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JUST-AIED: AN ESSAY ON JUST APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN EDUCATION

Chris Chambers Goodman, Esq. *

"We can't wait until a student is 16, 17, 18 to expose them to something for the first time when they've already solidified a lot of the ideas about who they are and where they fit. We have to introduce this so much younger to break those stereotype threats."

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She rushes up to the building and pounds on the closed door. She got lost, is late, and just wants to get inside. She had been given a card, not a key, and cannot find a place to insert it. She reaches for a phone, but all she sees is a blank screen. There is no dial, no button, no keypad.

The screen is voice-activated, and does not recognize her excited shouts as words. She bursts into tears as she tries again. The pitch of her voice is disregarded as background noise, not human.

She peers into the screen, hoping someone will see her. But it is dark outside and she is dark. The facial recognition program barely detects a shape, and categorizes her image as animal, not human.

And so, she sinks to the ground, crying in frustration, unseen and unheard. She has been locked out in the cold, missing her first college class. 

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* Professor of Law, Pepperdine Caruso School of Law, A.B. cum laude Harvard College, J.D. Stanford Law School. The Author wishes to sincerely thank Richard Re and all of the participants in the 2020 AI and Justice in 2035 Roundtable, sponsored by UCLA’s PULSE institute, and particularly Emily Taylor Poppe as commentator for an early draft of this Essay. Gratitude for inspiring this research goes to the panelists on the 2020 AALS Evidence and BioLaw joint program on Algorithmic Knowledge, Law, Science and Democracy: Andrea Roth, David Engstrom, Nicholson Price, and Arith Rai. For diligent editing and a fantastic 2021 Symposium, the author thanks the students of the West Virginia Law Review, and especially Jordan McMinn and Ashley Faulkner. This Essay is dedicated to all the K–12 teachers who pivoted to provide online education during the COVID-19 crisis, and to the students on digital diets who are being left behind. May they find the access they need to open the doors of their minds.


2 Facial recognition software can be problematic for people of color. For instance, remote proctoring systems used during the COVID-19 crisis failed to register the faces of some darker-complexioned test-takers. Monica Chin, ExamSoft’s Proctoring Software Has a Face-Detection Problem, VERGE (Jan. 5, 2021, 9:21 PM),
I. INTRODUCTION

Artificial Intelligence ("AI") opens up enormous possibilities for enhancing educational access and opportunity. Engineers are developing AI applications at an accelerating pace in the private sector, and government actors have been working on law, policies, and other initiatives. The White House even hosted a summit on AI in Government in the fall of 2019 to review the ongoing work towards achieving the objectives of an AI Executive Order issued earlier that year.

https://www.theverge.com/2021/1/5/22215727/examsoft-online-exams-testing-facial-recognition-report. The stereotype threat that many may already feel has been exacerbated for people of color taking the Fall 2020 bar examinations online. Id. Recent law graduates sitting for the 2020 bar examination were compelled to shine a light on their [darker] faces to ensure that the camera could see them and not flag a "discrepancy" in the remote proctoring software. Nathalie A. Smuha, Trustworthy Artificial Intelligence in Education: Pitfalls and Pathways 14 (Dec. 7, 2020) (unpublished draft), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3742421. This article discusses the ethical risks of AI and examines the seven requirements for trustworthy AI and policymaking considerations. It also provides an example of students of color who were "forced to project a white light on their face during the exam so as to ensure the application would continue to recognize them" for proctoring purposes. Id. (internal citations omitted).

3 For instance, on February 11, 2019, the President signed Executive Order 13859, entitled "Maintaining American Leadership in Artificial Intelligence." Exec. Order No. 13859, 84 Fed. Reg. 3,967 (Feb. 14, 2019). The Order first set forth policies and principles, which included to drive technological breakthroughs, develop appropriate standards, train current and future generations of workers, foster public trust, and promote a supportive international environment. Id. The Order then provided the following six objectives: (1) "promote sustained investment in AI R&D"; (2) "enhance access to high-quality and fully traceable federal data, models and computing resources"; (3) "reduce barriers to the use of AI technologies to promote their innovative application"; (4) "ensure the technical standards minimize vulnerability to attacks from malicious actors and reflect federal priorities"; (5) "train the next generation of American AI researchers and users"; and (6) "develop and implement an action plan." Id.

4 Summary of the 2019 White House Summit on Artificial Intelligence in Government, WHITE HOUSE OFF. OF SCI. & TECH. POL’Y, at 5 (Sept. 9, 2019). The Executive Order asked for plans to
With these and other initiatives promoted on the state, national, and international levels, society is poised for more exciting engagement with AI technologies and applications. A 2019 Report from the Center for Internet and Society notes the opportunities to enhance educational access, opportunities, and outcomes through “intelligent tutoring systems, tailored curriculum planning, and intelligent virtual reality.” Many of these technologies and applications are already available, and their use has increased with the COVID-19 crisis. Indeed, the forced use of technology may be a silver lining to the cloud of COVID-19 for many, as schools generously provided laptops, tablets, and Wi-Fi hotspots, and parents were reticent to limit “screen time” when so much of it was actually “class time.” Consequently, capitalizing on this rise in the use of technology for education is a developing task. As one scholar explains, “[t]he key is not to replicate the apparently workable pre-COVID-19 systems, but instead to build improved systems that allow accelerated learning for all students, drawing on digitized approaches.”

In fact, according to Stanford’s 100 Year Study on AI (“The 100 Year Report”), Generation Alpha is already developing some facility with AI. On the upside, children growing up with this exposure to AI applications will become adults who are much more comfortable and conversant with these interactions. Yet, notwithstanding the fascinating potential of AI, this Essay

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6 Hans d’Orville, COVID-19 Causes Unprecedented Educational Disruption: Is There a Road Towards a New Normal?, 49 PROSPECTS 11, 12 (2020) (“Extended school closures may not only cause loss of learning in the short-term, but also diminish human capital and economic opportunities for children and youth over the long term.”).

7 Id. at 13.

8 Current preschoolers are considered to be Generation Alpha as the children of Millennials for whom “technology is simply an extension of their own consciousness and identity, with social media being a way of life.” Id. at 14.

9 Artificial Intelligence and Life in 2030 42 (2016), https://ai100.stanford.edu/sites/g/files/sbiybj9861/f/ai_100_report_0831fnl.pdf (“Already children are increasingly exposed to AI applications, such as interacting with personal assistance on cell phones [and] with virtual agents and theme parks. Having early exposure will improve children’s interactions with AI applications, which will become a natural part of their daily lives. As a result, gaps will appear in how younger and older generations perceive AI’s influences on society.”).

