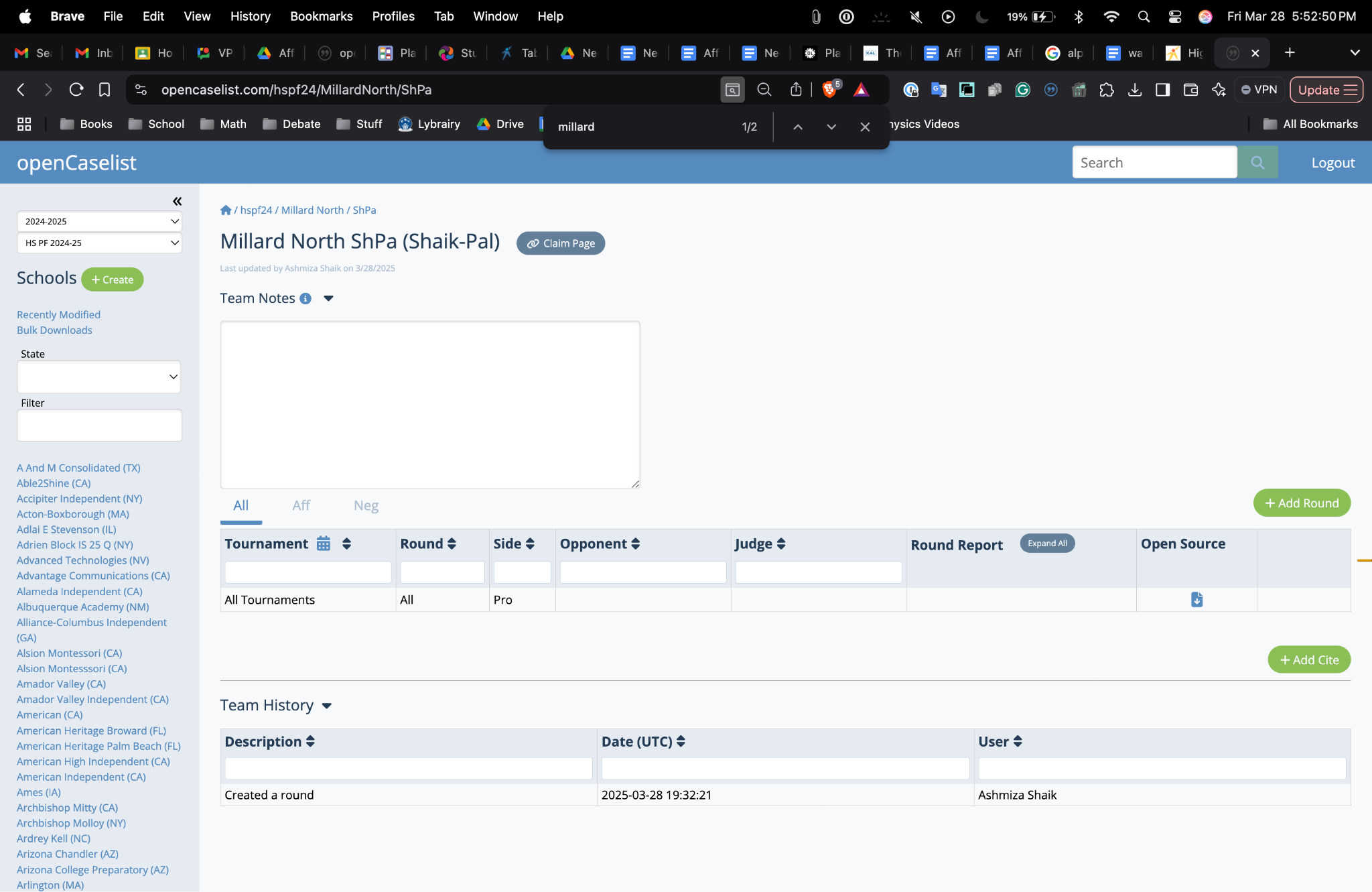
# 1st off

**A: Interpretation**: Debaters must fully disclose open-source with highlights all broken topical non-identity constructive positions from the current topic on the 2024-25 NDCA PF wiki under the proper competitor identification at least 30 minutes before the start of the round.

