How AI Can Improve K-12 Education in the United States

By Gillian Diebold and Chelsea Han | April 2022

Artificial intelligence (AI) has the potential to improve K-12 education in the United States. For students, AI can provide them a personalized learning experience tailored to their individual preferences and needs, immediate feedback on their work and answers to their questions, and increased access to tutoring and other educational materials. For teachers, it can help automate some of their workload, design better interventions, and reduce burnout. And for administrators, AI can monitor the student body and provide preemptive interventions with the help of predictive analytics. But while there are many benefits to AI in schools, there are a number of technical, operational, and social challenges that limit AI-driven innovation in the education sector. This report explores existing and potential uses of AI in K-12 education in the United States as well as the challenges that hinder the technology's adoption and effectiveness.

Personalized learning powered by AI provides a unique opportunity to close learning gaps between students in lower-income schools and those in wealthier ones, as well as improve educational outcomes for all students.

While some may fear greater use of AI in the classroom will eliminate jobs for teachers or invade student privacy, the fundamental purpose of AI in schools is to improve the quality of education for students. Personalized learning powered by AI provides a unique opportunity to close learning gaps between students in lower-income schools and those in wealthier ones, as well as improve educational outcomes for all students, regardless of income. By tailoring instruction to students' learning styles and areas of weakness, AI applications can expedite student progress and increase engagement in the classroom. This report outlines specific ways AI can support students, teachers, and administrators in improving education—and access to it.

The U.S. Department of Education should take the following steps to promote effective AI deployment and use:

- Develop a 10-year plan for AI in education, keeping in mind the challenges many schools face with limited digital capacity and resources, data quality, and stakeholder resistance

- Develop AI grants to foster the adoption of AI in education and explore the creation of a model data-driven school district

- Support AI product procurement for schools by strengthening information repositories that review AI products in education

OPPORTUNITIES

AI can increase access to education, facilitate the use of better pedagogical approaches, and support students in their academic journeys. For students, a variety of AI-powered tools, including intelligent tutoring systems (ITSs), intelligent digital assistants, and intelligent textbooks, can provide students with personalized instruction, while teachers can benefit from the use of learning analytics to improve support for students and drive classroom engagement. School administrators can use predictive algorithms to manage school operations and improve student retention rates.

APPLICATIONS FOR STUDENTS

Students learn at different rates. Although many students differ in their respective needs, skills, and learning styles, schools frequently "teach to the middle" and design lesson plans around the average student in a class. AI educational tools can enable more personalization in the classroom through dynamic adjustments to content and instruction based on students' motivation and abilities. These systems incorporate class learning objectives, instructional approaches, and instructional content and output to create an individualized experience for each student.

Increasing access to AI-powered classroom applications, including intelligent tutoring systems, intelligent digital assistants, and intelligent textbooks, will be pivotal to driving personalized learning and the expansion of educational opportunities for students. AI can also provide students with access to counseling and special education programs.

Intelligent tutoring systems

ITSs use AI to deliver personalized instruction to students.[1] Since the first appearance of ITSs in 1970, students around the world have used ITS to learn a variety of subjects, including foreign languages, math, geography, and science.[2] ITS can personalize instruction in different ways. Some ITSs base personalization around students' demonstrated abilities and understanding, spending more time on questions they find more difficult.

Other ITSs adapt the system to each student's personality and interests, explaining concepts to students based on their particular learning style.[3] ITSs save teachers time with remediation and provide detailed information on student progress and knowledge. These tools can also be used in after-school programs or during the summer months when students are at risk of falling behind.[4]

ITSs consist of three parts: a knowledge base, with the relevant subject matter knowledge; a pedagogical model, with rules to determine the best teaching strategy; and a student model, which tracks a student's knowledge and comprehension.[5] Depending on the machine learning models used, an ITS can vary widely in its capabilities, sophistication, and use of different AI methods.[6] For example, an ITS can use Bayesian knowledge tracing to determine a student's knowledge level by evaluating whether they provide a correct or incorrect answer to a given question.[7] An ITS can use reinforcement learning to adapt the sequence of content based on a student's needs, or neural networks to predict whether a student may have challenges with a particular area and then determine an appropriate difficulty level.[8]

