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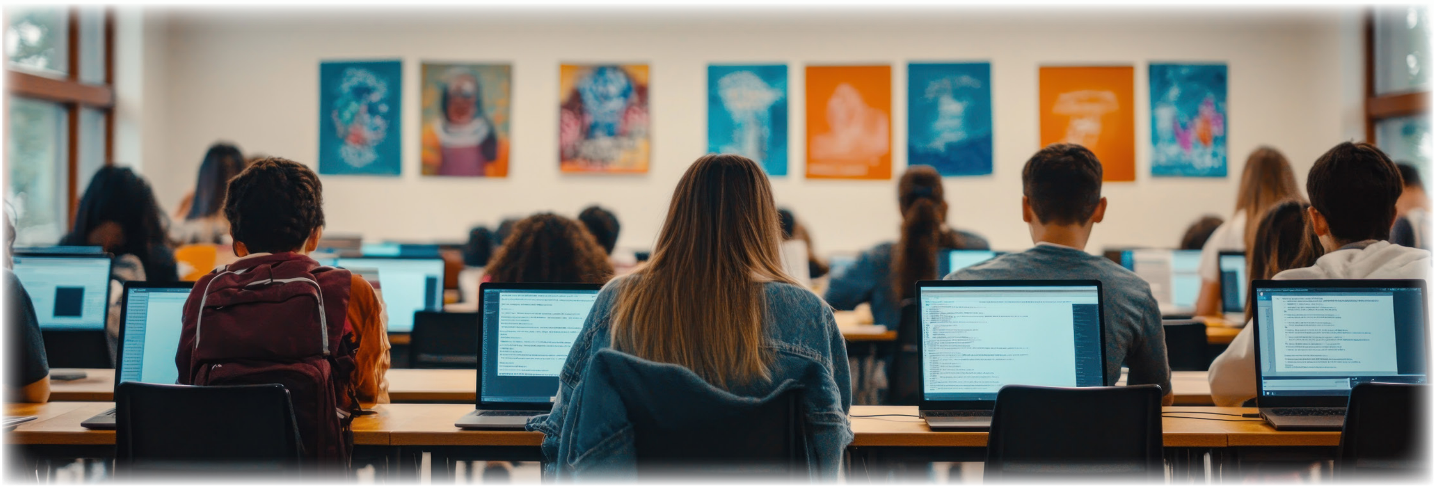
NEPC Review: Measuring Artificial Intelligence in Education (Bellwether, October 2025)



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Summary

Because of the rapid proliferation of AI-powered technologies in education, educators and others face urgent challenges around evaluating the potential impacts of these technologies on teaching and learning. Bellwether's October 2025 report, *Measuring Artificial Intelligence in Education*, aims to address such challenges by promoting logic models as a framework for moving beyond superficial metrics toward more robust evidence-based educational outcomes. Logic models involve determining four main components—inputs, activities, outputs, and outcomes—and they have a long history of use in program evaluation. The logic-model approach, however, has very real limitations that are not fully addressed in the report. Just as importantly, the report simply assumes that AI should indeed be integrated into education. That is, logic models function here as a methodological heuristic for ensuring AI fulfills its taken-for-granted potential. By positioning logic models as value-neutral, the report overlooks how such approaches ignore contextual complexity and the potential for unintended harms. Rather than offering critical guidance for assessing AI's role in education, the report provides methodological cover for predetermined conclusions about AI's inevitability and desirability. Policymakers seeking rigorous, evidence-based approaches will find little support in what is, at its core, a promotional document.