**B: Violation:** They don’t Screenshot: they didn’t disclose aff case from r1. The os on the wiki is a neg case



**C: Standards:**

1. **Evidence ethics** – disclosure allows debaters to check each other’s evidence before the round instead of using prep, meaning it’s easier to find misconstrued evidence. Better evidence allows for better in round and post round education.

2. **Research disparity** -- schools with big programs who bring more students and judges and are better connected will scout more rounds and have more flows; disclosure equalizes the gap by allowing more people to access arguments

3. **Clash** - disclosure allows opponents to prep out cases before the round, expanding depth of engagement, which minimizes the amount of squirrely and non educational debates.

4. **Breadth** -- Disclosure incentives teams to research new arguments and consistently improve older ones, which expands breadth and depth of education on the topic.

5. **Library** - creating an archive on the wiki of old cases means debaters can learn about old topics which deepens education

**D)Voters:**

**Vote on Fairness**, it’s needed for objective evaluation of the round **And, Education** - it’s why schools fund debate and the only long lasting skill

**Underview:**

Drop the debater for 2 reasons

a) Changing practices: losing rounds forces them to change their norms b) Norms: the ballot is used to set positive models for debate and create better norms

## 

## **Prefer competing interps, reasonability collapses into competing interps and incentivizes judge intervention where judges vote for what they think is more reasonable rather than who won**

**No RVIs For 3 Reasons:**

1) **Chilling**: no one tests norms in fear of losing defense on shell 2) **Baiting**: experienced debaters bait theory to win off RVI

3) **It’s illogical** - they shouldn’t win for proving they’re fair, that justifies a win for us as well

**Theory comes first** - you have to determine the rules of the game before you can play it.

# 2nd off

**​​Interpretation: Debaters must include author qualifications in the cites of all evidence read in round. To clarify, author quals = education, awards, positions, etc.**

**Violation: None of their evidence has quals**

**Standards:**

**1] NSDA Rules — Standard evidence rules in the NSDA manual say that the written cite must include qualifications, failure to abide by the same set of rules is the highest level of unfairness, since we came into the round held to all the practices the NSDA requires but they weren’t.**

**NSDA 25** [NSDA [NSDA is the leading governing body of high school debate; manual authors are high-ranking diamond coaches and/or NSDA administrators], "High School Unified Manual 2024-25", 2/19/2025, NSDA, https://docs.google.com/document/d/1hq7-DE6ls2ryVtOttxR4BNpRdP7xUbBr0M3SMYefek8/edit?tab=t.0#heading=h.xl2ogxg7zi2n, Accessed 03/19/2025] //ejs squad

**Evidence Rules for** Policy, **Public Forum**, Lincoln-Douglas, and Big Questions Debate **Evidence is one of the important components of arguments in debate rounds. All debaters involved are expected to act in an ethical manner that is in accordance with the rules**. In keeping with the National Speech & Debate Association Code of Honor, all participants are expected to use and interpret evidence, evidence rules, and procedures in good faith. The rules regarding use of generative artificial intelligence at the 2025 National Tournament can be found in the National Tournament Operations Manual section. 7.1. **Responsibilities of Contestants Reading Evidence** A. Evidence defined. Debaters are responsible for the validity of all evidence they introduce in the debate. Evidence includes, but is not limited to: facts, statistics, or examples attributable to a specific, identifiable, authoritative source used to support a claim. Unattributed ideas are the opinion of the student competitor and are not evidence. B. Oral source citation. In all debate events, contestants are expected to, at a minimum, orally deliver the following when introducing evidence in a debate round: primary author(s)’name (last) and year of publication. Any other information such as source, author’s qualifications, etc., may be given, but is not required. Should two or more quotations be used from the same source, the author and year must be given orally only for the first piece of evidence from that source. Subsequently, only the author’s name is required. Oral citations do not substitute for the written source citation. The full written citation must be provided if requested by an opponent or judge. C. Written source citation. **To the extent provided by the original source, a written source citation must include:** 1. Full name of primary author and/or editor 2. Publication date 3. Source 4. Title of article 5. Date accessed for digital evidence 6. Full URL, if applicable 7. **Author qualifications** 8. Page number(s)

**2] Evidence Comparison — Having qualifications readily accessible is key to making in-round arguments comparing the validity and quality of evidence. Two implications:**

**a) Key to clash and education since directly contradicting cards can be found for virtually every argument and comparison using qualifications is the only way to break said clash and expand topic knowledge beyond opposing warrants/ev.**

