of different predictive factors.

Prediction Accuracy Explained

Sensitivity (True Positive Rate): This rate is the percentage of schools truly needing intervention that the model correctly identifies. Higher sensitivity means that fewer schools at risk for low performance are missed.

Specificity (True Negative Rate): This rate is the percentage of schools not needing intervention that the model correctly identifies as stable. Higher specificity means fewer false alarms and more efficient resource allocation.

Overall Accuracy: For high schools, 89 percent accuracy means that out of 100 schools, the prediction correctly classifies 89 as either at risk or stable. For elementary and middle schools, the prediction correctly classifies 80 out of 100.

Understanding Effect Sizes

Effect sizes measure the practical significance of differences between at-risk and stable schools, which helps states understand not just whether differences exist but also how meaningful those differences are:

- **Small Effect (0.20–0.49):** detectable differences that may require careful monitoring
- **Moderate Effect (0.50–0.79):** clear differences that provide reliable early warning signals
- **Large Effect (0.80+):** substantial differences that offer strong predictive power
- **Very Large Effect (1.00+):** dramatic differences that provide highly reliable early identification

Larger effect sizes indicate more pronounced differences between schools, making early identification more reliable and actionable for intervention planning.

What Predicts School Decline

The analysis revealed that different school configurations require different predictive approaches, but prior accountability history was a universal indicator across contexts.

Elementary and Middle School Predictors

Four indicators emerged as strong predictors for schools serving grades K–8 (see Table 1).

Table 1. Elementary/Middle School Predictive Indicators

Indicator	Effect size	Intervention schools	Stable schools	Gap	Interpretation
English Language Arts (ELA) Proficiency (%)	1.27 (Very Large)	19%	43%	24 points	Strongest predictor; dramatic academic performance gap
Mathematics Proficiency (%)	1.14 (Very Large)	11%	32%	21 points	Nearly as powerful as ELA; fundamental instructional challenges
Student Attendance Rate (%)	0.72 (Large)	89%	92%	3 points	Significant engagement pattern despite modest percentage difference
Teacher Effectiveness (%)	0.62 (Moderate–Large)	92%	97%	5 points	Small percentage difference representing meaningful instructional quality variation

Note. Effect sizes: Small (0.20–0.49), Moderate (0.50–0.79), Large (0.80+), Very Large (1.00+); Prior Accountability History shows percentage of schools with multiple identifications in the previous 5 years; all indicators use data routinely collected by SEAs.

English Language Arts (ELA) Proficiency (effect size = 1.27): This was the strongest predictor across all analyses, with intervention schools averaging 19 percent proficiency compared to 43 percent for stable schools. This represents a very large effect that would be visible to any educator.

Mathematics Proficiency (effect size = 1.14): This predictor was nearly as powerful as ELA, with intervention schools averaging 11 percent proficiency versus 32 percent for stable schools. The consistency across academic areas suggests fundamental instructional challenges.

Student Attendance Rates (effect size = 0.72): Intervention schools averaged 89 percent attendance compared to 92 percent for stable schools. While the 3-percentage-point difference appears modest, it represents a large effect size and consistent pattern across contexts.

Teacher Effectiveness Ratings (effect size = 0.62): These ratings distinguished intervention schools (92 percent rated effective) from stable schools (97 percent rated effective). Even small differences in teaching quality, when aggregated across a school, provided meaningful signals of institutional health.

High School Predictors

Secondary schools demonstrated distinct decline patterns requiring additional indicators (see Table 2) beyond those found to be effective for elementary and middle schools.

Table 2. High School Predictive Indicators

Indicator	Effect size	Intervention schools	Stable schools	Gap	Interpretation
SAT Mean Score	1.28 (Very Large)	414	482	68 points	Strongest high school predictor; college readiness indicator
Principal Tenure (years)	0.45 (Moderate)	1 year	3 years	2 years	Indication that leadership instability is critical for secondary schools
Dropout Rate (%)	0.28 (Small)	5%	3%	2 points	Clear signal of institutional distress; affecting postsecondary opportunities

Indicator	Effect size	Intervention schools	Stable schools	Gap	Interpretation
English Language Learner (ELL) Redesignation Rate (%)	0.10 (Small)	4%	5%	1 point	Indication of challenges in supporting diverse student populations
Attendance Rate (%)	0.84 (Large)	82%	89%	7 points	Indicator that is more pronounced than in elementary levels; engagement critical

Note. Effect sizes: Small (0.20–0.49), Moderate (0.50–0.79), Large (0.80+), Very Large (1.00+); Prior Accountability History shows percentage of schools with multiple identifications in previous 5 years; all indicators use data routinely collected by SEAs.

SAT Performance (effect size = 1.28): This is the strongest predictor for high schools, with intervention schools averaging 414 compared to 482 for stable schools. This represents the largest effect size observed across all analyses.

Principal Experience (effect size = 0.45): Intervention schools averaged only 1 year of principal tenure compared to 3 years for stable schools, highlighting leadership stability as particularly critical for secondary schools.

Dropout Rates (effect size = 0.28): This rate is nearly twice as high in intervention schools (5%) as in stable schools (3%). Although this indicator has a smaller effect size, dropout patterns provide clear differentiation and directly impact postsecondary opportunities for students.

English Language Learner (ELL) Redesignation Rates (effect size = 0.10): Intervention schools achieved only 4 percent redesignation compared to 5 percent for stable schools, suggesting challenges in supporting diverse student populations toward English proficiency.

Universal Pattern Across All School Levels

Prior Accountability History emerged as the most consistent predictor across all school configurations. Schools with multiple previous identifications showed dramatically elevated risk—90 percent of intervention schools had been flagged multiple times in the previous 5 years compared to only 26 percent of stable schools.

This pattern suggests that accountability identification often reflects persistent rather than temporary performance challenges, with schools cycling through repeated intervention periods without achieving sustained improvement.