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I. Introduction

The ongoing expansion of artificial intelligence apps, services, and platforms in K-12 education has raised challenging questions about how to evaluate their impacts on teaching and learning, with federal policy encouraging AI use intensifying the challenge.[1] Despite such federal pressure—itself matched by that of the companies behind the profusion of AI tools in education[2]—educational leaders report significant gaps in policy guidance. Indeed, just 40% of educators say their districts have communicated AI policies to them.[3]

The stakes surrounding AI implementation are about more than questions of efficacy alone. In part, this is due to the role educational evaluation and accountability systems now play as central mechanisms for resource allocation, federal funding decisions, and school improvement interventions in response to policies like the Every Student Succeeds Act.[4] Yet determining how best to measure AI's impact in education remains difficult, since conventional approaches often focus narrowly on questions of efficacy without examining the larger conditions that shape how these technologies are designed, deployed, and applied in educational settings.[5]

Against this backdrop, the education policy nonprofit Bellwether has released various reports in recent years addressing the implications of artificial intelligence in K-12 schools.[6] Authored by Michelle Croft, Amy Chen Kulesa, Marisa Mission, and Mary K. Wells, the organization's most recent report, *Measuring Artificial Intelligence in Education*, reflects a focus on questions of evaluation and measurement in assessing the educational impact of AI.[7] Specifically, the report advocates for the use of logic models as an objective, systematic framework for assessing the outcomes of

AI integration in K-12 education.

II. Findings and Conclusions of the Report

The report finds that existing approaches to measuring and evaluating AI tools in education are insufficient, largely because they tend to focus on easily tracked metrics (e.g., login rates) as opposed to more direct measures of student learning. In response, the report advocates for the systematic use of *logic models*—an approach with a long history in program evaluation[8]—as an objective methodology for measuring and evaluating the outcomes of a given AI tool's use in K-12 education. The central argument is that by turning focus from superficial outputs to more meaningful outcomes, and doing so according to the objective structure provided by logic models, educational stakeholders can make rigorous, evidence-based decisions about AI adoption and avoid relying on "hype, popularity, and marketing claims."[9]

Logic Models as the Solution

The report positions logic models as a solution for what it acknowledges as a common criticism of AI in education, namely that such tools are "solutions in search of a problem,"[10] often designed more to highlight AI capabilities than to address educational challenges. A logic model, the report explains, clarifies the theory of change animating an intervention and provides a structured framework for articulating and measuring its anticipated outcomes. The report details four main components of a logic model: inputs, activities, outputs, and outcomes, with outcomes further categorized as short-term (within a year), intermediate-term (one-four years), and long-term (over four years).[11] Because they require developers and school leaders to articulate their expectations about how an AI tool will be used and what changes they expect to see, the report suggests logic models can enable stakeholders to think critically about whether and how AI adoption supports desired educational improvements.

Multiple Metrics and Measurement Frameworks

The report emphasizes the importance of employing multiple metrics when developing a logic model for AI integration, under the idea that measurement variety helps avoid overreliance on weak measures like self-reported surveys, which, the report suggests, can contain errors or bias.[12] Multiple metrics also enable additional ways to test assumptions with empirical evidence. Also, because long-term changes in educational outcomes occur over years, the report stresses the need for leading indicators that can signal progress. To do this, the report proposes evaluating AI tools across five dimensions: reach, efficiency, effectiveness, expanded capabilities, and unbiased outcomes. It includes sample metrics for each dimension along with detailed examples of how these metrics might evolve from immediate indicators to long-term educational impact.[13]

Barriers to Better AI Measurement

The report identifies three primary barriers that work against effective evaluation of AI tools in education: defining what to measure, logistical and legal obstacles to data collection, and insufficient market demand for rigorous empirical evidence. Taken together, these challenges often incentivize decision-makers to adopt tools based on peer pressure or marketing, as opposed to evidence.[14]

Addressing Challenges at the Stakeholder Level

In response to measurement barriers, the report offers targeted recommendations for three key stakeholder groups: District and school leaders should align AI tool selection with institutional objectives and establish accountability measures early in procurement; AI developers should prioritize transparency about specific problems their tools address; and philanthropic funders should support rigorous empirical research and shared infrastructure for objective evaluation.[15]