**b)It’s an in-round abuse since they were able to indict and make arguments about my authors at a glance whereas I had to Google their sources and learn their entire life story which presents a prep skew.**

**3] Problematic Authors — Forcing teams to research their authors’ backgrounds while cutting evidence greatly reduces the chance of unknowingly reading problematic authors; our model would drastically reduce the amount of “Bostrom IVI” rounds by ensuring those authors are not read in the first place.**

1. **Key to safety since racist, sexist, and other forms of problematic authors can directly harm debaters for whom their rhetoric is oppressive against.**

**Voters:**

**1] Fairness — debate is a competition and fairness indicates your ability to determine the winner. Your ballot carries no value otherwise.**

**2] Education — it's the reason schools fund debate and the only portable skill of debate.**

**3] Clash — controls the internal link to education and in its absence every round would be skewed.**

**4] Safety — no one would debate if they weren’t physically safe and schools wouldn’t fund it.**

**Cross app underview from first shell**

# Contention 2: Costs

**Integration of gen AI is a blatant attempt at corporate takeover of schools**

**Professors Williamson from the University of Edinburgh finds in 2024** (Ben Williamson is a Chancellor’s Fellow at the Centre for Research in Digital Education and the Edinburgh Futures Institute at the University of Edinburgh. Alex Molnar is a Research Professor at the University of Colorado Boulder. Faith Boninger is NEPC's Publications Manager and Co-Director of NEPC's Commercialism in Education Research Unit and holds a PhD from Ohio State University. Williamson, B. Molnar, A., & Boninger, F. (2024). “Time for a pause: Without effective public oversight, AI in schools will do more harm than good.” Boulder, CO: National Education Policy Center.<http://nepc.colorado.edu/publication/ai>) //Bellaire MC

School administrators and teachers already use an array of digital educational technologies in teaching and management.10 Their use has increasingly **obscured educational decision-making**, made a mockery of student privacy rights, and allowed student data to be exploited for non-school purposes.11 In the absence of effective public oversight, the introduction of AI systems and applications in education will likely intensify these problems and **create many more**.12,13 As existing school-focused platforms and applications are updated to include AI, the immediate danger facing educators is not a future apocalypse. Instead, the danger is that AI models and applications will become enmeshed in school processes and procedures in ways that allow **private entities** to **increasingly control** the structure and content of public education, to **reinforce surveillance** practices, and to **amplify existing biases** and inequalities.14 For decades, academic researchers have worked on AI models for use in schools.15 Today, however, it is commercial enterprises that are **aggressively pushing AI** (and its attendant risks) into classrooms.16 The campaign to promote AI in education follows the logic of a half century of commercial, political, and ideological efforts to privatize and **commercialize education.**17 Given this logic it is not surprising that, despite the known dangers, corporations, private researchers, and governments are aggressively promoting the use of AI18 before a statutory and regulatory framework has been put in place to ensure that AI programs are transparent and subject to effective public scrutiny and control.19 This puts schools under tremendous pressure to accept AI as an inevitable upgrade to existing processes.20 Computer scientists and software developers focus primarily on technical engineering questions21 and corporate leaders and **investors prioritize profit** 22 over the common good. Nevertheless, educators are being asked to trust that these people, who have **no educational expertise** and who stand to **financially benefit** when AI is used in schools, are best suited to imagine and lead educational transformation.

**AI systems take money from poor districts.**

**Williamson et.al 24** (Ben Williamson is a Chancellor’s Fellow at the Centre for Research in Digital Education and the Edinburgh Futures Institute at the University of Edinburgh. Alex Molnar is a Research Professor at the University of Colorado Boulder. Faith Boninger is NEPC's Publications Manager and Co-Director of NEPC's Commercialism in Education Research Unit and holds a PhD from Ohio State University. Williamson, B. Molnar, A., & Boninger, F. (2024). “Time for a pause: Without effective public oversight, AI in schools will do more harm than good.” Boulder, CO: National Education Policy Center.<http://nepc.colorado.edu/publication/ai>) //Bellaire MC