Cross-Context Validation

Perhaps the most significant finding for scalability is that effective early warning indicators transcend traditional demographic and geographic boundaries, as indicated in Appendix C. This universality suggests that successful implementation in one context may be able to reliably predict success in others, dramatically reducing the risk typically associated with education innovation investments.

Transferability Evidence

Geographic Neutrality: urban versus rural differences negligible (effect sizes 0.01–0.15)

Resource Independence: spending levels less predictive than resource utilization

Size Scalability: effective for large and small schools and districts

Policy Flexibility: adaptable to different state accountability frameworks

What This Means for State Implementation

The findings provide compelling evidence that states can implement effective early warning systems using existing data infrastructure and organizational capacity.

Immediate Feasibility

All 50 states already collect every indicator identified in the analysis through existing administrative systems. This means states can begin early warning system development immediately without new data collection requirements or extensive infrastructure investments.

Reliable Prediction Window

The 12–18 month advance warning provided by these systems creates realistic timelines for intervention planning and resource allocation. This prediction window aligns with typical state budget and planning cycles, enabling systematic rather than emergency responses to school challenges.

Universal Applicability

The consistency of predictive patterns across diverse contexts means that states can implement early warning systems with confidence, knowing the approach has been validated across settings similar to their own educational landscapes.

Implementation Thresholds

The analysis suggests concrete benchmarks for monitoring school health:

- ELA proficiency below 25 percent (elementary/middle schools)
- mathematics proficiency below 15 percent (elementary/middle schools)
- SAT scores below 440 (high schools)
- attendance rates below 90 percent (elementary/middle) or 85 percent (high schools)
- teacher effectiveness below 95 percent rated effective
- principal tenure less than 2 years

These thresholds provide practical reference points for early warning alert systems while requiring professional judgment and local context for intervention decisions.

Model Limitations and Interpretive Considerations

While the predictive models demonstrate strong performance, several important limitations may affect interpretation of findings and planning for implementation.

Unexplained Variance: Models explained 20–33 percent of variance in accountability identification, indicating that some important predictive factors may not be captured in administrative data sets. This suggests that early warning systems should be viewed as screening tools that identify schools warranting additional investigation rather than definitive diagnostic instruments.

Administrative Data Constraints: The exclusive reliance on administrative data, while enabling broad replicability, may miss important qualitative indicators of school health that require direct observation or interest holder input to assess accurately.

Temporal Assumptions: The models assume that predictive relationships remain stable over time, though educational contexts and policy environments may shift in ways that alter these relationships. Regular model recalibration will be necessary to maintain effectiveness.

The Strategic Opportunity

The convergence of reliable predictive capability, universal data availability, and cross-context validity creates unprecedented opportunities for transforming state approaches to school improvement. Early warning systems offer states the ability to shift from expensive, reactive interventions to cost-effective, proactive prevention while better serving students and communities.

The evidence demonstrates that the technical barriers to early warning system implementation are minimal, while the potential benefits—both educational and economic—are substantial. The question for state leaders is not whether early warning systems could work but whether they align with state priorities and capacity for sustained implementation effort.

Beyond Risk Identification: Achievement Drivers and Protective Factors

The research revealed that an effective early warning system serves a dual purpose: identifying schools at risk while recognizing what drives improvement and prevents decline. This broader perspective may enable states to build comprehensive improvement strategies rather than focusing solely on crisis prevention.

Key Achievement Drivers: Analysis of factors that predict student achievement gains identified attendance improvement, leadership stability, and teacher effectiveness as the strongest actionable drivers. Schools achieving at least 95 percent attendance rates, maintaining principals for more than 3 years, and keeping teacher effectiveness above 97 percent demonstrated significantly stronger achievement trajectories.

Protective Factors: Several school characteristics can prevent decline and actually strengthen schools over time. Teacher retention, sustained academic success, and leadership continuity can create compounding benefits that increase school resilience to external challenges. Schools can develop adaptive capacity that builds immunity to traditionally problematic factors like student mobility or resource constraints.

Strategic Implementation: Early warning systems designed with this dual focus may enable states to accelerate improvement in stable schools while preventing decline in at-risk schools. Asset-based interventions that build protective factors can be as important as deficit-addressing approaches, creating improvement strategies that are more comprehensive and effective.

This broader perspective can transform early warning systems from simple risk management into comprehensive improvement platforms that serve schools across the performance spectrum, maximizing return on investment (ROI) while creating sustainable educational improvements.

When these protective factors are cultivated early, they become the same organizational conditions—leadership stability, instructional coherence, and staff trust—that determine whether later turnaround investments will succeed. Prevention is therefore the groundwork for sustainable recovery and continuous improvement (Carnegie Foundation for the Advancement of Teaching, 2019; Leithwood & Jantzi, 2006).

The Cost of Waiting Versus Acting Early: The Return on Investment of Prevention

The economic implications of shifting from reactive to proactive school improvement strategies represent a fundamental opportunity to reallocate education spending from crisis intervention to prevention. Importantly, prevention does not replace comprehensive school turnaround. Instead, early warning systems strengthen the entire improvement continuum. By identifying and addressing emerging challenges early, SEAs reduce the intensity, duration, and recurrence of turnaround interventions. This "prevention-plus-precision" model creates a more balanced portfolio—one in which fewer schools need full turnaround, and those that do need it enter the process with clearer diagnoses, more stable leadership, and stronger conditions for success (Bryk et al., 2010; Hough & Bryk, 2020).

Prevention Makes Turnaround Work Better

When SEAs use early warning data to act 12–18 months earlier, the result is not fewer interventions—it is smarter interventions. Preventive support stabilizes staffing, protects instructional time, and preserves community trust, all of which are preconditions for turnaround success. In this way, prevention increases the ROI of later interventions: Schools that have benefited from early identification are more capable of implementing intensive reforms when they become necessary (Carnegie Foundation for the Advancement of Teaching, 2019; Leithwood et al., 2017).