10 Id. at 31. In the education realm, it predicts that there will be widespread use of AI tutors and classroom assistance as well as additional Virtual Reality applications. Id.
explores the need to promote justice in our present and future use of AI in education.\footnote{See Andre M. Perry & Nicol Turner Lee, AI Is Coming to Schools, and If We Are Not Careful So Will Its Biases, BROOKINGS: AVENUE (Sept. 26, 2019), https://www.brookings.edu/blog/the-avenue/2019/09/26/AI-is-coming-to-schools-and-if-were-not-careful-so-will-its-biases/ (“AI can level the playing field in classrooms, [and] we need more due diligence and intellectual exploration before we deploy the technology to schools. Systemic racism and discrimination are already embedded in our educational systems. Developers must intentionally build AI systems through a lens of racial equity if the technology is going to disrupt the status quo.”).}

One significant concern is that how we develop institutional knowledge may change as we become more dependent, conversant, and reliant upon AI.\footnote{Mariano-Florentino Cuéllar, A Simpler World? On Pruning Risks and Harvesting Fruits in an Orchard of Whispering Algorithms, 51 U.C. DAVIS L. REV. 27, 37 (2017).} A few years ago, California Supreme Court Justice Mariano-Florentino Cuéllar gave examples of how motorized transport changed human walking habits, such as the amount of walking humans did, their ability to walk, and their stamina.\footnote{ARTIFICIAL INTELLIGENCE AND LIFE IN 2030, supra note 9.} The 100 Year Report echoes this concern that AI applications will affect people’s “avoidances and capabilities,” such that with some tasks, “people’s ability to perform them may wither”\footnote{Id. at 45.} in much the same way that calculators diminished the math abilities of children, and consequently, of adults. We are already at the point where many people no longer attempt to recall basic facts and formulas where the answers are easy to access. We may continue to lose skills in basic math, including our ability to read clock faces, measure, and convert temperatures, among others. Less tangible skills and attributes may wither as well. For instance, a recent survey found that the greatest need for additional resources involves social and emotional learning, which AI is not designed to promote.\footnote{Id. at 3. The Rand Report notes that “district leaders indicated that remote learning, in at least some form, will outlast the Covid-19 pandemic.” Id. “One in five districts were considering, planning to adopt, or had already adopted a virtual school or fully online option, while about one in ten have adopted or are planning to adopt a blended or hybrid form of instruction.” Id. at 11. Shortages of substitute teachers in the virtual environment was noted by many districts. Id. at 15. Insufficient staff funding is another need expressed by both richer and poorer districts. Id. at 17.}

For those in the lower income and resource categories, fundamental issues such as internet and technology access are equally important concerns.\footnote{Laura Stelifano, Sy Doan, Ashley Woo, Melissa Diliberti et al., The Digital Divide and COVID-19, RAND CORP. 5–6 (2020), https://www.rand.org/pubs/research_reports/RRA134-3.html.}

A key predictor of whether school work was being completed by students was whether the teacher predicted or estimated that there was home internet access.\footnote{Laura Stelifano, Sy Doan, Ashley Woo, Melissa Diliberti et al., The Digital Divide and COVID-19, RAND CORP. 5–6 (2020), https://www.rand.org/pubs/research_reports/RRA134-3.html.}
When remote learning was mandated, “[o]nly 30 percent of teachers in schools in the highest category of school poverty . . . reported all or nearly all the students have access to the Internet, which was 53 percentage points lower than reports of teachers in the lowest-poverty category.” Internet hotspots were provided by only 45% of schools, although a larger percentage provided information about how to access the internet. Of course, this report is limited by its reliance upon teacher estimates of internet access.

While inconsistent internet access impeded student learning during the current crisis, the problem is not unique to this particular crisis. This crisis has also exacerbated the “digital divide” between the haves and have-lesses, and without focused interventions, that gap likely will widen as the crisis subsides. Moreover, this increased use of technology during and after the COVID-19 crisis likely will further expand the chasm already existing in the degrees of digital nativism between younger and older generations, and more and less privileged (wealthier and more impoverished, respectively) people. For those on “digital-diets,” those with less access to technology, their accessibility and visibility will decrease further, in part because they will not be adapting to the presence of technology.

Consider this example from everyday life: you are calling customer service and voice-activated AI technology answers the call. While you have the technology (a telephone) necessary to make the call, you may not be able to effectively use the access that your telephone provides. You are given nine choices, each choice corresponding to a number on the telephone keypad;

18 Id. at 3. The highest category of school poverty has 76% to 100% of students eligible for free and reduced price lunch (“FRPL”) while the lowest category has 0% to 25% FRPL eligible students.

19 Id.

20 Id. at 1. This study used data from almost 6,000 teachers on a state and national basis, drawn from the American Instructional Resources Survey, which was conducted in May and June 2020 with RAND Corporation American Educator panels and state representative samples. Id. at 2. “Surveys from spring 2020 revealed that during school closures, schools and teachers faced challenges related to student engagement and students’ lack of Internet access. Moreover, these challenges were more prominent in high-poverty schools than low-poverty schools.” Id. at 1.

21 Id. at 3. “Disparities in internet access for households with higher levels of poverty in rural areas were documented before the pandemic began. Access to the internet remains a serious concern for teachers’ capacity to deliver high-quality remote instruction during the 2020–2021 school year.” Id. at 1.

22 d’Orville, supra note 6 (“But a danger looms: a new type of digital divide is bound to arise as students need laptops, tablets, or phones, as well as some type of Internet access, in order to benefit from access to online material.”).

23 Id. at 13 (recognizing that “[t]here is a risk that educational AI systems and personalization could increase inequities: after the coronavirus crisis, they could become high-priced commercial services affordable only to a small share of the population. This would induce a new digital divide”).

24 ARTIFICIAL INTELLIGENCE AND LIFE IN 2030, supra note 9.
however, none of those choices accurately or even remotely describes what you wish to address in the call. You can ask for “more choices,” and see what happens. Some voices are not understood by the machine (“Please say that again.” “That is not an option I can help you with.” “Please select from the following menu”). You can listen to the list again and decide which choice fits closest or seems to be in the same category as yours, or you can try to figure out which button (new customer!) will most likely lead you to a human voice.