Overall Conclusions

The report concludes that effective AI measurement and evaluation require balancing the drive for innovation with evidence-based decision-making processes. It argues that a focus on educational outcomes over superficial metrics can enable stakeholders to ensure that the AI tools they adopt actually serve teachers and students. The report positions logic models as a guiding heuristic for aligning AI implementation with meaningful educational impact, emphasizing their capacity to enable decision-makers to base AI adoption on durable outcomes.[16]

III. The Report's Rationale for Its Findings and Conclusions

The report's underlying rationale is that logic models provide a systematic, objective response to what it positions as a crucial measurement problem for AI in education. It argues that current measurement practices focus on superficial "outputs," like log-in rates, rather than deeper educational "outcomes," leaving schools vulnerable to marketing and peer conformity when adopting AI tools. Guided by what it describes as "expert interviews, case examples, and proven evaluation methods," the report centers logic models as a tried-and-true methodology for sidestepping hype because they require stakeholders to articulate clear theories of change that align AI tools with desired educational impacts. This rationale leads to the report's conclusion that focused guidance for stakeholders can help enact systemic changes to ensure AI adoption prioritizes educational outcomes over technological capabilities.

IV. The Report's Use of Research Literature

The report's claims about its grounding in "expert interviews, case examples, and proven evaluation methods"[17] are weakened by limited empirical research. Though not without relevant citations—such as the American Psychological Association's *Standards for Educational and Psychological Testing*[18] and select peer-reviewed articles on measurement bias[19] and student engagement[20]—the report primarily relies on practitioner-facing materials,[21] industry publications,[22] and Bellwether's own published reports on AI in education. This overreliance on non-peer-reviewed sources would perhaps be less problematic if the report presented itself as a practitioner guide, but its unqualified claims about "proven evaluation methods" imply a more rigorous research foundation than what it actually provides.[23] This mismatch between the report's sweeping prescriptions about AI measurement practices and its limited engagement with existing research raises questions about the credibility of its guidance for stakeholders in search of evidence-based thinking about AI adoption.

The report's treatment of logic models as straightforward, technical solutions ignores foundational and contemporary literature on their inherent complexity and limitations, particularly in educational settings. Research has emphasized that logic modeling can lead stakeholders to focus on overly simplistic questions while encouraging hyperfocus on end outcomes that elide implementation complexities.[24] Research has also consistently identified fundamental limitations: Logic models struggle with dynamic contexts, use linear structures that fail to account for emergence and recursion, ignore competing causal mechanism, and often overstate or understate impact based on narrowly scoped interventions.[25] Logic models can also undermine critical thinking by assuming interventions are sensible responses to challenges, while hardening into static representations detached from changing contexts.[26] Such limitations have crucial implications for AI in education, where technological interventions enter into complex, dynamic school contexts that vary dramatically in their infrastructures, cultures, and student populations. By not engaging with the substantial scholarship investigating logic models across different settings, the report misrepresents them as an unproblematic methodological solution when studies across disciplines have consistently documented their contingency and limitations.

Even within the logic model tradition championed by the report, scholars have identified a crucial limitation it ignores: the failure to account for "dark logic," or the undesirable, unintended outcomes or harms that interventions can inadvertently precipitate.[27] Though briefly acknowledging that AI tools may lead to harm, including those related to privacy and bias,[28] and positioning logic models as remedies for them, the report does so without engaging with literature about how such frameworks themselves can obscure or amplify negative impacts. The report's light treatment of research on AI's documented and potential harm reflects a serious omission for a document providing evidence-centered guidance. Studies have demonstrated systematic bias in automated scoring systems,[29] algorithmic discrimination in facial recognition systems,[30] and the commodification of teachers' emotional labor through AI platforms that transform systemic problems into ones of individual efficiency.[31] Such findings align with scholarship showing how ostensibly neutral technologies can reproduce social harms within institutional settings.[32] Had the report engaged with such literature in more depth and breadth—that is, had it undertaken its own practice of dark logic within the methodological tradition it claims—it may have developed a more robust framework for anticipating and measuring AI's impacts, including negative ones, in K-12 education.