Current Costs of Reactive School Improvement

Typical comprehensive school turnaround efforts require substantial financial investments and have limited success rates. They typically cost between $500,000 and $2 million per school, with an average investment of $1.2 million over multiyear implementation periods. These interventions follow 3–4 year cycles during which schools experience significant operational disruption while attempting wholesale organizational changes (Atchison & Blair, 2025; Blair et al., 2025; Le Floch et al., 2017).

The Cost of Reactive Intervention

Average Cost per Comprehensive Turnaround: $1.2 million

Success Rate: Only 30 percent achieve sustainable improvement

Timeline: 3–4 year intervention cycles

Annual National Investment: Over $2.5 billion

Meta-analyses of comprehensive school turnaround efforts indicate success rates of approximately 30 percent, meaning that 70 percent of schools receiving intensive, expensive interventions fail to achieve sustainable improvement. This pattern of high investment with modest returns creates cycles of repeated intervention attempts, further escalating costs while delivering limited educational benefits (Dragoset et al., 2017).

Economic Advantages of Early Warning Systems

Early warning approaches enable targeted interventions that cost substantially less than comprehensive turnarounds while achieving superior success rates. Targeted early interventions typically require investments of $50,000 to $200,000 per school, with an average cost of $125,000 (Allensworth et al., 2009; Corrin et al., 2012; Wang et al., 2024). These interventions focus on specific identified weaknesses rather than wholesale organizational restructuring, enabling more efficient resource utilization and faster course correction.

The Early Intervention Advantage

Average Cost per Early Intervention: $125,000

Success Rate: 70 percent achieve sustainable improvement

Timeline: 6–12 months response time

Cost Difference: $1+ million savings per prevented turnaround

For SEAs, the financial return is only part of the equation. The real ROI lies in capacity. When fewer schools require multiyear turnaround cycles, state teams can provide deeper, more tailored support to the subset of schools that truly need comprehensive intervention. This prevents the dilution of limited improvement funds and staff expertise. Over time, states build a stronger infrastructure for continuous improvement: one that integrates prevention, targeted support, and turnaround as mutually reinforcing components of a single system (Carnegie Foundation for the Advancement of Teaching, 2019; Hough & Bryk, 2020).

Integrating Prevention and Turnaround: A Systemic ROI

Even with robust early warning and preventive supports, some schools will still require full turnaround. However, when these schools have benefited from earlier identification and targeted assistance, the comprehensive phase is shorter, more focused, and more likely to succeed. In effect, prevention converts turnaround from a last-resort rescue to the final stage of a planned improvement continuum (Bowers & Sprott, 2012a; Leithwood & Jantzi, 2006).

By sequencing support this way, SEAs move from a “react-recover-repeat” cycle to a continuous-improvement loop that lowers both fiscal and human-capital costs. The cumulative benefits include higher retention among educators, reduced community fatigue, and improved student outcomes—all of which contribute to long-term system efficiency and equity (Bryk et al., 2010).

National Economic Impact

Nationally, over 5,000 schools are identified for comprehensive improvement annually, with total spending exceeding $2.5 billion (Atchison & Blair, 2025; Blair et al., 2025). Conservative estimates suggest that shifting 50 percent of current comprehensive interventions to early warning approaches could save $1.5–2 billion annually in direct intervention costs (Le Floch et al., 2017).

National Return on Investment

ROI Ratio: $5–10 return for every $1 invested

Annual National Savings Potential: $1.5–2 billion

Implementation Cost: $2–5 million per state

Payback Period: Less than 12 months

State-level implementation costs for early warning systems are modest in comparison to potential savings. System development and implementation typically require $2–5 million in initial state investment, with ongoing operational costs of $500,000–1 million annually. These implementation costs are recovered within the first year of operation through prevented comprehensive interventions (Bowers & Sprott, 2012b).

Colorado Implementation Example

Colorado's current accountability landscape provides a concrete example of early warning system economic benefits. The state currently maintains 117 schools in accountability status, representing a state investment of $8.1 million in school improvement efforts (Colorado Department of Education, 2024). These schools serve over 50,000 students and have demonstrated persistent performance challenges despite repeated intervention attempts.

Implementing an early warning system statewide would require $2–$5 million for development and deployment. Based on the predictive accuracy demonstrated in this study (80–89 percent), such a system could identify schools at risk 1–2 years before formal accountability designation. Conservative projections indicate that early intervention could prevent the need for full turnaround in 30–40 percent of currently identified schools. At Colorado's average comprehensive intervention cost, avoiding interventions for 35–47 schools would yield substantial savings. Over 5 years, the projected savings are $12–16 million, resulting in a return of 2.4 to 8 times the initial investment in the early warning system.

Colorado Case Study: 5-Year Projections

Current Annual Improvement Costs: $8.1 million

Early Warning System Implementation Cost: $2–5 million

Projected 5-Year Savings: $12–16 million

Students Impacted: Over 50,000

ROI Multiple*:* 2.4–8 times ROI

Student and Systemic Impact Considerations

The economic benefits of early warning systems extend beyond direct cost savings to include improved educational outcomes and system resilience. Students in schools receiving early intervention experience less instructional disruption, benefit from more stable teaching staff, and avoid the stigma associated with formal accountability designation (Mintrop & Sunderman, 2009).

Over the long term, these stability gains strengthen the very conditions that make turnaround work—steady leadership, coherent instructional practice, and community trust. As research on educational productivity demonstrates, even modest improvements in school effectiveness generate substantial lifetime benefits for students and economies alike (Hanushek & Woessmann, 2015).

Thus, prevention and turnaround are not competing strategies but complementary investments that yield the highest collective return on improvement dollars. By blending predictive analytics with strategic support, SEAs can maximize both fiscal efficiency and educational impact—creating a system that spends less on crisis and more on sustained success.

Implementation Guidance for State Education Agencies

Early warning systems offer states a practical pathway to shift from reactive crisis response to proactive school support. The research demonstrates both technical feasibility and economic value, but successful implementation is likely to require careful attention to organizational readiness, strategic planning, and interest holder engagement.