You can also do what many people actually do—hang up. You are unable to be heard and so you cannot accomplish your task. Those who disconnect the call will not have learned how to interact with the technology even though they have access to it. Those who cannot effectively interact will still be denied opportunities to correct the problem that motivated the customer service call. Those who disconnect the call will not learn the language of machine-human engagements and will be like characters without any speaking parts in a play. If there is no avenue through which to speak, then there is no opportunity to be heard, so while they have access to technology, they cannot make effective use of it. They are present but might have little or no impact on the direction of events. Without both access and ability to interact, they cannot be a part of the processes creating new technologies and may also be excluded from the data sets on which the existing technologies operate and the new technologies learn.

In contrast, those whom the technology can recognize will be a part of how the technology is trained. The rest will be outcasts, rendered virtually invisible. Choices of private industry, such as those who determine which options the call center can comprehend, actually may end up making public policy decisions.

Instead, we need to be mindful of this caution in creating, expanding, and implementing AI in education: “Big Data processes codify the past. They did not invent the future.” Our fate is what we make, and “we” made it that way. So, how can we make it the right way for justice in education?

25 Id. at 43 (noting that “AI could widen existing inequalities of opportunity if access to AI technologies—along with the high-powered computation and large-scale data that fuel many of them—is unfairly distributed across society. These technologies will improve the abilities and efficiency of people who have access to them”); providing an example of translation technology that may only be available in English, which will then widen the divide for English language learners as compared to other language learners).

26 RUHA BENJAMIN, RACE AFTER TECHNOLOGY 12–14 (2019) (noting that we need to “consider how private industry choices are in fact public policy decisions” and recognize that “[w]e are more like unwitting constituents who, by clicking submit, have authorized tech giants to represent our interests”). The past of structural racism means that AI designers and programmers of facial recognition software use mostly white faces for their tests. Id. at 14. Thus, it is no surprise that dark faces may not register when public institutions use the same software, thus perpetuating the discrimination in future data.

27 CATHY O’NEIL, WEAPONS OF MATH DESTRUCTION 204 (2016). In terms of advice, the author says she relies upon a form of Hippocratic oath by financial engineers Emanuel Derman and Paul Wilmott after the 2008 financial crisis: to recognize that the world “doesn’t satisfy my equations,”
This Essay addresses the intersections between AI and justice in the context of K–12 education. Part II provides some foundational context, defining the scope of AI and some aspects of justice that especially apply to educational access and opportunity. The next part sketches an answer to the question: What should we do to promote AI for justice? Part IV considers the potential pitfalls of augmenting AI in K–12 education. The final part makes a bold call to action.

II. AI AND JUSTICE IN EDUCATION

This Section provides some context by defining the terms “AI” and “Justice” for the purposes of this Essay. On the issue of justice, numerous preliminary questions have been addressed in more detail in other works. For this Essay’s purposes, one brief note of particular relevance is whether we want to focus on the anti-classification principle or the notion of equal outcomes. “Anti-classification” means not using things like race and gender explicitly in the decision-making process. “Statistical parity” is based on equal likelihoods for all groups.

These approaches cannot co-exist, and so a necessary prerequisite is to select which aspect of fairness one wishes to pursue. The algorithms used in

be not “overly impressed with mathematics,” and “never sacrifice reality for elegance without explaining why.” Id. at 205.


The authors recognize the limitations of these approaches to fairness noting that it is important to appreciate, however, that measures of fairness are often completely inadequate [as] they seek to validate models that are deployed on groups of people that are already disadvantaged in society because of their origin, income level, or sexual orientation. We simply cannot “optimalize” around” existing economic, social, and political power dynamics.

Id. at 15 (internal citations omitted).
AIED, like any algorithms, classify. Along which lines they classify may seem inevitable, but it really is up to the designers.

There are two approaches to defining AI: this first defines AI as “that activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment.” The second approach defines AI as a “branch of computer science that studies the properties of intelligence by synthesizing intelligence.” There are four considerations in defining AI based on what the application is designed to do: (1) think humanly, (2) act humanly, (3) think rationally, and (4) act rationally. Because these can be conflicting goals, the ability to synthesize data and adapt to environments is crucial.

AIED refers to AI used for educational purposes, and it may include intelligent tutoring systems, adaptive learning, pedagogical agents, and learning analytics. AEID may be enabled by smart classrooms, learning environments and institutions, education and administrative management systems, and also learning analytics. Proctoring software has emerged alongside AIED as schools and test administrators are resorting to increased use of AI to promote testing integrity.

32 Safiya Umoja Noble, Algorithms of Oppression: How Search Engines Reinforce Racism 17–23, 140 (2018) (illustrating results of the author’s online search of the term “black girls”). Classification systems reflect mainstream valuations, and how terms are indexed impacts what is included and excluded in databases, just like library catalogs for paper books. These classifications similarly impact search engines, such as auto-correction biases that change names to male and finish search queries with terms reflecting negative group stereotypes. Id. at 140. In addition, Cathy O’Neil laments that algorithms have turned the American motto e pluribus unum on its head, in that they have carved “one into many” in terms of silos that are often designated by race, class, geography, zip code, and other overlapping identities. O’NEIL, supra note 27, at 200.

33 O’Neil notes that the resulting “widespread damage . . . often passes for inevitability,” hence the need to shine a light on darker faces for proctoring purposes. O’NEIL, supra note 27, at 201.

34 Artificial Intelligence and Life in 2030, supra note 9, at 12 (quoting Nils J. Nilsson, The Quest for Artificial Intelligence: A History of Ideas and Achievements (2009)).

35 Id. at 13.


37 Erica Southgate, Artificial Intelligence, Ethics, Equity in Higher Education, NAT’L CTR. FOR STUDENT EQUITY IN HIGHER EDUC. 6 (2020).

38 Id. A recent systematic review of AI in education “found that there was inadequate theoretical connection to pedagogical theory and perspectives, limited critical reflection of challenges and risks of AIED, and a need for more research on the ethical implications of using the technology in education.” Id. at 7–8 (discussing human rights principles known as PANEL: participation, accountability, non-discrimination and equality, empowerment, and legality).

39 Smuha, supra note 2. This article discusses the ethical risks of AI and examines the seven requirements for trustworthy AI and policymaking considerations. See id. Smuha uses the example
Larger questions aside, for this Essay’s purposes, the premise is that one necessary aspect of justice is civic participation—the ability, opportunity, and actual participation of members of society in making, interpreting, and enforcing the laws and regulations that govern them. Education is a precursor to meaningful civic participation, and therefore, educational access and opportunities are essential components of justice, broadly defined.

III. PROMOTING AI FOR JUSTICE IN EDUCATION

With these framing concepts in mind, what should we do to promote AIED for justice? The answer is relatively straightforward: focus on giving underprivileged students a chance to be seen and heard in the digital realm. The rest of this Section explains how to accomplish this goal.