Many educational experts acknowledge the need for remedial learning to both ensure students stay connected to their studies and fill gaps left by disruptions in the classroom. One-on-one tutoring interventions have been proven effective for accelerating student learning.[9] While experts worry about the lack of available tutors, ITSs alleviate the need for increased staff at a time when shortages are already rampant at schools nationwide.[10] Applications, such as the Cognitive Tutor Authoring Tools from Carnegie Mellon University, allow educators to create their own ITS.[11]

Intelligent digital assistants and chatbots

Students can use intelligent digital assistants, such as Siri, Alexa, Cortana, and Google Assistant, for personal enrichment and to assist with information retrieval.[12] These devices use natural language processing to communicate naturally with individuals using spoken language, allowing even students who cannot read or use a computer access to information.[13] For example, students can use intelligent digital assistants to listen to a story, take notes, look up information, or quiz themselves. Apps on intelligent digital assistants can be developed to provide students easy access to certain information, such as in-depth knowledge about a topic of study or how to navigate around a campus.

Relatedly, chatbots are computer programs individuals interact with conversationally. They assist students by allowing them to ask questions outside classroom hours and receive real-time answers and advice. For example, the company Ocelot offers a chatbot platform that uses a mixture of AI and live chat to give students round-the-clock access to assistance. It

also allows students to ask questions anonymously to avoid the embarrassment that can come with asking questions repeatedly.[14]

Chatbots can also help students find information. For example, a chatbot called Pounce at Georgia State University provides answers to students based on a dataset of 2,000 text-based answers to questions commonly asked by incoming freshmen.[15] In a K-12 classroom, chatbots such as the one included in Symphony Classroom, an AI hub built by the edtech company Merlyn Mind, could have the answers to commonly asked questions, or be able to provide a student with additional information on a subject that interests them.[16]

Intelligent textbooks

Intelligent textbooks use AI to provide customized and interactive content. These textbooks can cover any subject or age group, from elementary readers to high school biology students. An intelligent textbook suggests questions and concept summaries based on a user's reading progress, helping boost comprehension and retention.[17] Intelligent textbooks enable students to synthesize concepts in a nonlinear way compared with paper textbooks, which present information in a set sequence. Intelligent textbooks alleviate the need for rote memorization by presenting comprehension questions throughout the reading to test the reader's understanding of factual knowledge. These textbooks are designed to be used with remote or hybrid learning environments, so students can receive personalized instruction in and out of the classroom. An ongoing experiment from Stanford University has even shown that students using intelligent textbooks in a biology course obtain higher grades than students using traditional textbooks.[18]

Some intelligent textbooks use speech recognition so students can read aloud and receive real-time feedback on their reading proficiency. The intelligent textbook can detect when a student is struggling with word identification or pronunciation and measure the time spent practicing. Read-aloud intelligent textbooks are particularly useful for English Language Learner (ELL) students, as those with different language backgrounds will have different familiarity levels and thus different needs.[19]

AI for school counseling

Advances in natural language processing and conversational interfaces have led to a rise in synchronous, human-to-computer counseling for both mental health issues and career guidance. AI improves the scalability, accessibility, availability, and cost effectiveness of counseling initiatives for students. It can also improve the quality of online counseling and help sustain meaningful relationships between youth and professional counselors.[20]

Natural language processing and machine learning can pick up on cues that indicate a variety of mental health issues and assist in identifying suicidal ideation or the potential for violent behavior. AI can detect keyword indicators for mental health problems and flag vocal patterns that indicate emotional distress.[21] For example, Crisis Text Line leverages machine learning techniques to flag messages that indicate a high risk for a suicide attempt or self-harm.[22] The San Marcos Unified School District in San Diego County, California, reported that its use of the AI monitoring tool Lightspeed on school-issued devices helped the district identify five instances of potential self-harm during the first week of school in September 2021.[23]