Dangers in Administration¶ Increased Costs¶ Learning management systems already used in many schools, such as Google Classroom,¶ Blackboard, and Canvas, are beginning to integrate AI into their platforms.150 Google Classroom, with its suite of nominally “free” software and low-cost Chromebook hardware, dominates the market.151 It has already announced the launch of AI-based adaptive learning addons to Classroom, with associated additional costs for schools, as well as plans to upgrade¶ Classroom further with generative language AI.152 “Practice Sets” is Google’s AI-based adaptive learning system for education, and “Duet AI” is its “collaboration partner” for teachers.153 In addition to any pedagogical implications associated with using Google Classroom,¶ its integration of further AI and automation into many aspects of school functioning also¶ carries potentially significant administrative implications.154¶ The most significant of these is to obscure the rationale for administrative decisions about¶ critical institutional issues when decision-making is ceded to opaque machine learning systems controlled by tech firms. Google Classroom, for example, integrates with hundreds of¶ other ed tech products and can synchronize with a school’s student information systems.155¶ It offers Google cloud services such as single sign-on, identity management, and device management, as well as plagiarism detection, automated grading, teaching templates, student¶ grouping, and administrative analytics to facilitate “data-driven decisions.”156 Such management systems facilitate the **transfer of control** of schools from the **public to private** corporations by acting as central conduits through which all of a school’s digital activities must¶ pass—making it hard for educators or administrators to see how any decisions based on the¶ data have been made.157¶ Because running AI is costly, the use of AI programs in schools will necessarily require¶ schools to pay for operating costs for an increasing number of pedagogic and administrative¶ AI applications. The promise that AI can save schools money by reducing staffing costs is¶ likely illusory, as schools will probably be required to pay costly fees for accessing AI facilities. In other words, rather than saving money, administrative applications are more likely¶ to shift existing funds to monopolistic technology providers.¶ Khanmigo and Google Classroom already illustrate how this works. Khan Academy, when it¶ provides Khanmigo to districts, currently charges those districts **$60 per student** for annual¶ use, citing high computing costs associated with OpenAI’s GPT-4 as the justification for the charges.158 Likewise, districts must also pay for Google Classroom’s AI upgrades. To access¶ its latest adaptive learning application, Practice Sets, they must switch from the free basic¶ offering to a for-fee premium package.159 In other words, tech firms are **extracting value**¶ from school budgets to defray the high computing costs associated with AI (and grow company value).160

Increased Threats to Student Privacy¶ AI applications collect and aggregate data in order to function. In so doing, they normalize digital surveillance and privacy invasions in school.161 In practice, education technology¶ companies use applications like Google Classroom to routinely collect as much data as possible, well beyond that required to perform their assigned tasks.162¶ Although proponents of using AI in education tend to emphasize the efficiency of data-driven¶ administrative systems, privacy-related threats to equity are inherent in it.163 This is because¶ AI models are built using massive data sets that can be used to profile, compare, and assess¶ individuals who are then subject to potentially discriminatory decisions based on “statistical¶ dossiers” of their personal lives.164 Thus, a significant danger of digital technology in general,¶ and of the privacy-invasive model of AI in particular, is that they can reproduce and amplify¶ existing forms of inequality in education by using datasets containing examples of historic¶ bias and discrimination.165 For example, if a big data set indicates that certain marginalized¶ groups have underperformed historically, then a software application may be biased against¶ individuals from such groups in the future, singling out and targeting them as “at-risk” and¶ closing down or limiting their opportunities to access information and resources.166¶ Moreover, school data systems are vulnerable to breaches, hacks, ransomware, and denial-of-service attacks.167 A data breach at the student-tracking ed tech company Illuminate,¶ for example, compromised the educational data of at least a million public school students¶ and prompted New York City’s Department of Education to ask schools to stop using Illuminate’s products.168 School data systems feature highly detailed and intimate student¶ information, including personal and demographic data, grades, attendance, behavioral information, and other confidential information. Increasing AI capacity in ed tech products¶ may exacerbate these vulnerabilities, as student data are collected at even greater scale by a¶ wide range of companies—including AI companies—that offer only vague data privacy protections.169 Reduced Transparency and Accountability¶ Finally, enabling AI to play a role in school administration will reduce the transparency and¶ accountability of decision-making.170 Many digital products already used in schools are neither transparent nor accountable because current law and regulation allows companies to¶ shield the inner working of their products behind proprietary protections.171¶ AI is even more opaque than other digital programs.172 Black box machine learning and AI¶ models are so complicated that their outputs are often impossible to explain or interpret.173¶ Although in many cases simpler and more accessible statistical models can produce equally accurate results, companies benefit from selling access to proprietary models that require¶ customers to trust the systems and simply accept being unable to verify results.174 If the¶ system makes a mistake, it might never be identified or redressed and the public suffers the¶ consequences. For example, the facial identification systems used for remote testing often¶ fail to accurately identify individuals or mistakenly flag student behaviors as suspicious, but¶ they are very hard for students to challenge.175¶ In high-stakes decision-making in a sector like education, allowing such impenetrable models to assume responsibility for key administrative procedures necessarily means the creation of schools in which school leaders and teachers will be unable to exercise judgment,¶ provide a rationale, or take responsibility for classroom and institutional decisions.176¶ Considerations for the Future¶ Is AI Development Responsible?