A. Why Should We Do It?

Students from low or very low-income households, and those from neighborhoods of concentrated poverty, lag behind their more affluent peers academically. These disparities are most pronounced in two specific academic areas: language ability (including the size of vocabulary and language processing) and executive functioning (working memory, cognitive control, and the ability to order and prioritize tasks). This academic lag is evident in standardized test scores, as numerous studies have demonstrated a correlation between scores and socioeconomic status (“SES”).

As standardized tests are a key component of the meritocracy culture, score disparities on top of racial, ethnic, and economic disparities keep the gap wide. The Scholastic Aptitude Test (“SAT”) was developed to promote “merit” of students of color who were “forced to project a white light on their face during the exam so as to ensure the application would continue to recognize them” for proctoring purposes. Id.

40 Joshua E. Weishart, Democratizing Education Rights, 29 WM. & MARY BILL RTS. J. 1, 67 (2020) (explaining that “[p]ublic schools were created to restore faith that we could live and thrive democratically so long as we instill in children the virtues of democracy and the moral virtues of citizenship”).


44 Rajeev D.S. Raizada & Mark M. Kishiyama, Effects of Socioeconomic Status on Brian Development and How Cognitive Neuroscience May Contribute to Levelling the Playing Field, 4 FRONTIERS HUM. NEUROSCIENCE 1, 3 (2019).
over pedigree, to counter the culture in the Ivy League universities of what had become a “hereditary elite,” and to admit kids from Nebraska into Harvard.45 James Bryant Conant, the President of Harvard College in the 1940s, wanted a way to identify intelligent high school students from around the country, rather than focusing on those who attended the New England prep schools that brought forth the majority of Harvard applicants.46 Notwithstanding the initial goal, the SAT ended up being biased in other ways, focusing on certain conceptions of merit, which now can be learned and are based on income as much as intellect.47

B. How Should We Do It?

AI designers and creators can now expand their influence for educational good, by making AI available to underprivileged students to help them develop the skills that will enable them to succeed in their educational endeavors. Specifically, AI should be developed to teach underprivileged students—as teachers’ assistants and tutors (“AITAs”) to do rote, remedial, and even tailored, intensive individualized instruction on fundamentals.48 These AITAs would be in-person robots for those students with actual in-person class sessions, with chatbots and other options being used for schools still in remote and distance learning, and for homework and outside of class assistance.

Employing an intelligent adaptive learning system can provide the individualized attention and focus needed to achieve educational equity49 or make significant progress towards that goal. Personalized AITAs is a focused way to reduce the achievement gap,50 particularly (and perhaps only) if the AITA supplements the human teacher.51 This individualized attention can transform the

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45 I am indebted to Andrea Roth, a roundtable participant, for emphasizing this point.
47 Id. at 164–65.
48 “AI systems are used to monitor asynchronous discussion groups, thus affording teachers with information about learners’ discussions and support for guiding learners’ engagement and learning,” Pedro et al., supra note 36, at 12.
49 Intelligent Adaptive Learning Systems (IALS), Squirrel AI Learning, http://squirrelai.com/product/ials (last visited Feb. 21, 2020) (“Our mission is that every child become people who are capable and decent. When everyone has the most knowledgeable AI teacher beside every time s/he needs, then education equity is not just a slogan, but every child can realize his/her own different dream completely.”).
50 Sameer Maskey, Artificial Intelligence in Education Transformation, FORBES (June 8, 2020, 7:10 AM), https://www.forbes.com/sites/forbestechcouncil/2020/06/08/artificial-intelligence-in-education-transformation/?sh=41f97c2032a4 (“Equipping educators with AI-power technology can help alleviate some of these challenges. For example, using AI systems that act as personal tutors can help the student-teacher ratio problem by providing feedback and support when teachers don’t have the bandwidth.”).
51 Pedro et al., supra note 36, at 13 (“A dual-teacher model entailing a teacher and a virtual teaching assistant, which can take over the teacher’s routine tasks, frees up teachers’ time, enabling
learning experience for low-income students,\textsuperscript{52} just as it can and does for high-income privileged students whose families can pay for similar services. The data analytics can also help solve individual students’ learning problems and give them concrete and effective strategies for academic improvement, based on what has previously helped other students with similar challenges.\textsuperscript{53}

Additionally, these AITAs can create new tests from existing databases of past tests, to test and re-test students and produce reports that humans can evaluate, to see where the educational deficiencies come from and, then, design more systems to specifically teach the students what and how they need to learn in order to do better in these areas.\textsuperscript{54} Like the GRE, which is section-adaptive—

\begin{quotation}
\small
\textit{them to focus on student guidance and one-to-one communication.”}). Such personalized tutors are already being used in some settings for focused academic subjects. For instance, the Artificial Intelligence and Life in 2030 report states,

Though quality education will always require active engagement by human teachers, AI promises to enhance education at all levels, especially by providing personalization at scale. Interactive machine tutors are now being matched to students for teaching science, math, language, and other disciplines. Natural language processing, machine learning, and crowdsourcing have boosted online learning and enabled teachers in higher education to multiply the size of their classrooms while addressing individual students’ learning needs and styles.

\textbf{Artificial Intelligence and Life in 2030, supra note 9, at 7.}

\textsuperscript{52} Maskey, supra note 50 ("Introducing supporting tools like these from the ground up can help eliminate the socioeconomic discrepancies in schools, changing the way students perceive themselves, their peers and their overall learning experience.").

\textsuperscript{53} YJ Yang, Education: AI Can Help Solve America’s Education Crises, FORTUNE (July 14, 2020, 5:00 PM), https://fortune.com/2020/07/14/education-crisis-artificial-intelligence/ ("These AI tutors, software systems the students interact with online, can give everyone individualized attention. Suddenly 1-on-1 teaching can scale. AI tutors are eternally patient. What’s more, the teaching is not based on guesswork or intuition but on data. Learning algorithms can uncover patterns about how individual students perform, and companion algorithms optimize teaching strategies accordingly."); see also Andre Parry & Nicole Turner-Lee, AI Can Disrupt Racial Inequity in Schools, or Make It Much Worse, HECHINGER REP. (Sept. 25, 2019); Maskey, supra note 50.

Furthermore, data must also account for inequities, providing insights, for example, on learning outcomes disaggregated according to demographic factors such as age, gender and socio-economic background. The ability to generate such analyses allows education systems to determine the educational disadvantage experienced by specific marginalized [sic] or vulnerable populations. However, data on disadvantaged groups still currently tend to be incomplete and even absent.