Many students, particularly those in low-income areas, may lack access to career counseling in order to make educational and career transitions from high school to higher education and beyond.[24] AI can complement conventional career and college counseling. For example, AI-enabled software can help students practice mock interviews and optimize their resumes to succeed in college and beyond.[25] It can also help students with career exploration. Students can provide data on their interests and goals and receive in-depth recommendations on potential career paths.[26]

AI for students with physical and learning disabilities

AI can help support students with various physical and learning disabilities. AI-enabled technologies such as intelligent tutors, intelligent textbooks, and wearable assistive technology can greatly enhance the school experience for students with special needs. ITSs can use different AI methods to keep student engagement by tailoring lessons to students' specific interests and needs. For example, a student with a learning disability who has a proclivity for sports statistics can have that topic incorporated into many different lessons, allowing them to learn new material while retaining engagement and comfort.

Assistive technologies, such as text to speech (TTS), broadens opportunities to access learning materials for students with reading disabilities (e.g. dyslexia) by making books and other materials accessible. While audiobooks provide access to a recording of a specific book, TTS provides a broader range of digital text available in books and online platforms that can be read aloud.

For those with visual impairments, AI-enabled technologies using speech recognition can help students in the classroom with reading and notetaking. Apps can help students recognize their peers' faces, helping them adapt to and socialize in a typical classroom. Microsoft's Seeing AI app allows visually impaired users to recognize faces, identify money, read handwriting, and differentiate between products.[27] Similarly, AI can assist those with hearing impairments by enhancing hearing aids. Classroom

environments often have background noise that can make it difficult for hearing-impaired students to differentiate sounds. AI-equipped hearing aids can learn to distinguish primary sounds and voices from background noise.[28]

Lastly, students with social-behavioral disorders can use AI to help them interpret social situations. As the ability of AI to accurately gauge and interpret emotions increases, and these technologies become common in wearable technologies such as augmented reality glasses, this technology will help users better understand interactions and respond appropriately.[29]

Box 1: AI and Remote Learning

Over the course of the COVID-19 pandemic, schools have had to rapidly adapt to remote learning environments and embrace digital technologies.[30] While some remote learning is synchronous—such as an instructor leading a lesson for a classroom during a live Zoom call—a lot of remote learning is asynchronous, wherein students learn at their own pace, such as watching recorded presentations or completing assignments independently.

AI shows great promise in enhancing remote learning. Emerging AI-enabled applications can provide students with access to engaging content for virtual, asynchronous learning even when they are not in a physical classroom. For example, the AI company Alelo offers an online learning platform that uses AI to offer avatar-based simulations to provide interactive and personalize content to students.[31] Other companies such as Edugo.AI help students practice their foreign language skills using natural language processing to give feedback on vocabulary, pronunciation, and translation.[32] The Boston-based company Knowledge AI offers an AI system that uses a digital pen to record and analyze a student's handwritten work, either at school or at home, allowing for automated grading of assignments and detailed metrics about student performance.

Remedial services provided by AI applications can help keep students on track after more than a year of educational disruptions. AI applications such as intelligent tutoring systems can ease the rapid transitions between in-person and virtual learning that students and educators have been forced to experience by identifying key knowledge gaps and providing targeted practice on weaker subjects. Tools such as Century, an AI-powered online learning platform, help with remediation and returning to in-person learning.[33] The app looks at the strengths and weaknesses of a student in a variety of subjects and subsequently advises the teacher on adjusting lesson plans or providing additional support. Many schools also use Century during remote-learning periods in order to keep students engaged and on a concrete path to progress, even when they miss a few

days of in-person instruction. The platform provides real-time intelligence to teachers to help monitor student performance and engagement, even without in-person interaction.

APPLICATIONS FOR TEACHERS

Administrative duties for teachers are continually increasing. Educators spend hours outside the classroom on tasks such as lesson planning, grading, responding to parents, and administrative paperwork. From automating evaluations to monitoring student engagement, AI can save teachers time on these tasks so they can focus their energy on providing quality classroom support to students.

