

Responsible Inference Engines: Safeguarding Students with Learning Differences in the AI Era

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The forthcoming brief *Prioritizing Students with Disabilities in AI Policy* (EALA/New America) highlights a critical reality: 73% of students with disabilities use AI for coursework, and 57% of special educators use it to draft IEPs. Yet, 0% of AI-based interventions in a 2025 [systematic review](#) rate as “Low Risk” for algorithmic bias. Framing responsible AI as critical, the brief anchors four operational pillars, leveraging the [SAFE Framework](#). This article proposes a framework for responsible AI and assessment innovation for students with learning differences.

Quality Inferences to Serve Students who Learn Differently

Too often, inferences about neurodivergent students fail to recognize their intelligence, creativity, and potential. While schools rely on measurement to screen learners, calibrate interventions, operationalize plans, monitor progress, and coordinate specialized instruction, current tools consistently fail to provide the quality, useful data educators need.

Redefining the Architecture of Ability

The AI era demands we upgrade our approach regarding the accuracy and appropriateness of the inferences we make about learners and learner variation. Multimodal AI models are inference engines, translating a student's voice, performance, or behavior into a statistical conclusion with consequences.

For decades, the industry equated fairness with identical conditions, a “fairness as sameness” orientation that penalizes neurodivergent learners. We must shift to Conditional Inference: standardizing the targeted knowledge, skill, or attribute while varying the delivery modality. Universal Design for Learning (UDL) acts as the operational blueprint, proactively stripping away construct-irrelevant noise so a student's true capability emerges. Superimposing flashy AI atop flimsy, dated psychometric architectures merely automates and amplifies pathological inferences about learners.

Advancing Quality and Safety

For students with disabilities, AI-powered inferences are a fundamental civil rights issue. Designed intentionally, AI-powered tools act as an *ambient* assessor, subtly gathering multimodal evidence to serve as an essential assistive ramp. However, ensuring safety requires *Human-in-the-Loop* oversight. Just as educators are mandated reporters for physical safety, they must address algorithmic missteps. If an AI generates biased IEP goals or uses [deficit-focused language](#), educators must intervene.

Emerging Principles for Measuring for Students with Learning Differences

This section introduces the user-informed principles and features of multimodal AI assessment tools that are likely to be usable and useful.

Context & Content

- **Validated Learning Progressions:** Visually report student progression along validated cognitive trajectories. Display a student's ability to transfer skills across varying contexts, allowing educators to classify growth from novice to proficient.
- **Instructional Sensitivity:** Demonstrate sensitivity by detecting student learning changes resulting from instruction. Map response patterns to specific misconceptions, empowering educators to immediately adjust daily lesson plans.
- **Predictive Linkage:** Provide reporting dashboards with clickable crosswalks linking each assessed competency to verified empirical research on post-secondary and career readiness.
- **Configurable Domains:** Generate discrete sub-scores for relevant cognitive, intrapersonal, and interpersonal domains.
- **Standards Alignment Verification:** Cover 100% of relevant state-adopted learning standards. Output a coverage map verifying that academic depth and developmental benchmarks are assessed within the core curriculum.
- **Content Authenticity:** Provide customizable task libraries reflecting local demographic and sociocultural contexts. Administrators must be able to select problem-solving scenarios empirically validated to reflect the lived experiences and identities of their target population.

Scientific Soundness

- **Do-No-Harm:** Enforce algorithmic guardrails to prevent isolating neurodivergent learners. Embed anti-bias checkpoints in observation rubrics, decoupling construct mastery from neurodivergent expressions to prevent automated score penalties.
- **Construct Disentanglement:** Statistically separate academic proficiency from construct-irrelevant factors (e.g., sensory overload). Utilize longitudinal sampling to distinguish temporary states from stable traits, preventing unwarranted IEP modifications based on anomalous data.
- **Algorithmic Transparency & Human-in-the-Loop:** Routinely audit models for bias, exposing logic via Explainable AI (XAI) readouts. Empower educators to override AI insights, ensuring the teacher remains the final arbiter.
- **Public Transparency:** Provide plain-language public portals summarizing data collection. Auto-generate visual data health dashboards for school boards.