Pedro et al., supra note 36, at 30.

\textsuperscript{54} Of course, it may be an even better use of our time to develop tests that actually test skills attorneys need to have effective in law practice, such as the lawyer effective measurement instrument that Professors Zedeck and Shultz developed. See, e.g., Kristen Holmquist, Marjorie Shultz, Sheldon Zedeck & David Oppenheimer, Measuring Merit: The Shultz-Zedeck Research on
meaning if a person does poorly on the first verbal section, then the second verbal section presented in the computer version of the test will be less difficult—new technologies can use more refined processes to teach rather than merely test.\textsuperscript{55} These processes can guide students to do better on the underlying material, rather than simply confirm what the students have not learned.

Unfortunately, public schools cannot afford this technology.\textsuperscript{56} Paradoxically, they cannot afford to not to use this technology. Currently, fewer investment dollars are committed to AI research that does not have any commercial application, and low-SES students will not be able to afford these technologies.\textsuperscript{57} Accordingly, other incentives must be found.\textsuperscript{58} This decision point is where public-private partnerships with Big Tech will be crucial.

This Article urges Big Tech to provide the AI, AITAs, robots, Wi-Fi access/hotspots, and programming on a proprietary basis. But why would private companies want to get on board? Those who design and train AI have the great power to expand access to knowledge, teach in new ways, and substantially increase the educational opportunities of those who have access to it. And as Spiderman says, “with great power comes great responsibility.”\textsuperscript{59} That power is being exercised in a way that can, will, and already has widened the gap of educational opportunity between those who have substantial access and those who have little or no access to AI technologies. This increasing gap will expand, perhaps exponentially, in the course of the next several years if we do not make conscious, effective efforts now to expand AI access for underprivileged students to teach them how to excel on their assessments.

\textit{Law School Admissions}, 63 J. LEGAL EDUC. 565 (2014). The academy has not picked up on that suggestion. Thank you to Roundtable commentator Emily Poppe for highlighting this approach.

\textsuperscript{55} \textit{Frequently Asked Questions About the GRE General Test}, EDUC. TESTING SERV., https://www.ets.org/gre/revised_general/faq (last visited Mar. 1, 2021) (“[T]he difficulty level of the second section of each of the measures depends on your overall performance on the first section of that measure. For example, if for the Quantitative Reasoning measure, you do very well on the first section, the second section of the Quantitative Reasoning measure will be at a higher level of difficulty.”). The former electronic version of the GRE adjusted subsequent questions to be more or less difficult depending on the right and wrong answers submitted to previous questions, rather than sections.

\textsuperscript{56} Weishart, \textit{supra} note 40, at 59 (explaining that states will need federal government assistance to make up for funding shortfalls due to COVID-19, and yet states spend less than about 3\% of their GDP on K–12 education. As that GDP declines, so do education finances.).

\textsuperscript{57} \textit{Id.}

\textsuperscript{58} The 100 Year Study recommends “targeted incentives and funding priorities.” ARTIFICIAL INTELLIGENCE AND LIFE IN 2030, \textit{supra} note 9, at 7–8. One significant concern is that sharing student data will be the cost of an AIED that impoverished schools must pay in order to obtain access to the technology. Smuha, \textit{supra} note 2, at 20 (noting that payment in the form of sharing student data in exchange for technology is already happening in less well-resourced European schools).

C. How Will It Work To Reduce the Achievement Gap?

The next question that will inevitably arise is “How can AITAs alleviate the achievement gap when other schools and their students with more resources can simply obtain their own AITAs?” The answer is within our capacity. Imperatively, this technology must be licensed and provided by private technology companies to only a subset of schools for four reasons. First, a pilot program focused on the lowest SES students will leverage the limited funding, hardware, software, and trained teachers available to implement the program in the initial stages. The program will include AITA robots, technical support specialists in AIED to train the algorithms, as well as the teachers and aides to make the most effective use of the technology.

Second, the AI must be proprietary, not open source as so many recommend. Unrationed, unregulated or open access to these AITAs would only increase the digital divide, as the high-SES students with devices and bandwidth enjoy greater access to personal tutors than the low and very-low SES, digitally dieting students who most need the extra educational help.

Third, from a distributive justice perspective, an argument can be made that directing the resources to the lowest SES schools and to their students is more equitable than an equal allocation. While there are numerous ways to define the subset, the percentage of free and reduced price lunch eligible students, or listing as a Department of Education Title I school, is the best way to determine the members of the subset. Some may be asking why the subset is not comprised of schools with the lowest performance metrics. The answer is,

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60 I extend my gratitude to AI Roundtable participant Eugene Volokh for identifying this potential counterargument.

61 Bettina Berendt, Allison Littlejohn & Mike Blakemore, AI in Education: Learner Choice and Fundamental Rights, 45 LEARNING, MEDIA & TECH. 312, 313–14 (2020). This article is discussed infra note 74 and concludes with this caution: “The sooner regulation is implemented, the faster learners, teachers and all citizens can avoid the risks of AI in education undermining their fundamental human rights.” Id. at 321.

62 The 100 Year Study further explains that, “AI could widen existing inequalities of opportunity if access to AI technologies—along with the high-powered computation and large-scale data that fuel many of them—is unfairly distributed across society. These technologies will improve the abilities and efficiency of people who have access to them.” ARTIFICIAL INTELLIGENCE AND LIFE IN 2030, supra note 9, at 49. “Policies should be evaluated as to whether they foster democratic values and equitable sharing of AI’s benefits, or concentrate power and benefits in the hands of a fortunate few.” Id. at 11.

63 RAWLS, supra note 28, at 61, 74 (advocating that the “distribution of wealth and income, and the hierarchies of authority, must be consistent with both the liberties of equal citizenship and equality of opportunity,” id. at 61, while acknowledging that “[t]here is no more reason to permit the distribution of income and wealth to be settled by the distribution of natural assets than by historical and social fortune,” id. at 74); see also Goodman, Beneath the Veil: Corollaries on Diversity and Critical Mass Scholarships from Rawls’ Original Position on Justice, supra note 28, at 290–93.
like so many answers these days, "because COVID-19." Because COVID-19 likely reduced the performance metrics of otherwise privileged schools as well, but those schools and their students began their downward spiral from a relatively advantaged position.