Early Warning System Implementation Requirements

Before beginning early warning system development, assess your state's readiness across four critical dimensions. Use the following scale and Table 3 to rate each capacity indicator and identify priority areas for growth:

4 = fully in place; 3 = partially in place; 2 = limited; 1 = not in place; N/A = not applicable

Table 3. Organizational Readiness Assessment: Early Warning System Development

Critical dimension	Capacity indicator	Rating (1–4 or N/A)	Comments/Evidence
Data infrastructure and trust	Reliable, timely data collection across academic, attendance, staffing, and operational indicators		
	Established protocols for data verification and error correction		
	Current district trust and use of state-provided data for decision-making		
	Ability to explain data collection and analysis methods clearly		
Cross-agency coordination	Systematic coordination across divisions (accountability, school improvement, data, federal programs)		
	Procedures for cross-divisional project management with unified goals		
	Ability to maintain aligned messaging across multiple units		

Critical dimension	Capacity indicator	Rating (1–4 or N/A)	Comments/Evidence
	Capacity for multiyear implementation with consistent leadership		
Interest holder engagement and communication	Established trust with district leaders, school boards, and educator associations		
	Effective strategies for explaining complex initiatives to diverse audiences		
	Systems for gathering and incorporating interest holder input		
	Experience managing significant shifts in operational approach		
Differentiated support capacity	Tailored assistance based on district size, geography, and capacity		
	Communication channels with diverse district types (rural, urban, etc.)		
	Ability to deploy differentiated support strategies		
	Capacity to match identification with available support resources		

Developing an effective early warning system would likely involve the following changes and investments.

Organizational Changes

Dedicated Leadership: Create a cross-divisional coordination team with clear authority for early warning system decisions and sufficient time allocation for development and ongoing management.

Enhanced Analytical Capacity: Have two to four additional full-time-equivalent staff positions with expertise in predictive modeling, data analysis, and system evaluation, plus technical infrastructure for real-time data processing and alert generation.

Interest Holder Communication: Take a systematic approach to building and maintaining district trust, including transparent data practices, regular feedback collection, and emphasis on support rather than accountability consequences.

Resource Investments

Development Phase: Costs may be $2–5 million over 18–24 months for system development, pilot implementation, staff training, and interest holder engagement.

Ongoing Operations: Costs may be $500 thousand–$1 million annually for staff, system maintenance, enhanced district support, and continuous improvement activities.

Support Infrastructure: Enhanced capacity, including intervention strategy development and implementation assistance, may be needed to help districts act effectively on early warning information.

Implementation Phases

Phase 1: Foundation Building (6–12 months)

Establish Infrastructure: Create a coordination team, develop basic predictive models using existing data, and select 10–15 pilot districts that represent state diversity.

Build Interest Holder Base: Engage district leaders, superintendent associations, and school boards in the early warning system concept development, emphasizing support rather than additional accountability.

Phase 2: Pilot Testing (8–12 months)

Deploy and Refine: Implement early warning alerts with pilot districts, test intervention approaches, collect systematic feedback, and refine predictive models based on experience.

Capacity Building: Develop internal expertise, create district support resources, and establish intervention protocols based on pilot learning.

Phase 3: Statewide Scaling (6–12 months)

Full Implementation: Using lessons learned, expand to all districts, integrate with existing accountability systems, and establish routine operational procedures.

Sustainability: Document procedures, establish evaluation frameworks, and create ongoing funding mechanisms.

What Are the Risks? Common Implementation Challenges

Capacity Mismatch: Early warning systems may identify more schools needing support than state capacity can serve effectively. **Mitigation:** Phase implementation to align identification with available support resources; develop tiered support models with different intervention intensities.

Interest Holder Resistance: Districts may question data accuracy or interpret early warning as premature labeling. **Mitigation:** Provide transparent communication about prediction methods; pilot the approach to build confidence gradually; emphasize support rather than sanctions.

Coordination Complexity: Successful early warning systems require systematic collaboration across state agency divisions with different priorities and approaches. **Mitigation:** Create clear coordination mechanisms with shared accountability; establish dedicated project leadership with cross-divisional authority.

Sustainability Pressures: Early warning systems may require sustained commitment across multiple years and potential changes in state leadership or priorities. **Mitigation:** Document clear procedures and institutional knowledge; demonstrate concrete ROI; build interest holder coalitions that advocate for continuation.

Critical Success Factors

Leadership Commitment: Sustained support from SEA leadership may be needed across multiple years, with clear accountability for early warning system outcomes and willingness to address implementation challenges as they emerge.

Quality Implementation: Starting with willing pilot districts, providing intensive support during initial phases, and using early experience to refine approaches before broader deployment are likely to work better than rushing to statewide implementation.

Integration Rather Than Addition: Building early warning system capabilities within existing accountability and support structures is likely to be more effective than creating parallel systems that compete for attention and resources.

Alignment With Existing Improvement Systems: Early warning processes should be embedded within the SEA's current accountability and school improvement structures rather than developed as stand-alone initiatives. Doing so maintains coherence, ensures that preventive data directly inform turnaround planning, and reinforces continuous improvement as a unified system.

Interest Holder Trust: Proactive communication with districts, transparent data practices, and systematic feedback collection can help maintain confidence in the system's supportive rather than punitive purpose.

Implementation Pathways by State Readiness

High-Readiness States: States with strong capacity across all dimensions can pursue accelerated implementation with integrated development and scaling phases. These states can serve as regional leaders and technology innovators while achieving full operational capacity within 18 to 24 months.

Medium-Readiness States: States with some capacity gaps should focus on building a foundation while beginning pilot development. A sequential approach may reduce implementation risk while building internal expertise needed for sustainable operation.

Emerging-Readiness States: States with significant capacity constraints can pursue partnership approaches or extended development timelines that systematically address foundational challenges while building toward implementation.