The rapid creation of AI applications for schools raises the urgency of prioritizing ethics,¶ student rights, and social responsibility in their development.177 Responsible AI development would ensure that products are safe and trustworthy, designed to benefit people, communities, and society, and mitigate harms.178 As yet, there is little indication that such values are adequately addressed in education applications.179 Unfortunately, academic AIED¶ researchers have tended to ignore them or delegate addressing them to the educational tech¶ industry and policy centers.180 This complacency—along with the money and power held by¶ commercial actors—enables commercial rather than educational imperatives to guide the¶ development of AI and furthers political interests promoting relentless testing and school¶ surveillance.181¶ Responsible governance would require the companies developing AI to commit to transparent and responsible product design, and also to monitoring, understanding, and mitigating¶ the continuous impacts of AI in various contexts. Of particular concern is the automation¶ of decisions with “irreversible and severe consequences.”182 For example, technologies to¶ identify emotions are currently being developed to assess if a person is lying and cheating.183¶ These technologies are inherently inaccurate, however, and an inaccurate judgment that a¶ student has cheated or that a witness is lying could have dire consequences for their lives.¶ Responsible AI governance might lead to delaying or indefinitely pausing development of¶ such technologies.¶ Although several responsible AI initiatives have produced principles, frameworks or checklists for safe and trustworthy AI development and accountability,184 these agendas can be¶ manipulated through various forms of industry lobbying and efforts to water down their¶ scope or possibilities of enforcement.185 Expanding responsibility for product safety to include the wide range of people or organizations that build and use AI—rather than leaving it¶ to technicians and business alone—would mitigate such dangers.186¶ Among the many obstacles to the implementation of responsible policies governing AI is¶ their cost. The goal of profit-seeking business is to shift to the public as many costs as possible while garnering the highest possible private rate of return on investments. Public oversight of AI necessarily entails either public ownership or a comprehensive regulatory regime¶ adequately financed to achieve its mission. The question is, where will the money come¶ from?¶ Moreover, the required regulation flies in the face of 50 years of policy devoted to deregulation and privatization. It would demand a fundamental rethinking of the government’s¶ relationship to commercial interests. Such rethinking would, without a doubt, be attacked¶ by self-interested parties as not only too costly but also as stifling innovation and promoting¶ inefficiency. While these arguments may be relevant in individual circumstances, they are¶ neither generally nor self-evidently true.¶ From the perspective of education, responsible governance of AI therefore entails significantly more commitment than the simple principles of responsible development issued by¶ industry. It also requires costly and ongoing monitoring of the effects of AI in classroom¶ contexts. It may also require delays and indefinite pauses in development where warranted—such as, for example, in cases where commercial AI providers seek to introduce products into schools with insufficient evidence that they produce beneficial outcomes, or when¶ those products automate professional judgement with potentially negative consequences, or¶ when they inadequately address questions of AI ethics directly relevant to education.¶ Is AI Inevitable?¶ AI products are moving into schools at dizzying speed. As we have noted, this is in part the¶ result of the pressure on schools to “modernize” by adopting the latest products that the¶ technology industry offers. There is already a consensus of sorts that the move to AI is inevitable. The director of educational technology at Newark Public Schools made the case to the¶ New York Times when he explained why his district adopted Khanmigo: “It’s important to¶ introduce our students to it, because it’s not going away.”187¶ The de facto requirement that students serve as a technology company’s experimental subjects might be explained by the initially low entry cost for school districts. Struggling districts, especially, might be willing to gamble that a technological innovation might turn¶ things around for their students. However, before placing that bet it would be valuable to¶ first ask some fundamental questions. Computer scientist Joseph Weizenbaum posed such¶ concerns 50 years ago, essentially arguing that no technology—including AI—should be implemented unless we know that it is both necessary and good.188