Fourth, designing AI specifically for the characteristics of the people with whom they interact would be the most appropriate way to assist low-SES students and those in low-resourced schools.\(^64\) AI specifically designed in ways to help these students would not be as useful to others and therefore less likely to be pirated, borrowed, or stolen by the wealthier districts. In this sense, designing a teacher's aide robot, as well as learning management systems, for low-SES students from low-resource schools could actually give them a boost over the high-SES students from well-resourced schools because the AI technology would not be relatable to the more affluent students for the most part.

For instance, there are several teaching robots already on the market. For the older children, cognitive tutors, such as the one by Carnegie Mellon University, have been used for mathematics and other topics.\(^65\) The type of hints and clues that a cognitive tutor would provide to a low-SES student may be very different than to a high-SES student. If low-SES students are within the data set from which the AI is developed, trained, and learns, then the AI could be much less useful to the well-resourced schools and to their high-SES students.\(^66\)

\[D. \text{ Will This Program Survive Constitutional Scrutiny?}\]

While some may call this a parlor game (hide the technology from the rich kids who can afford to buy it and already have a leg up on technological proficiency), this proposal is not an end-run around race-based remediation for unequal (and often quite separate) educational environments. If race were to be the distinguishing factor, then the state action of a public school district would require a compelling government interest to justify a narrowly tailored race-based remedy. While the current Supreme Court of the United States is unlikely to expand the diversity rationale from higher education to K–12, it is unequally

\(^{64}\) Systems designed to interact with people with certain characteristics will be the answer. The 100 Year Study notes that: "Over the next fifteen years, the Study Panel expects an increasing focus on developing systems that are human-aware, meaning that they specifically model, and are specifically designed for, the characteristics of the people with whom they are meant to interact." ARTIFICIAL INTELLIGENCE AND LIFE IN 2030, supra note 9, at 17.

\(^{65}\) Id. at 32. "Cognitive tutors use software to mimic the role of a good human tutor by, for example, providing hints when a student gets stuck on a math problem. Based on the hint requested and the answer provided, the tutor offers context specific feedback." Id. For younger students, there is Ozobot, which teaches children deductive reasoning and coding and Cubelets for logical thinking. Id. at 31.

\(^{66}\) In the area of learning analytics, "current projects seek to model common student misperceptions, predict which students are at risk of failure, and provide real-time student feedback that is tightly integrated with learning outcomes." Id. at 33.
unlikely to find *de facto* school segregation to constitute past or present discrimination remediable under the Fourteenth Amendment.

And so, the sorting mechanism is not race, but rather school poverty, where under-resourced schools are determined based on their local property tax base, as well as parental contributions, not individual student demographic characteristics. SES, as every student of constitutional law knows, is not a suspect class. SES distinctions by governmental actors are subject to mere rational basis review. Rational basis review requires (1) a legitimate government reason for the distinction and (2) that the means used (providing AI programs and access to the least resourced schools) are rationally related to that goal.67 Here, providing remedial education and promoting digital literacy for youth is certainly a legitimate exercise of governmental power, and providing AI programs and access to the least resourced schools is rationally related to that goal.

IV. AND NOW FOR THE DOWNSIDES: UNINTENDED CONSEQUENCES AND ETHICAL IMPLICATIONS

AI systems can do much good,68 and can do much harm, as any technological advance also sprouts the possibility of technological nightmares.69 Indeed, the main strengths of using artificial intelligence in the education context "also constitute its main liabilities when left unchecked."70 A recent Consortium Report71 cautions K–12 school districts to be mindful of unintended consequences when adopting AI technologies,72 including unjustified infringements on privacy and perpetuating biases and inequities.73 To start, as is
now well known, algorithms can confirm existing process biases. To the extent that the AI is trained on the answers of high-achieving white and suburban (or private school students), its measurement of student achievement from other groups may be skewed in damaging ways. While this concern may be just as valid with human teachers, the AI training data can be more effectively manipulated to develop more appropriate bases for comparison in student learning.

Other unintended consequences abound. Data may be repurposed or used in ways that were not anticipated, thus further exacerbating privacy and accuracy issues. Those who seek to “game” the system and “teach to the test” (which has been a part of education and testing protocols for decades) will create poor quality data, particularly pernicious to machine learning applications where that poor data is nonetheless used to further train the machine. If the machine determines that a particular student needs more watching, then watching that student more leads to observing more areas of concern—just as

74 Berendt, supra note 61 (“Algorithms may be designed to conform to existing processes and to be trained on data that includes existing biases. Thus, the use of these systems amplifies existing prejudices, such as gender or ethnicity biases, making it more difficult to change educational approaches and systems.”) (internal citations omitted)); see also Southgate, supra note 38 and accompanying text.

75 Rauf, supra note 72.

76 Berendt, supra note 61, at 313 (“AI systems can (inadvertently) exert influence and control through making decisions that have serious and ill-considered risks and drawbacks associated with them. For example, linking academic performance predictions with university or job applications will likely have a serious impact on an individual’s future choices. These risks of AI in education are not always apparent because they are unseen, unintended or unanticipated consequences of the use of AI systems in education.”) (internal citation omitted).

77 Berendt, supra note 61, at 315 (“For example, the system may make sure students achieve the grades they need to ensure sufficient income stream for the organization; tutors might focus on preparing students for the exams, rather than on learning specific concepts.”). Consider the following: “Goodhart’s law states: ‘when a measure becomes a target, it ceases to be a good measure,’ and this general observation applies in educational settings as much as in the business field where it was conceptualized.” Id.

78 Id. (“Systems that invite ‘gaming’ behavior, where people tend to act in ways that they believe will offer them benefits, rather than behaving naturally, affect data quality. Poor quality data will negatively impact equity, which, in turn, may lead to unwarranted surveillance of ‘poorly performing’ students.”).

79 Id. (explaining that “surveillance is a major problem of large-scale data collection and analysis and data protection laws aim at eliminating unnecessary data collection and processing”). The article also addresses a system that was tested in China where students wore headsets that monitored their brain activity and let the parents know if they were losing focus or not paying much attention. This monitoring and reporting caused a lot of stress for the parents and children. Concerns about whether an opt-out is possible and effective arise in this context. Id. at 316.
traffic officers observing a driver for an extended period of time (almost) inevitably witness infractions that justify traffic tickets.