Decreasing teacher workload

High burnout and attrition rates are increasingly common among teachers, particularly in lower-income areas.[34] In the United States' lowest-income school districts, teacher turnover exceeds 16 percent per year.[35] Many factors contribute to teacher burnout, including low wages, parental and administrative scrutiny, and increasing workloads. Teachers are spending less time in direct instruction and engagement and more time in preparation and administrative duties. In 2020, McKinsey Global Institute reported that teachers work around 50 hours per week, with at least 11 of those hours in preparation activities.[36] AI shows great potential for decreasing teacher workload, through automating evaluations and administrative tasks such as scheduling and organizing lesson plans.

Consider some of the opportunities for automation. Workflow automation tool Zapier can save teachers time by sending out automated reminders for students and parents about assignments and forms.[37] Tools such as Schoolytics can generate a list of missing assignments for a student and create personalized progress reports for parents.[38] Rather than teachers having to spend time tracking down missing items, these tools can identify when a student has not turned in an assessment or alert parents about signing permission slips.[39]

Similarly, chatbots can help teachers answer questions outside working hours, enabling them to create work-life boundaries while still providing support with assignments.[40] Conversational AI powered by natural language processing and machine learning lets students ask repetitive questions without requiring a teacher to be online. Parents can ask chatbots questions on their own schedules and receive answers about upcoming assignments and events younger students might not remember. Fort Wayne Community Schools in Indiana have embraced these chatbots, using the Let's Talk! Assistant. In the first eight months of deployment, community members rated their satisfaction 9.6 out of 10 on average.[41] Similarly, school leaders from the Lansing School District in Michigan have deployed Mini the Minutes Matter Chatbot from AllHere to help reduce

chronic absenteeism and enable teachers to reach parents through their preferred communication method: text.[42] Services such as Juji and Intercom allow schools to create personalized chatbots and collect information about the types of questions asked and determine response satisfaction.[43]

Learning analytics

The term "learning analytics" refers to the process of collecting, measuring, analyzing, and reporting data about learners and their interactions with educational material.[44] Learning analytics equips teachers with data that allows them to make informed decisions about what strategies work best for their students. This data includes student performance, educational background data, student characteristics, and more.[45] Access to robust learning analytics augments teacher decisions when identifying learning difficulties and opportunities for support. Learning analytics can even provide insight into student engagement. Moreover, learning analytics provides insights for individuals, helping students monitor their own attention level and pace, and better understand their own mastery of a subject.

AI enables real-time evaluation of student engagement. Machine learning models can analyze cognitive, behavioral, and physical correlations of student engagement and assist educators in intervening in a personalized manner. AI can estimate learners' attention levels and detect mind wandering to measure the effectiveness of instruction.[46] Depending on the model, different AI applications can detect the level of boredom or excitement, or the level a student is listening to an instructor. When cameras are located around a classroom, machine learning techniques can use video footage to gauge student engagement. This technology can then predict whether a new instructional strategy will hold students' attention. It also can be used in teacher training programs for new teachers to see if their approach connects with a class and adjust accordingly.[47]

Student evaluation

Using AI for student evaluation can expedite the assessment and grading process and save teachers time. Educators have long used technology to automate the grading of multiple-choice tests. AI-based tools use natural language processing algorithms to provide automated scoring for academic exams, including the grading of short answers, evaluation of free-text responses, and pre-assessment of students' academic levels.[48] AI tools such as PrepAI and Quillionz can even generate new test questions, thereby saving teachers time while creating assessments each year.[49]

AI has improved detection of plagiarism and student cheating in test administration, using pattern recognition to identify similarities among

texts.[50] Online tools can identify instances of plagiarism and paraphrased content based on a scan of 60 trillion pages in databases and the Internet.[51] For example, the online service Turnitin can identify similarities to other submissions as well as existing publications, giving each submitted document a similarity report for teachers to review.[52]