**The impact is tradeoff – programs like special education will be cut first when AI saps public budgets.**

Sinha 24 (Tannistha Sinha covers education, housing, and politics in Houston for the Houston Defender Network as a Report for America corps member. She graduated with a master of science in journalism from the University of Southern California in 2022, and was the recipient of the Annenberg Graduate fellowship. , "Texas school districts face $300 million federal special education funding cut", DefenderNetwork, https://defendernetwork.com/news/education/texas-special-education-funding-cuts/, 1-26-2024, DOA: 2-21-2025) //Bellaire MC

Texas public schools unexpectedly lost $300 million per year in federal special education funding amidst rising costs, the Texas Health and Human Services Commission notified school districts on Dec. 15.¶ The cuts are to the School Health and Related Services (SHARS), a federal special education program that allows Texas local educational agencies (LEAs) and shared service arrangements (SSAs) to request reimbursement for Medicaid health-related services. School districts are eligible for partial reimbursements when they directly offer medical services to students with special needs, instead of relying on a doctor or nurse.¶ The loss in annual funding relates to Medicaid reimbursements for special education students. It followed a court ruling in a billing disagreement between school districts and the federal government, dating back to 2017.

**That hurts millions:**

**Jaracz 24** [Jill Jaracz, "Public School Students with Disabilities Lack Sufficient Support", 10/27/2024, AccessiBE, https://accessibe.com/blog/knowledgebase/assistance-for-public-school-students-with-disabilities-vaires-by-state#:~:text=The%20law%20covers%20a%20range,the%20public%20school%20student%20population., Accessed 03/07/2025] //ejs squad

“When you're a kid, going to school feels like a given—no matter how much you beg to play outside instead. But **for** school-aged **children with disabilities**, going to school wasn't always a guarantee. For decades, many states legally refused to properly support the educational needs of children with disabilities, often putting them in institutions that did little to impart vital knowledge and life skills. This unequal treatment also burdened their families, who rarely had other options or access to resources to educate children at home. That changed in 1975 when Congress enacted the law known today as the Individuals with Disabilities Education Act (IDEA). IDEA ensures that students with disabilities can access appropriate public school education free of charge from the ages of 3 to 21. The law covers a range of disabilities, the most common being learning disabilities and speech impairments. Nationally, **IDEA covers 7.3 million students representing 15% of the public school student population**. The vast majority go to regular schools, with just 5% enrolled in specialized schools, private schools, or other types of programs, according to the Department of Education. Also, 2 in 3 students with disabilities spend 80% or more of their school day in general classes—a practice that would have been unthinkable pre-IDEA.”

# Rebuttal

**AI is discriminatory and inherently can’t incorporate outlier data**

Eileen **O’Grady** (Eileen is the former managing editor of the The Scope at Northeastern University, an experimental digital magazine focused on telling stories of justice, hope and resilience in Greater Boston. She is also a former staff writer for The Shelburne News and The Citizen, with bylines in The Boston Globe, U.S. News & World Report, The Bay State Banner and VTDigger. She holds a BA in politics and French from Mount Holyoke College and a MA in journalism from Northeastern University.), 4-3-20**24**, "Why AI fairness conversations must include disabled people — Harvard Gazette," Harvard Gazette, https://news.harvard.edu/gazette/story/2024/04/why-ai-fairness-conversations-must-include-disabled-people/, accessed 2-25-2025 //ejs squad

“A lot of research so far has focused on how AI technologies discriminate against people with disabilities, how algorithms harm people with disabilities,” Shah said. “My aim for this project is to talk about how even the conversation on AI fairness, which was purportedly commenced to fix AI systems and to mitigate harms, also does not adequately account for the rights, challenges, and lived experiences of people with disabilities.” For his research, he’s interviewing scholars who have studied the issue and evaluating frameworks designed to maintain AI fairness proposed by governments and the AI industry. Shah said developers often consider disability data to be “outlier data,” or data that differs greatly from the overall pattern and is sometimes excluded. But even when it’s included, there are some disabilities — like non-apparent disabilities — that are overlooked more than others. If an AI is trained on a narrow “definition” of disability (like if data from people who stutter is not used to train a voice-activated AI tool) the outcome will be that the tool is not accessible.