Further, additional AI interaction instead of, rather than in addition to, human interaction\(^\text{80}\) likely will impact the development of social and emotional intelligence,\(^\text{81}\) as well as other higher-order thinking skills, and exacerbate the achievement gap.\(^\text{82}\) In addition, privacy and liberty concerns may outweigh the benefits of data generation that AI monitoring can promote.\(^\text{83}\)

Moreover, there are a number of ethical ramifications to carefully consider before implementing widespread use of AITAs. In 2019, the European Commission identified seven components of ethical, or trustworthy AI: “1) human agency and oversight, 2) technical robustness and safety, 3) privacy and data governance, 4) transparency, 5) diversity, nondiscrimination, and fairness, 6) societal and environmental well-being, and 7) accountability.”\(^\text{84}\) Each of these components is fraught with potential dangers in the education context, which Professor Smuha explains in detail in her article, *Trustworthy Artificial Intelligence in Education: Pitfalls and Pathways.*\(^\text{85}\)

First, on the human agency issue, one concern is how AI can influence the behavior of students both in ways that may assist the students to become better students and in ways that may “benefit those developing and deploying the technology whilst not necessarily being in the learners’ interest.”\(^\text{86}\) Teachers would need to be vigilant and have enough understanding of the technical processes and the difference between what “must” and what “could” be done. That is asking a lot of the already overburdened teachers.

\(^\text{80}\) Rauf, *supra* note 72. This report explains that “given teacher shortages and retention issues across the country, AI could be viewed as a means of providing ‘something’ where ‘nothing’ otherwise exists.” *Id.*

\(^\text{81}\) *Id.* (“For example, if students spend more time interacting with or through technology than in face-to-face settings, it can negatively impact their ability to interact socially.”).

\(^\text{82}\) The assessment in the report continues,

And yet, this approach has the potential to further perpetuate education inequity by advancing a cheaper but inferior education system. . . . More concerning, if students only, or predominately, learn the AI . . . they may not have opportunities to develop higher-order thinking skills. Therefore, education leaders need to be aware that AI could lead to greater achievement gaps.

*Id.*

\(^\text{83}\) Berndt, *supra* note 61, at 313 (noting that “using tools continually to monitor individual students can grow into aggressive tracking and potentially can be used for more sinister applications, such as state monitoring of citizens”).


\(^\text{85}\) Smuha, *supra* note 2.

\(^\text{86}\) *Id.* at 8.
In the same vein, the technology can also be used to influence the behavior of teachers. For instance, curriculum changes that teachers may be resistant to employing can be easily accomplished without teacher input through AI.\(^{87}\) One way to alleviate this concern is a "human-in-command" approach in which the human decides when and whether to use a particular system and how it should be used. Another is a "human-on-the-loop" approach, which requires continual human monitoring; another is a "human-in-the-loop" approach, where "human intervention is made possible in every decision cycle of the AI system."\(^{88}\)

However, adding human decision-makers onto, or into, or in charge of, the loop will make the outcomes more unpredictable and perhaps less reliable.\(^{89}\) Because of the misguided notions that humans have of themselves, as well as the inscrutability of their decision-making process at times, we may encounter more biased, less accurate, and inconsistent results.\(^{90}\) And perhaps then we are back where we began.

Second, when addressing technical robustness and safety, the importance of mitigating security and data leaks is not heightened significantly in the AITA context, but monitoring accuracy when assessing students—particularly those from different cultural backgrounds or profiles that deviate substantially from the subjects used for the training data—may be.\(^{91}\) Given the charge to design the AITAs specifically for the subset students, accuracy may be higher, but post-training monitoring of the machine learning processes still will be necessary.\(^{92}\)

Third, on the issue of privacy, concerns about monetizing the data that is collected on students, particularly personalities as well as socioeconomic and demographic factors, could be a liability. What sort of informed consent parents and guardians can knowingly give may be an issue as well. Opting out may not be a feasible restraint, as Smuha notes, "either because of the pressure exerted

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\(^{87}\) Id. at 9.

\(^{88}\) Id.

\(^{89}\) Kimberly A. Houser, Can AI Solve the Diversity Problem in the K–12 Industry? Mitigating Noise and Bias in Employment Decision-Making, 22 STAN. TECH. L. REV. 290, 322 (2019) ("The problem is that humans are unreliable decision-makers; the judgments are strongly influenced by irrelevant factors, such as the current mood, the time since her last meal, and the weather. This variance in decisions is known as noise." (quoting Daniel Kahneman, Noise: How To Overcome the High, Hidden Cost of Inconsistent Decision Making, HARV. BUS. REV., Oct. 2016)).

\(^{90}\) For instance, "relying on humans to make employment decisions produces not only biased and inconsistent results, but also less accurate ones. Kahneman and others suggested incorporating AI into the decision-making process can mitigate the impact of illogical human decisions." Id. at 323. A similar logic may apply to teachers making critical but less quantifiable assessments of students.

\(^{91}\) Smuha, supra note 2, at 10.

\(^{92}\) For a more detailed discussion of post-training auditing of algorithms, see Goodman, AI/Esq.: Impacts of Artificial Intelligence in Lawyer-Client Relationships, supra note 28, at 177.
upon students and parents to conform to the will of the majority who might believe the application’s benefits outweigh the risks, or because the physical infrastructure is put in place and does not technically allow for deviations of the system’s use." 93 School districts will need to develop processes to address this concern.

Fourth, transparency concerns often begin with tracing how the AI made a particular decision, which has been addressed in prior literature. 94 Too much transparency contributes to gaming the system. 95 Figuring out which decisions made by AIED were inaccurate or otherwise unfair, such as when the algorithm was used in an unexpected way, can create conflicts with intellectual property rights of the developers. 96 Policing this potential liability requires explanations to support the decisions/recommendations made by the technology, 97 as well as

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93 Smuha, supra note 2, at 11.

Lack of transparency is also an inherent characteristic of self-learning algorithms, which alter their decision logic (produce new sets of rules) during the learning process, making it difficult for developers to maintain a detailed understanding of why certain changes were made. However, this does not necessarily translate into opaque outcomes, as even without understanding each logical step, developers can adjust hyperparameters, the parameters that govern the training process, to test for various outputs. In this respect, Martin stresses that, while the difficulty of explaining ML algorithms’ outputs is certainly real, it is important not to let the difficulty incentivize organ[iz]ations to develop complex systems in order to shirk responsibility.

Tsamados et al., supra note 30 (internal citations omitted).
95 Tsamados et al., supra note 30 ("Transparency can enable individuals to game the system. Knowledge about the source of the dataset, the assumptions under which sampling was done, or the metrics that an algorithm uses to sort new inputs, may be used to figure out ways to take advantage of an algorithm."). "This is why it is important to distinguish between the different factors that may hinder transparency of algorithms, identify their cause, and nuance the call for transparency by specifying which factors are required and at which layers of algorithmic systems they should be addressed." Id. Other sub-issues under transparency include verifiability, non-deception and honesty, and intelligibility. Southgate, supra note 38, at 11.
96 Smuha, supra note 2, at 12. "Explainability is particularly important when considering the rapidly growing number of open source and easy-to-use models and data sets." Tsamados et al., supra note 30.