Assessments help keep students learning and mastering content, and AI creates new opportunities to innovate on traditional assessments. AI can enrich student learning by generating new test items personalized to a student's interests. As teachers move away from typical multiple-choice assessments toward project-based learning and other types of competency tests, AI can assist in creating personalized assessments geared toward each student's learning style.[53] Stealth assessments have emerged as a way to reduce student stress and remove the visibility of testing in the classroom.[54] In this assessment type, performance-based assessments are embedded into a digital game. The game adjusts as students play, and adds or removes obstacles based on their performance. These games are often incorporated into intelligent tutoring systems.[55]

APPLICATIONS FOR ADMINISTRATORS
AI provides school administrators with data-driven insights on school operations and management. These applications ensure optimized decision-making and help streamline administrative tasks. AI can also give administrators a better understanding of their student body and offer predictive intelligence to help them make better decisions.

Identifying situations for intervention
More than 50 percent of public high schools in the United States use predictive algorithms as an early warning system to identify students at risk of dropping out.[56] AI not only flags when a student shows warning signs of academic struggle, but can help design appropriate interventions to increase academic resilience. In the past, early-warning systems primarily identified students as on or off track based on preset thresholds.[57] Newer systems use machine learning models to track different predictive indicators, such as student performance, gender, socioeconomic background, and school infrastructure, to more accurately identify students at a higher risk of dropping out.[58] Two models have been widely classified as the most accurate. The Chicago Early Warning Indicator, based on years of research in the Chicago public school system, focuses on ninth grade students, their accumulated credits, and low or failing grades.[59] Similarly, Growth Mixture Modeling (GMM) allows educators to identify different types of students at risk of dropping out.[60] This method uses data on the trajectories of students based on their noncumulative grade point averages and has a high accuracy rate. GMM allows educators to create more individualized interventions rather than treating dropouts as a monolithic category. For example, some students might need to reconnect with the

school community, while others need more academic instruction or counseling on life events.[61]

These early-warning systems can also help educators identify youth with various behavioral and mental health issues. Software on school-issued devices can monitor student browsing history to screen for potential warning signs of mental health struggles.[62] Some school districts have explored tools to monitor student activity on social media to flag certain words that could indicate suicidal ideation or the possibility of school violence.[63] Schools are also exploring the use of predictive analytics to identify the likelihood of a gun violence incident.[64] Algorithmic monitoring is an ongoing and evolving area of research in the educational technology field.

Admissions and enrollment management

AI applications can also support school administrators with admission and enrollment management in K-12 education. While the use of AI applications to enhance admissions in higher education has garnered attention over the years, the potential of AI to match students for elementary, middle, and high schools is also gaining traction. Common enrollment systems, also known as universal or unified enrollment systems, use student placement algorithms to assign students to schools.[65] These systems allow families to complete a single application to indicate their desired school choices in a school district by a single deadline. A matching algorithm in the common enrollment system places students based on their preferences for schools, school admission requirements, school availability, their proximity to a school, and family characteristics, such as whether a sibling is already enrolled in the school in question.[66] Since the first use of a common enrollment system by the New Orleans Recovery School District in 2012, other school districts, such as Denver, Newark, Washington, D.C., Camden, and Indianapolis, have leveraged student placement algorithms to allocate students to schools.[67] Machine learning models can augment these enrollment systems to better predict trends over time, leveraging both historical data and external data such as unemployment levels, to avoid problems such as under- or over-enrollment.[68]

Enhancing school operations

Numerous applications of AI can enhance school operations, including the optimization of bus schedules, cleaning procedures, and building energy management. AI-assisted school bus operations management has gained prominence in recent years for its focus on real-time fleet optimization. AI can optimize bus routes and predict the shortest amount of distance traveled by buses and make busing allocation decisions accordingly.[69] With these tools, districts can determine the optimal pick-up and drop-off times. Likewise, AI-equipped buses can increase student safety at stops. Cameras

on buses can detect when cars try to illegally pass after the bus stop signs have been deployed.[70] School officials can then access data collected from these buses and share the information with law enforcement to improve safety at violation hotspots.