**AI has implicit biases against people with disabilities.**

**Fetzer 23** [Fetzer, Mary. “Trained AI Models Exhibit Learned Disability Bias, IST Researchers Say | Penn State University.” *Psu.edu*, Penn State University, 30 Nov. 2023, www.psu.edu/news/information-sciences-and-technology/story/trained-ai-models-exhibit-learned-disability-bias-ist. Accessed 1 Mar. 2025.] //ejs squad

¶ UNIVERSITY PARK, Pa. — A growing number of organizations are using sentiment analysis tools from third-party artificial intelligence (AI) services to categorize large amounts of text into negative, neutral or positive sentences for social applications ranging from health care to policymaking. These tools, however, are driven by learned associations that often contain biases against persons with disabilities, according to researchers from the [**Penn State College of Information Sciences and Technology**](https://ist.psu.edu/) (IST).¶ In the paper “[**Automated Ableism: An Exploration of Explicit Disability Biases in Artificial Intelligence as a Service (AIaaS) Sentiment and Toxicity Analysis Models**](https://trustnlpworkshop.github.io/papers/5.pdf),” **researchers detailed an analysis of biases against people with disabilities contained in the natural language processing (NLP) algorithms and models they tested.** The work, led by Shomir Wilson, assistant professor in IST and director of the [**Human Language Technologies Lab**](https://shomir.net/research.html), received the Best Short Paper Award from the 2023 Workshop on Trustworthy Natural Language Processing at the 61st Annual Meeting of the Association for Computation Linguistics, held July 9-14 in Toronto, Canada.¶ “We wanted to examine whether the nature of a discussion or an NLP model’s learned associations contributed to disability bias,” said [**Pranav Narayanan Venkit**](https://ist.psu.edu/directory/pnv5011), a doctoral student in the College of IST and first author on the paper. “This is important because real-world organizations that outsource their AI needs may unknowingly deploy biased models.”¶ *“Organizations that outsource their AI needs may unknowingly deploy biased models.”¶* Pranav Narayanan Venkit, *doctoral student in the College of IST*¶ The researchers defined disability bias as treating a person with a disability less favorably than someone without a disability in similar circumstances and explicit bias as the intentional association of stereotypes toward a specific population.¶ A growing number of organizations are using AIaaS, or Artificial Intelligence as a Service, for easy-to-use NLP tools that involve little investment or risk for the organization, according to the researchers. Among these tools are sentiment and toxicity analyses that enable an organization to categorize and score large volumes of textual data into negative, neutral or positive sentences. ¶ Sentiment analysis is the NLP technique for extracting subjective information — thoughts, attitudes, emotions and sentiments — from social media posts, product reviews, political analyses or market research surveys. Toxicity detection models look for inflammatory or content — such as hate speech or offensive language — that can undermine a civil exchange or conversation.¶ The researchers conducted a two-stage study of disability bias in NLP tools. They first studied social media conversations related to people with disabilities, specifically on Twitter and Reddit, to gain insight into how bias is disseminated in real-world social settings.¶ They crawled blog posts and comments from a one-year period that specifically addressed perspectives on people with disabilities or contained the terms or hashtags “disability” or “disabled.” The results were filtered and categorized and then statistically analyzed with popular sentiment and toxicity analysis models to quantify any disability bias and harm present in the conversations.¶ “Statements referring to people with disabilities versus other control categories received significantly more negative and toxic scores than statements from other control categories,” said contributing author [**Mukund Srinath**](https://ist.psu.edu/directory/mus824), a doctoral student in the College of IST. “We wanted to test whether these biases arise from discussions surrounding conversations regarding people with disabilities or from associations made within trained sentiment and toxicity analysis models and found that the main source of bias disseminated from the models rather than the actual context of the conversation.”¶ The researchers then created the Bias Identification Test in Sentiment (BITS) corpus to help anyone identify explicit disability bias in in any AIaaS sentiment analysis and toxicity detection models, according to Venkit. They used the corpus to show how popular sentiment and toxicity analysis tools contain explicit disability bias. ¶ "**All of the public models we studied exhibited significant bias against disability," Venkit said. "There was a problematic tendency to classify sentences as negative and toxic based solely on the presence of disability-related terms, such as ‘blind,’ without regard for contextual meaning, showcasing explicit bias against terms associated with disability.”**