Learner Variability

- **Whole-Child Profiling & Productive Struggle:** Output a multi-dimensional profile mapping academic, social, and emotional strengths. Log student errors as 'productive struggle' diagnostics, recommending environmental and instructional optimizations rather than applying immediate score penalties.

- **Accessibility:** Meet WCAG 2.1 AA standards and natively embed UDL accommodations. Offer a 'Choice Menu' allowing students to select measurement contexts while maintaining rigorous psychometric standards.
- **Flexibility:** Natively support multiple task completion pathways (audio, text, kinesthetic) without requiring formal IEP flags. Minimize deficit-oriented language, outputting data strictly as mastered skills and next-step growth targets.
- **Skill Isolation:** Algorithmically decouple domains so disabilities in one area (e.g., reading) do not artificially depress scores elsewhere. Provide Construct Integrity Reports verifying accommodations did not alter measurement targets.
- **Environmental Metadata:** Automatically capture and report learning environment metadata (e.g., accessibility tool utilization, task engagement times, UI friction).

Useability & Experience

- **UX Integration & Cognitive Motivation:** Strip away decorative graphics and culturally-specific idioms from the UI to reduce cognitive load.
- **Rapid Insights:** Deliver score reports within 60 seconds. Utilize LLMs and Natural Language Processing to score open-ended, constructed responses in real-time, reducing reliance on selected-response formats.
- **Interoperability:** Integrate with SIS/LMS platforms to eliminate duplicative testing, replacing disconnected interim tools with a single, continuously updating ecosystem.
- **Stealth Administration:** Deploy as a background application or embedded digital routine within existing classroom tools.
- **Data Privacy:** Enforce Role-Based Access Control, end-to-end encryption, and FERPA/COPPA compliance. Allow system leaders to configure data retention timelines, anonymization protocols, and automated parent consent workflows.

Useful & Valuable

- **Actionable Stakeholder Value:** Provide interactive feedback for **learners**; generate differentiated recommendations for **educators**; push home-language updates to **families**; and aggregate real-time leading indicators so **system leaders** can audit curricular efficacy without punitive accountability models.

Guidance for Policy and Procurement

To bridge the gap between human oversight and systemic implementation, the field must protect neurodivergent learners:

- **Ground Frameworks in Civil Rights Law:** Because measurement calibrates mandated specialized instruction [AI assessment](#) guidance must explicitly anchor in IDEA and Section 504.
- **Elevate Responsible AI:** School systems must demand proven efficacy and *Accessibility by Design*. Leaders should leverage precedents like the [Duolingo English Test's responsible AI](#) to evaluate assessment architectures.

About the authors

Eric M. Tucker is the President and CEO of the Study Group, which exists to advance the best of artificial intelligence, assessment, and data practice, technology, and policy. He has served as President of Equity by Design, Superintendent and Executive Director of Brooklyn Laboratory Charter Schools, CEO of Friends of Brooklyn LAB, Cofounder of Educating All Learners Alliance, Executive Director of InnovateEDU, director at the Federal Reserve Bank of New York, and Cofounder and Chief Academic Officer of the National Association for Urban Debate Leagues. As an entrepreneurial, strategic, and impact-focused leader, Eric has over 25 years of experience building catalytic partnerships in education, securing over \$300 million of investments for enterprises and initiatives that have transformed outcomes for learners and educators. Eric has expertise in measurement and assessment system innovation, participatory and advanced R&D, analytics, and human infrastructures for improvement and co-edited *The Sage Handbook of Measurement*. He earned a doctorate and a masters of science in measurement sciences from the University of Oxford and bachelors degrees from Brown University. Eric served as an ETS MacArthur Foundation Fellow with the Gordon Commission on the Future of Assessment in Education. He served as a Senior Research Scientist at the University of California, Los Angeles, National Center for Research on Evaluation, Standards, and Student Testing (CRESST).

About the Study Group

The Study Group exists to advance the best of artificial intelligence, assessment, and data practice, technology, and policy; uncover future design needs and opportunities for educational systems; and generate recommendations to better meet the needs of students, families, and educators.

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