In the public health sphere, schools have adopted AI-led sanitation practices during the COVID-19 pandemic to ensure classrooms are disinfected and safe for students. The Manassas City Public School system has adopted the use of portable sanitation robots from UBTECH Robotics Corporation.[71] These robots use UV-C light to destroy pathogens, including COVID-19. This means classrooms can be thoroughly cleaned within minutes each time students and teachers leave for the day.

AI can also help schools save money via more efficient building energy management. Each year, schools nationwide spend more than $6 billion on energy expenses.[72] With AI, school heating and cooling systems can be optimized to save money and power. AI systems can also recognize when a classroom is not in use and reduce energy accordingly.

CHALLENGES

The U.S. education system lacks the workers, data, technology, and funding to deploy AI in K-12 schools. Many students, teachers, and administrators still lack the necessary technological competence needed for effective digital learning or deploying AI in the classroom. Moreover, many school districts do not have in place the technological or data infrastructure to make use of AI. Furthermore, the Department of Education has not yet provided AI-specific funding or guidance to educators, leaving it up to individual school districts whether to use this technology—and how to do so. Finally, any introduction of new methods or technologies is always likely to be met with resistance from various stakeholders.

DIGITAL DIVIDE

Disparities in digital literacy and technology use have been a longstanding challenge in education. As a new wave of AI-enabled technologies emerges to improve education, schools will need to close existing digital divides or risk exacerbating existing inequalities in education. Moreover, less digitally savvy schools may struggle to use AI solutions without additional resources. Conversations about closing the digital divide between different socioeconomic groups in society regarding their access to high-speed Internet at home and in schools should also include digital literacy and adoption of technology.

Since 1996, the U.S. Department of Education has published six National Education Technology Plans (NETPs) to articulate equitable educational technology policy and provide guidance on new developments.[73] The most

recent NETP highlights the "digital use divide," which is the gap between students using technology in ways that transform their learning and students who use technology to passively consume content.[74] Although most students have access to technology at home, many merely use the technology to complete traditional classroom activities such as paper worksheets, just on an electronic device. If use of technology in ways that transforms education is unequal, the benefits of the technology will be dispersed unevenly.

The digital divide is connected to income levels. A 2016 survey from the Pew Research Center reports that Americans with lower incomes were less likely to have access to technologies such as high-speed Internet or smartphones[75] In 2021, Pew discovered that 36 percent of low-income parents found it very or somewhat difficult to help their children use technology as an educational tool.[76] Students whose parents or guardians have low levels of digital literacy may not receive the support they need at home to become active technology users.

STAKEHOLDER RESISTANCE

Resistance from a variety of educational stakeholders and even society at large continues to hinder the deployment of AI in education at scale. Common fears relating to technology, such as loss of privacy from increased data collection or loss of jobs through workforce automation, result in parent and teacher resistance to AI in the classroom.[77]

Fear of automation is intimately tied to fear of job loss in many professions.[78] Some teachers fear the impact of AI in education, with concerns that their jobs could be replaced with computer-based tutors or that automating certain aspects of teaching could diminish the value of the profession overall and lead to decreased wages.[79] As a result, national teachers' unions have spoken out against automation in education. For example, the National Education Association's (NEA's) position paper on technology and education reflects these concerns, arguing that instructional technology should not be used to "reduce positions, hours, or compensation," and emphasizing the need to subject digital learning technologies to "local collective bargaining agreements."[80] Similarly, the American Federation of Teachers (AFT), which represents 1.7 million educators, has been outspoken in its opposition to the technology, expressing hostility to AI in education in its 2018 resolution on the future of teaching and technology, stating that "for-profit organizations seek to replace educators with technology."[81] Despite these fears, there is virtually no possibility of AI replacing teachers. For example, according to a study by McKinsey, which estimates elementary school teachers could have automation replace activities that take up approximately 40 percent of their time, "It is important to note that technology is very unlikely to fully displace teachers—indeed, it is possible that the need for teachers will

increase as automation and technology enter the classroom."[82] While the nature of the job may change—such as teachers spending less time on administrative work and more time engaging directly with students, personalizing lesson plans, and advising students and parents—there is no reason to expect a decrease in pay or increase in teacher unemployment.