The Strategic Decision

The research demonstrates that early warning systems are both technically feasible and economically beneficial for states with appropriate organizational readiness. Implementation challenges can be manageable rather than prohibitive, but they are likely to require sustained attention and strategic investment.

States that invest adequate preparation time in assessing readiness and building a foundation may achieve early warning systems that are more sustainable and effective than those of states that focus primarily on technical development without sufficient attention to organizational and interest holder dynamics.

The pathway to successful implementation is clear: honest readiness assessment, a systematic development approach, quality pilot implementation, and sustained commitment to evidence-based improvement. States meeting these requirements can achieve both immediate benefits for students and long-term transformation of school improvement effectiveness.

Policy Implications

Policymakers need not choose between accountability and prevention. The opportunity lies in connecting them—rewarding states for improving schools after identification *and* for preventing decline before formal identification occurs. A prevention-to-turnaround continuum ensures both fiscal responsibility and educational equity, aligning early warning investments with the core intent of ESSA (Bryk et al., 2010; U.S. Department of Education, 2017).

The research findings provide a compelling foundation for policy transformation to enable a shift from reactive to proactive school improvement. Rather than requiring extensive new legislative frameworks, early warning systems can be implemented through strategic policy evolution to remove barriers and create the conditions for prevention-focused approaches.

Federal Policy Opportunities

Federal education policy unintentionally incentivizes delayed intervention, prioritizing support after schools have entered crisis. Realigning these incentives to reward prevention and early intervention would transform a reactive framework into one focused on continuous improvement and sustained success (U.S. Department of Education, 2015).

Every Student Succeeds Act (ESSA) Reauthorization Priorities

Accountability Framework Evolution: Future ESSA reauthorization should allow states to use predictive indicators alongside traditional performance measures, giving credit for preventing decline rather than only rewarding successful turnarounds. This policy shift would eliminate the perverse incentive to wait for formal failure before accessing intensive support resources.

Title I Formula Enhancement: Federal funding formulas could incorporate prevention effectiveness metrics, creating financial incentives for states that demonstrate success in early identification and intervention. States showing measurable prevention of school decline could receive enhanced Title I allocations, making early warning investment directly profitable.

Research and Development Mandates: ESSA reauthorization could require states to develop and test early warning approaches as a condition of federal funding, building the national evidence base while ensuring widespread implementation capacity.

Immediate Federal Actions

Competitive Grant Prioritization: The Department of Education can immediately prioritize early warning system proposals in existing grant competitions, including School Improvement Grants and Education Innovation Research funding streams.

Technical Assistance Investment: Federal resources should support state capacity-building for predictive analytics through existing networks, providing states with expertise needed for rapid early warning system implementation.

Multistate Research Initiatives: Federal funding should commission replication studies across diverse state contexts, accelerating evidence development and creating implementation guidance for different organizational structures.

State Policy Leadership

States hold primary authority for transforming school improvement practice. The required policy changes are achievable within existing governance structures yet represent fundamental shifts in education strategy.

Legislative Policy Changes

Statutory Early Warning System Authorization: States can seek legislation explicitly authorizing early warning systems, providing political protection across leadership changes while ensuring dedicated funding streams that survive budget pressures.

Accountability Framework Modification: Legislative action can modify state accountability frameworks to include prevention effectiveness metrics, rewarding districts and schools that successfully use early warning information rather than only recognizing recovery from failure.

Data Sharing and Privacy Frameworks: States may need legislative updates to enable secure data sharing for early warning system development while maintaining privacy protections, particularly for multistate collaboration opportunities.

Administrative Policy Opportunities

Resource Reallocation Authority: Within existing budget authority, states can redirect portions of comprehensive intervention funding toward early warning system development and preventive interventions, creating immediate financing for early warning system implementation.

Accountability Timeline Modification: SEAs can establish administrative frameworks that trigger support based on predictive risk rather than waiting for formal accountability designation; this would enable intervention during optimal effectiveness windows.

Professional Development Requirements: States can establish certification or training requirements for staff involved in early warning system operation, ensuring consistent expertise across different districts and regions.

Policy Barriers to Address

Data and Privacy Constraints

Predictive Information Classification: Policies should clarify the status of early warning predictions within existing public information and accountability frameworks, preventing premature public disclosure that could undermine intervention effectiveness while maintaining appropriate transparency.

Federal Reporting and Accountability Integration

Prevention Versus Reaction Metrics: Current federal accountability frameworks focus primarily on outcomes rather than prevention effectiveness. Policy alignment should ensure that early warning system activities and outcomes are appropriately reflected in federal reporting requirements.

Funding Stream Flexibility: Existing categorical funding structures may limit states' abilities to reallocate resources from reactive intervention to proactive prevention. Enhanced flexibility in federal funding usage could accelerate early warning system adoption.

Local Education Agency Policy Enablers

Authority and Resource Flexibility

Early Intervention Authority: Districts need policy authority to deploy interventions based on early warning signals rather than waiting for formal state identification; this would enable response during optimal intervention windows without bureaucratic delays.

Resource Reallocation Flexibility: Districts require authority to redirect existing improvement resources toward prevention efforts without penalty for not using funds as originally designated; this would enable responsive resource deployment based on early warning information.

Regulatory Alignment

Evaluation and Improvement Planning: Policy should align early warning activities with existing improvement planning requirements, ensuring the early warning system enhances rather than duplicates district planning and evaluation processes.

Staff Development and Training: Policies should enable districts to use professional development resources for early warning system training and capacity-building as eligible improvement activities.

The Policy Transformation Opportunity

The convergence of research evidence, economic benefits, and implementation feasibility creates unprecedented policy opportunities to transform American school improvement. Early warning systems offer policymakers the rare chance to improve educational outcomes while simultaneously reducing costs.

Federal Policy Opportunity: The prevention focus aligns with fiscal responsibility priorities and educational goals, creating opportunities for bipartisan policy support that transcends typical partisan division on education issues.