V. Review of the Report's Methods

The report's methodology is fundamentally opaque. Despite asserting its grounding in "expert interviews, case examples, and proven evaluation methods,"[33] it provides no account of how interview participants were selected, what questions were asked, how long the interviews lasted, or what analytical approach was used to synthesize findings into recommendations. This methodological vacuum is particularly ironic given the report's central assertion that educational stakeholders should look to adopt more rigorous measurement practices for evaluating AI tools. What little can be discerned about the process raises concern about bias, with the selection of interview participants seeming to center voices from the technology, business, and nonprofit sectors who may have financial or professional interests in AI adoption in schools. Critical voices are also conspicuously absent. For a report that positions itself as an authoritative guide for educational decision-makers, this basic disjuncture between what it preaches and what it practices is a fatal flaw that leaves its conclusions unverifiable, its recommendations suspect.

VI. Review of the Validity of the Findings and Conclusions

The report identifies real challenges stakeholders face as AI tools proliferate in education. It is true, for example, that a narrow focus on superficial metrics like login rates tells us little about whether an AI tool meaningfully supports learning. It correctly observes that schools are vulnerable to AI marketing hype and institutional peer pressure when making technology adoption decisions.[34] And the core argument that evaluation processes should align AI adoption with a clear theory of change responds to a legitimate need for systematic approaches to educational technology assessment.[35] These valid observations are, however, undermined by the report's own methodological shortcomings.

The report's central problem is that it delivers no careful assessment of its own focal premise: that logic models are the solution to AI measurement problems in education. To be clear, the issue here is not with logic models themselves, which may hold value in particular contexts. Rather, the issue lies in the report's portrayal of them as simple, straightforward, and value-neutral solutions, despite limited evidence of their effectiveness in the context of assessing AI in education and no discussion of their documented limitations and complexities. The report's conclusions rest entirely on unverifiable expert interviews that fail to meet basic standards of transparency.[36]

VII. Usefulness of the Report for Guidance of Policy and Practice

The report concludes with the assertion that "the path forward requires balance: embracing innovation while grounding choices in evidence," promising that "AI can move from a source of hype to a force for lasting improvement in teaching and learning."[37] This framing underscores a bias that runs throughout the report: Embracing innovation is an unqualified good that does not require stakeholders to question whether particular innovations merit embrace at all.[38] The report offers a framework that assumes AI integration is both inevitable and beneficial, which is the kind of predetermined conclusion that rigorous policy guidance should help stakeholders avoid.

As AI expands in K-12 education, decision-makers need guidance that can help them identify tools that meaningfully advance learning. But they also need frameworks for weighing risks against speculative benefits—logic models that undertake the kind of dark logic that surfaces harms before they happen, and methods fit to reckon with the social, technical, and political-economic aspects of AI while centering the welfare of students, educators, and their communities.[39] For stakeholders looking for a critical, evidence-guided account of measuring AI in schools, this report offers little more than sophisticated marketing disguised as policy guidance.

Notes and References

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Croft, M., Weber, N., & Foster, K.R. (2025, February 13). *Surveying school system leaders: What they are saying about artificial intelligence (so far)*. Bellwether. Retrieved October 29, 2025, from https://bellwether.org/publications/surveying-artificial-intelligence-and-schools/?activeTab=1

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The report's detailed recommendations include the following: for *school leaders*, identifying outcome measures before piloting tools and creating data agreements with vendors for privacy protection; for *developers*, implementing internal evaluation processes including rapid-cycle studies rather than relying on surface-level usage metrics; and for *funders*, supporting evaluation processes that connect internal studies with externally validated research and investing in industry-wide benchmarking practices and shared datasets.

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