Concerns over student privacy inundate many conversations about technology in the classroom, including the use of AI.[83] Different AI applications have different purposes, collect different amounts and types of data, and present different risks and benefits.[84] There are multiple federal laws that protect students' and children's privacy, such as the Family Educational Rights and Privacy Act (FERPA), the Protection of Pupil Rights Amendment (PPRA), and the Children's Online Privacy Protection Act (COPPA). Schools should always consider the privacy and security implications of the technologies they choose to use in their classrooms, including AI-based technologies. Unfortunately, attempts to collect and analyze student data can sometimes face significant stakeholder resistance because of fears about loss of privacy.[85] For example, InBloom, Inc., a $100 million nonprofit initiative backed by the Gates Foundation and Carnegie Corporation that aimed to improve the management and use of student data, ultimately collapsed after unfounded concerns that InBloom would sell student data resulted in widespread parental backlash.[86]

Another cause for resistance among some stakeholders is issues of fairness, often due to concern about the potential for algorithms to make decisions that are disadvantageous for students, teachers, or others.[87] Implementing a machine learning model's recommendation in an educational setting can have high-stakes implications for individual students and create a ripple effect throughout the broader education system.[88] Some stakeholders fear that educators may rely too heavily on predictive models, trumping common sense or professional expertise.[89] For example, many school districts use value-added modeling (VAM) to evaluate teacher effectiveness. These models incorporate a variety of characteristics, such as students' test scores the previous year, their educational backgrounds, and the predicted scores generated by machine learning models, which are then compared with the actual scores.

As algorithms become more sophisticated, VAM will hold more promise for teacher evaluation. Still, their predictive validity has come under widespread scrutiny in recent years. In the case of *Lederman v. King*, a judge ruled that the New York State Growth model was "arbitrary" and "capricious" in producing an "unfair evaluation."[90] Lederman was a fourth-grade teacher who was found to be "ineffective," with a score of 1 out of 20 possible points in the 2013–2014 school year. She had previously been declared "effective" in 2012–2013 based on a score of 14. The

model was unable to account for the steep decline in her score of 14 to 1, and there was no process to challenge the score through an administrative appeal or appeal to the Education commissioner. The Court determined that value-added modeling exhibits "bias against teachers" with a small classroom size based on a predetermined bell curve of classifying teachers in "highly effective," "effective," "developing," and "ineffective" categories.[91]

In Washington, D.C., public schools (DCPS), teachers are scored yearly by the IMPACT evaluation and feedback systems. IMPACT uses four measures to score teachers: instructional practice, student achievement, instructional culture, and collaboration. While VAM plays a partial role in the evaluation, it is only one measure used in the overall scoring system. IMPACT was originally designed as an alternative to the strict numerical targets created under the 2002 No Child Left Behind Act (NCLB), but local and national teachers unions objected to administrators using it to quantify teaching performance.[92] In response to mounting complaints, DCPS commissioned a study in 2019 to review the system's validity. Results showed that IMPACT had been effective at transitioning out low-performing teachers and retaining high-performing ones, but the results also showed potential signs of racial bias, as white teachers consistently scored higher than Black and Hispanic teachers, even within similar schools.[93] DCPS has chosen to continue using IMPACT, with the DCPS chancellor noting, "This system has worked for us, but we know it has imperfections ...There are elements of systemic racism embedded in all systems and organizations. Having greater clarity of where those lines of disparities are allows us to be more responsive than we have in the past."[94] The DCPS case shows that schools should carefully evaluate the reliability of using algorithms for teacher evaluation, as well as consider how to interpret the results.