State Policy Leadership: Early adopter states can demonstrate national leadership in prevention-focused education reform while achieving immediate benefits for students and communities. These states can influence federal policy development and build expertise that positions them as national models.

Local Policy Innovation: Districts can advocate for state and federal policy changes that provide tools and resources needed for effective early intervention, moving beyond crisis response to proactive approaches that better serve students and communities.

The policy pathway is clear: strategic modifications to existing frameworks rather than wholesale system replacement. The evidence base is strong, the economic benefits are substantial, and the implementation feasibility is demonstrated.

Amplifying Early Warning System Impact Through Strategic Technology

Technology can create unique opportunities to amplify early warning system effectiveness while reducing operational burden on state agencies. Whereas basic systems can achieve 80–89 percent accuracy using existing data and staff, strategic technology investments can improve efficiency, expand reach, and enhance intervention targeting (Siemens & Long, 2011).

Major Technology Opportunities

Artificial Intelligence (AI) Enhancement

Advanced Pattern Recognition. Machine-learning approaches can identify complex, nonlinear interactions among leading indicators that traditional regression models often miss—boosting prediction accuracy from the upper 80s into the low 90s range and reducing false-positive rates (Wu et al., 2024).

Research on educational AI systems demonstrates comparable gains in predictive accuracy, with machine learning models routinely outperforming traditional regression approaches by 10–15 percentage points in early identification accuracy (Holmes et al., 2019; U.S. Department of Education, Office of Educational Technology, 2023a; Zhang & Aslan, 2022).

Intervention Recommendations: AI systems can analyze successful interventions across similar contexts to suggest specific strategies based on what has proven effective for comparable schools.

Automation and Efficiency

Real-Time Monitoring: Automated systems can monitor hundreds of schools simultaneously, providing immediate alerts when risk thresholds are crossed rather than requiring manual analysis (U.S. Department of Education, 2020).

Streamlined Operations: Technology can reduce staff time required for system operation by 40–60 percent, enabling states to serve more schools without proportional staffing increases. Evaluations of data automation in SEA and LEA settings show similar efficiencies, reducing manual analysis time by up to half while improving data accuracy and timeliness (Gallagher & Smith, 2021; IBM Center for the Business of Government, 2022; Means et al., 2010; U.S. Government Accountability Office, 2024).

Multistate Collaboration—Shared Platforms: Secure systems can enable states to collaborate on model validation, share intervention strategies, and reduce individual development costs by 50–70 percent through joint technology investments. States that share interoperable data and analytic infrastructure report savings of 50–70 percent on model development costs through shared procurement and joint validation efforts (Baker & Inventado, 2014; Data Quality Campaign, 2021; Education Commission of the States, 2022; U.S. Department of Education, Office of Educational Technology, 2023b).

Multistate Collaboration—Evidence-Based Practice: Advanced analytics can systematically analyze intervention outcomes across multiple states, identifying consistently effective practices for evidence-based guidance.

Return on Investment

Technology enhancements typically generate returns through improved operational efficiency (40–60% staff time reduction), enhanced intervention effectiveness (10–15 percentage point improvement in success rates), and accelerated implementation timelines (6–12 months faster development). Cross-national evidence confirms that education technology initiatives that combine predictive analytics and automated reporting typically achieve cost recovery within 12–18 months, largely through reduced manual labor and improved intervention targeting (Baker, 2019; OECD, 2021; World Bank, 2023).

Technology investments often recover costs within the first operational year through prevented comprehensive interventions while creating sustainable platforms for ongoing system improvement and expansion.

Strategic Implementation

High-Capacity States can pursue integrated technology adoption alongside basic early warning system development for maximum long-term value. **Medium-Capacity States** should implement basic systems first, then add technology enhancements as experience and readiness develop. **Emerging-Capacity States** can leverage partnerships to access technology capabilities beyond individual development capacity.

The convergence of proven early warning system effectiveness with advancing technology creates unprecedented opportunities for states to transform school improvement practice. Technology can serve as both an implementation accelerator and a capability multiplier, enabling prevention outcomes that exceed what basic systems alone could accomplish.

Conclusion

The Numbers Do Not Lie

The United States invests roughly $2.5 billion each year in comprehensive school improvement and turnaround efforts—yet nearly 70 percent of those interventions fail to produce lasting gains. Early warning and prevention strategies, by contrast, cost about 90 percent less and succeed 70 percent of the time. The math is clear: By coupling prevention with turnaround, states could redirect billions toward strategies that stabilize schools earlier and make subsequent interventions more effective. Every dollar invested in early identification and targeted support yields an estimated $5–$10 in avoided crisis spending and improved student outcomes.

With 89 percent accuracy, it is possible to identify which schools will struggle next year using data every state already collects: academic proficiency, attendance patterns, teacher effectiveness, and accountability history. New systems, new laws, and new funding are not needed—just the will to use what states already have.

Technology Changes Everything

Education systems are no longer limited to hindsight. Machine learning, real-time analytics, and predictive modeling now make it possible to anticipate decline and guide human judgment with evidence. These tools do not replace professional expertise. They sharpen it. By linking prevention and turnaround through data-driven precision, education leaders can move beyond reaction to foresight, beyond managing crisis to sustaining improvement.

Students Are Watching

Right now, thousands of children sit in classrooms where the warning signs are visible—schools that could be identified and supported today. Without early action, many will spend 3 to 4 years in systems under stress: confidence fading, teachers leaving, learning time eroding. By the time a school enters formal turnaround, much of the preventable damage is already done.

These students do not get their elementary years back. They do not get a second chance at the foundational skills that determine their futures. When systems wait for formal identification rather than acting on early evidence, opportunity is lost—not through neglect but through inertia that new tools can now overcome.

The Moment of Truth

The path forward is not to abandon turnaround but to make it rarer, faster, and more effective by acting earlier and smarter. Prevention and turnaround are complementary, not competing, strategies—each strengthening the other and together forming the foundation for sustained school improvement.