Unwanted bias also occurs due to improper deployment of an algorithm. Consider transfer context bias: the problematic bias emerges when a functioning algorithm is used in a new environment. For example, the research hospital’s healthcare algorithm is used in a rural clinic and assumes that the same level of resources are available to the rural clinic as the research hospital, the healthcare resource allocation decisions generated by the algorithm will be inaccurate and flawed.

Id.
97 Smuha notes that any time

the use of an AI-system can have a significant impact on a person’s life, such explanation should always be given proactively, allowing the person to understand how the impacting decision came about. This explanation needs to
traceability. For instance, in the United Kingdom, when a final administrative decision is made by a computer program, the claimant must be informed, so that he or she has the opportunity to contest the decision. In the United States, we need to research the efficacy of detailed explanations for AI outcomes and other constraints on computer-assisted, legal decision-making, analyze what constitutes fair notice and an appropriate process for deprivations of liberty, and formulate proposals to promote the interests of justice as the technology develops. The fifth issue of diversity, equity, and inclusion has been addressed above.

Sixth, one societal well-being issue identified above is how interaction with machines as opposed to humans will impact students' "social skills and mental well-being." Because the data analysis requires information to be reported in relatively standardized ways, there is a concern that using AI may lead to more standardization in student assessment rather than less, despite the opportunity for more individualized instruction and learning. Some districts may replace human teachers with software, which may exacerbate student struggles.

Seventh, for accountability, Smuha suggests providing safeguards for whistleblowers so that all who have a concern about the negative impacts or potential impacts of an application can feel empowered to express the concern and confident that the designers will address it. She cautions that "if the job be provided in a language that is adapted to the knowledge of the person concerned.

Smuha, supra note 2, at 13.

Traceability "refers to technical inspection of which norms have been implanted, for which contexts, and how norm conflicts are resolved by the system. This can reveal biases which may have been built into a system." Southgate, supra note 38, at 10; see, e.g., Tsamados et al., supra note 30. This is an update of earlier research on the ethics of algorithms. It identifies epistemic concerns which are inconclusive evidence, inscrutable evidence, and misguided evidence, and normative concerns such as unfair outcomes, transformative effects, and traceability.

The insights that can be extracted from datasets are fundamentally dependent on the assumptions that guided the data collection process itself. For example, algorithms designed to predict patient outcomes in clinical settings rely entirely on data inputs that can be quantified (e.g., vital signs and previous success rates of comparative treatments), whilst ignoring other emotional facts (e.g., the willingness to live) which can have a significant impact on patient outcomes, and thus undermine the accuracy of the algorithm prediction.

Tsamados et al., supra note 30, at 5 (internal citation omitted).


Smuha, supra note 2, at 15.

Id.

Perry & Lee, supra note 11, at 4.

Smuha, supra note 2, at 15–17.
can be done just as well with a much simpler algorithm or with far less (personal) data—and less risks—an alternative should be considered. . . . [I]t is not because
an AIED application can be built, that it also should be built.” 104

These ethical issues are not without solutions. Being mindful of their
presence during the design and implementation process can mitigate their
negative impacts.

V. CONCLUDING THOUGHTS

Why do we need to implement this AITA plan now? Most importantly,
we need to prepare for the so-called “sunset” of affirmative action in 2028. While
scholars have debated whether Justice O’Connor intended to place an “end date”
on affirmation action in higher education, 105 the current Supreme Court of the
United States could grant certiorari on a case that permits it to decide to end
affirmative action even sooner. 106 Support for race-based affirmative action in
college admissions continues to decrease in public opinion surveys, 107 and a
ballot measure to restore affirmative action in California lost in the November
2020 election. 108

Without substantial intervention now, the gap in educational
achievement that results from the gap in access to AI technologies for teaching
and learning in K–12 will continue to grow. If racial and ethnic diversity is
decimated when the Court holds that race-based affirmative action is no longer
a narrowly tailored way to accomplish a compelling government interest (as has
happened in several states that outlawed affirmative action in the 1990s and
2000s), then the AI and other tech designed in 2028 and beyond will be more
homogeneous and less representative of the increasingly diverse society. With
the designers and creators of AI being less diverse, the processes and applications

104 Id.

from now, the use of racial preferences will no longer be necessary to further the [diversity as a
compelling] interest approved today”); see also Christine Chambers Goodman, A Modest Proposal

106 Justices on the current Supreme Court of the United States have expressed resistance to the
notion of stare decisis and set criteria for which precedents are worthy of deference and which are
ripe for overturning. See Ramos v. Louisiana, 140 S. Ct. 1390, 1414–16 (2020) (Kavanaugh, J.,
concurring in part). Some may argue that the Court likely will wait to overturn Grutter until 2028
because there is less incentive to do so until the date approaches. However, the urgency remains,
as we are living in uncertain times.

107 See, e.g., Frank Newport, The Harvard Affirmative Action Case and Public Opinion,
GALLUP (Oct. 22, 2018), https://news.gallup.com/opinion/polling-matters/243965/harvard-

108 Proposition 16 was defeated on California statewide ballot in November 2020. Jessica Wolf
& Melissa Abraham, Prop. 16 Failed in California. Why? And What’s Next?, UCLA NEWSROOM
may be worse, not better, for students of color and impoverished students, exacerbating inappropriate biases and associations and reducing the efficacy of AI for educational applications.109

Students currently in elementary school, grades transitional kindergarten through 8th grade, will be entering high school, college, and applying to graduate schools in 2028. Those with technology proficiency and degrees will be the designers, programmers, and coders for whatever iteration of AI technology exists at that time. They will be making our machines learn, our artificial intelligence adapt, and our algorithms analyze. And some of them will work with AI designers to update software and teaching programs that help determine their academic futures. Let us make the most of what we can do while the sun still shines, preparing for the sunset of affirmative action—so that all students can be seen and heard, acknowledged and understood, by AIED.

109 Some other key questions on the topic of diversity, equity, inclusion, and belonging, which are outside the scope of this Essay are the following:

How can AI serve the education provided to disadvantaged groups and populations? How can digital education and AI grow faster in developing countries to close the educational gap between the rich and poor students of the world? What are the good practices on AI for women and girls to close gender gaps?

Pedro et al., supra note 36, at 28.