State leaders hold the power to transform American education today, not tomorrow, not next budget cycle, not after the next study. The research exists. The technology exists. The economic case is strong. The only question is whether leaders will integrate their existing resources into a coherent system of prevention, targeted support, and turnaround.

Every month of delay costs children learning they cannot recover and maintains costly cycles of crisis response. Prevention creates the runway; turnaround provides the lift. Together, they complete the flight path toward lasting success for students and schools.

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Appendix A: Comprehensive Data Documentation

Data Collection Overview

The analysis used longitudinal administrative data from the Colorado Department of Education (CDE) spanning the 2019–20 through 2024–25 academic years. Data sources included both publicly available downloads from the CDE website (https://www.cde.state.co.us/cdereval) and additional non–personally identifiable information (non-PII) data sets obtained through secure data sharing agreements with the CDE's data management team (see Table A1).

Complete Variable Dictionary

Table A1. Data Used in Analysis

Indicator	Variables
Outcome	State Accountability—"on the clock" • Predict schools identified on the accountability clock in 2023–24 • Predict schools identified more than once on the accountability clock in the past 5 years
Operations and finance	• Learning Environment Expenses • Operations Expenses

Indicator	Variables
Talent	School Level • Pupils per teacher • Percentage of teachers effective (Educator Effectiveness) • Average years the principal has been at the school • Percentage of teachers with shortage credentials • Average salary of teachers • Average salary of paraprofessionals • Average years the teacher has been at the school District Level • Full-time staff turnover rate • Rate of unfilled roles • Average superintendent salary • Percentage of effective principals (Educator Effectiveness) • Teacher turnover rate • Principal turnover rate • Paraprofessional turnover rate
Culture	School Level • Attendance rate • Truancy rate • Mobility rate • Stability rate • Mobility Incidence rate • Matriculation rate • Dropout rate
Instruction	School Level • SAT mean scaled score • PSAT mean-scaled score • Graduation rate • Colorado Measures of Academic Success (CMAS) ELA proficiency • CMAS math proficiency • CMAS science proficiency • ACCESS for ELL percentage redesignation

Data Preparation

Publicly available data sources were downloaded directly from the CDE's website (https://www.cde.state.co.us/cdereval). The requested data sources were downloaded from the secure data sharing site. Although different data sources followed varying formats and requirements, the research team applied standard business rules consistently across the data as the data were processed.

- Suppressed values were recoded to the highest potential value. For example, a student count was suppressed if it was lower than 20. Researchers recoded this to be "20."
- The district reflects the most recent district in which the school was located.
- Missing data were treated with listwise deletion. Some sources were missing at random, and others were not. Expansion of this study should explore potential ways to impute missing data.
- The designation "0" reflects a true zero and that the datum was not missing.

Data Access and Replication

Data Availability

- Public data sources available through the CDE website with documented URLs
- Secure data elements available through a formal data sharing agreement with the CDE
- Analysis data sets available to qualified researchers through the CDE's data request process

Replication Support

- Complete data preparation syntax available upon request
- Variable construction documentation provided for all derived measures
- Quality assurance logs maintained for all data processing decisions

Appendix B: Technical Methodology and Statistical Results

Analytical Framework and Model Specifications: Multilevel Logistic Regression

The study employed multilevel logistic regression to account for the nested structure of educational data (schools within districts) while modeling binary accountability outcomes. The general model form addresses both fixed effects of school-level predictors and random effects of district-level clustering.

Model Development and Analytic Approach

The present study employed multilevel regression models to predict the percentage of points schools earned under Colorado's 2024 Performance Framework. Given the nested structure of educational data, multilevel modeling was employed with schools nested within districts to account for shared contextual factors and potential intracluster correlation at the district level.

Separate models were estimated for schools serving different grade configurations, given the presence of distinct performance indicators across educational levels. Elementary and middle schools were analyzed using indicators such as standardized test scores and attendance rates, while high schools incorporated additional measures, including graduation rates, dropout rates, and college-readiness indicators. The temporal structure of the analysis used 2023–24 predictor variables to forecast 2024–25 accountability status, providing a 1-year predictive window that aligns with practical implementation timelines for early warning systems.

The modeling process employed a systematic approach to variable selection and model refinement. Initial models included school-level variables across five theoretical domains: leadership stability, talent management, organizational culture, financial operations, and instructional programming. During model development, relationships among covariates were examined through correlation analysis and variance inflation factors to identify and remove variables that exhibited high collinearity or measured redundant constructs. The final models prioritized parsimony while maintaining predictive accuracy, focusing on variables with strong theoretical justification, empirical significance, and practical availability in administrative data sets.

Appendix C: How At-Risk and Stable Schools Actually Differ

Understanding the descriptive differences between struggling and stable schools provides important context for the predictive findings and confirms what many education professionals observe in their daily work (see Tables C1–CE).

Table C1. Elementary, Middle, and High School by Intervention Status—Prior Accountability History

	Elementary/Middle schools		High schools	
Variable	**Intervention**	**Stable**	**Intervention**	**Stable**
Never identified	41%	83%	4%	96%
Identified once in 5 years	31%	11%	26%	5%
Identified multiple times in 5 years	29%	7%	52%	6%

Table C2. Elementary, Middle, and High Schools by Intervention Status—Academic Performance

	Elementary/Middle schools		High schools	
Variable	**Intervention**	**Stable**	**Intervention**	**Stable**
Percentage met or exceeded CMAS ELA proficiency	19%	43%	12%	38%
Percentage met or exceeded CMAS math proficiency	11%	32%	7%	23%
SAT mean scale score	--	--	414	482
Attendance rate	89%	92%	82%	89%
Dropout rate	--	--	5%	3%

Table C3. Elementary, Middle, and High Schools by Intervention Status—Organizational and Operational

	Elementary/Middle schools		High schools	
Variable	**Intervention**	**Stable**	**Intervention**	**Stable**
Pupils per teacher	15	16	19	18
Effective teachers percentage	92%	97%	91%	96%
Teachers with shortage credentials percentage	11%	10%	14%	14%
Average teacher years of experience	9	9	8	10

Average principal years of experience	2	4	1	3
Learning environment expenses	$3,962,754	$3,639,753	$7,277,024	$5,451,357
Operations expenses	$522,120	$523,816	$1,119,583	$794,893
Percentage Native Hawaiian or Pacific Islander	<1%	<1%	<1%	<1%
Percentage free or reduced-price lunch	15%	10%	15%	10%
Sample size	117	1,463	23	505

Table C4. Elementary, Middle, and High Schools by Intervention Status—Geographic

	Elementary/Middle schools		High schools	
Variable	**Intervention**	**Stable**	**Intervention**	**Stable**
Denver metro	51%	44%	52%	35%
Outlying city	6%	5%	9%	6%
Outlying town	8%	12%	4%	15%
Remote	12%	12%	13%	19%
Urban/Suburban	23%	26%	22%	22%

Table C5. Elementary, Middle, and High Schools by Intervention Status—Demographic

	Elementary/Middle schools		High schools	
Variable	**Intervention**	**Stable**	**Intervention**	**Stable**
Percentage American Indian/Alaska Native	<1%	<1%	<1%	<1%
Percentage Asian	<1%	1%	<1%	<1%
Percentage Black or African American	3%	1%	3%	1%
Percentage Hispanic or Latino	23%	13%	26%	15%
Percentage Multiracial	1%	2%	1%	2%
Percentage Native Hawaiian or Pacific Islander	<1%	<1%	<1%	<1%
Percentage free or reduced-price lunch	15%	10%	15%	10%
Sample size	117	1,463	23	505

Prior Accountability History

As mentioned above, schools with multiple previous identifications showed dramatically elevated risk—90 percent of intervention schools had been flagged multiple times in the previous 5 years compared to only 26 percent of stable schools.

Academic Performance Gaps

The academic performance differences between intervention and stable schools are not marginal—they represent substantial gaps that would be apparent to any educator walking into these schools. Intervention schools average 19 percent ELA proficiency compared to 44 percent for stable schools, and intervention schools average 11 percent mathematics proficiency compared to 34 percent for stable schools.

Organizational and Operational Factors

In addition to academic achievement, the following organizational characteristics distinguish intervention schools from stable schools:

Teacher Quality and Stability: Teacher effectiveness ratings were significantly lower in struggling schools, with 92 percent of teachers rated as effective compared to 97 percent of teachers in stable schools. While both percentages seem high, this 5-percentage-point difference represents significant variation in instructional quality across an entire school.

Student Engagement: Attendance rates differed meaningfully across school levels, with intervention elementary and middle schools averaging 89 percent compared to 92 percent for stable schools. High school attendance differences were more pronounced, with intervention schools at 82 percent compared to 89 percent for stable schools.

Resource Utilization: Interestingly, intervention schools maintained slightly lower pupil-to-teacher ratios (15:1 versus 16:1), suggesting that staffing levels alone do not explain performance differences. This indicates that how schools use their resources matters more than total resource availability.

Cross-Context Validation: Do These Patterns Work Everywhere?

One of the most significant findings for state implementation is that effective early warning indicators seem to work consistently across different contexts.

Geographic Consistency

The analysis revealed remarkable consistency in predictive patterns across diverse geographic contexts. Effect sizes showed minimal variation between urban, suburban, and rural settings (differences of 0.01–0.15), suggesting that the underlying mechanisms of school decline transcend location-specific factors.

Demographic Neutrality

The predictive indicators maintained their effectiveness across schools serving different demographic populations. Although schools serving higher percentages of students from families with low income face additional challenges, the early warning indicators worked equally well across different demographic contexts.

Resource Independence

Contrary to common assumptions, per-pupil expenditure levels showed weak predictive power. How schools used their resources appeared more important than total resource availability, suggesting that organizational effectiveness, rather than funding levels, may drive early decline patterns.

Descriptive Differences Across School Types

Elementary and Middle Schools

Schools identified for Priority Improvement or Turnaround status demonstrated markedly different characteristics compared to stable schools.

Academic Performance: The most pronounced differences emerged in student achievement, with intervention schools averaging 19 percent ELA proficiency compared to 44 percent for stable schools and 11 percent mathematics proficiency versus 34 percent for stable schools.

Organizational Factors: Teacher effectiveness ratings were lower in intervention schools (92% effective) compared to stable schools (97% effective). Attendance rates also differed meaningfully, with intervention schools averaging 89 percent compared to 92 percent for stable schools.

Accountability History: Prior identification emerged as a critical distinguishing factor, with 90 percent of intervention schools having been flagged multiple times in the previous 5 years compared to only 26 percent of stable schools. This pattern suggests persistent rather than temporary performance challenges.

Resource Utilization: Interestingly, intervention schools maintained slightly lower pupil-to-teacher ratios (15:1 versus 16:1), indicating that staffing levels alone do not explain performance differences.

High Schools

Secondary schools showed more complex organizational challenge patterns.

Academic Indicators: Intervention schools averaged significantly lower SAT scores (414 versus 482) and represented one of the largest gaps observed. Dropout rates were nearly double (5% versus 3%).

Leadership and Staffing: Leadership instability was particularly pronounced, with intervention schools averaging only 1 year of principal tenure compared to 3 years for stable schools. Teachers also showed less experience (8 versus 10 years on average).

Student Support: Intervention schools achieved lower English Language Learner redesignation rates (4% versus 5%), suggesting challenges in supporting diverse student populations toward English proficiency.

Attendance Challenges: Attendance differences were more pronounced at the high school level than at the elementary and middle school levels, with intervention schools averaging 82 percent compared to 89 percent for stable schools.

These descriptive patterns provide the foundation for understanding why certain indicators emerged as strong predictors in the statistical models.