Admissions policies in K-12 schools are sometimes highly contested, and when schools use algorithms for admissions decisions, critics of their admissions policies may try to make the algorithm a scapegoat. For example, some New York City residents argue that admissions to the city's elite specialized high schools should not factor in race, while others argue that these schools should seek a racial composition that matches the student population.[95] Some critics have sought to blame New York City's use of a school-matching algorithm for outcomes they disagree with, but their real disagreement is not with the algorithm but with the underlying policies.[96] As a result, many of the efforts to regulate public sector use of AI, including in education, are misguided from the start.[97]

Lastly, many stakeholders in education are resistant to data-driven innovation in the classroom due to their experiences under NCLB.[98] Although it has since been replaced by the Every Student Succeeds Act, NCLB left a legacy of aversion toward national standards and other

attempts to create a more data-driven educational system. Entering into law in 2002, NCLB tied school funding to strict numerical performance metrics, which created a system many viewed as "test first, learning second."[99] The "teaching to the test" mindset led to wider resistance to strict numerical targets, and some stakeholders fear these targets will return with an increase in algorithmic decision-making.

DATA QUALITY

Data quality remains a critical issue in the education sector. AI has the potential to transform K-12 education, but without robust, interoperable, and accessible data, educators will be unable to effectively leverage the technology and may exacerbate existing inequalities in education. A myriad of data types contributes to education data, including aggregate test scores, educator information, demographic data, data on participation in school and community events, disciplinary data, fiscal data, postsecondary and workforce data, and individual performance reports. Data allows educators to make informed decisions about resource allocation, targeted interventions for students, and maximizing investment in technology. Every school district and state collects information about students, but most of this information remains at the local level.[100] Policymakers must account for these variations in data collection when considering the best ways to implement AI in classrooms.

A lack of high-quality data continues to be an obstacle to schools taking full advantage of the opportunities afforded by AI. Data poverty, or a dearth of data on a given community, can stifle access to certain innovations for people in those communities.[101] For example, a school that does not already collect longitudinal data about its students' academic performance may find it difficult to immediately take advantage of certain predictive analytics tools. When high-quality data is not collected about certain communities, technological progress made elsewhere may not reach those groups effectively and may lead to disparities. This "data divide" is typically connected to socioeconomic status, meaning lower-income communities often lack quality data. In addition, inaccurate counting among certain demographics with the American Community Survey or the U.S. Census affects federal funding for schools and may negatively impact educational outcomes in affected communities.[102]

Effective data collection and sharing is also made difficult due to the Family Educational Rights and Privacy Act (FERPA), as well as school and district-level policies. FERPA protects education data privacy and provides families the right to review information collected about their children.[103] This creates both a relative absence of fine-grained demographic information and other obstacles to using information, which in turn deepens the complexity of applying machine learning models in education. For example, developers may face a challenge in assessing students'

datasets, which means they lack detailed information on instructional methods and students' learning styles.[104] If available information is limited to test scores, basic demographic information, and disciplinary results, developers may create ineffective or overgeneralized tools that lack the personalization capacity needed by educators and students.

DATA INFRASTRUCTURE

Schools often lack the necessary infrastructure for data-driven education, thereby hindering the implementation of AI in schools. A truly robust educational data system links student data from early childhood through their entry into the workforce and relies on substantial data warehouses. Data warehouses store all the data from schools' learning management systems and student information systems, including information on classroom performance, disciplinary actions, academic history, and health records.[105] But many schools lack the specialized systems needed to aggregate and analyze these data sources, which may contain multiple data formats themselves.

Statewide Longitudinal Data Systems (SLDSs) are comprehensive data warehouses that help states manage their educational data. These systems store data on education from pre-K to the workforce (P-20W). Linking student records throughout the entire education system would allow for large-scale analysis of existing disparities and opportunity gaps across states, and answer questions about student preparation for the workforce.[106] As of March 2020, 49 states as well as the District of Columbia, Puerto Rico, the Virgin Islands, Guam, and American Samoa have received at least one federal grant to build an SLDS.[107] New Mexico is currently the only state without one. While having an SLDS is critical, as of 2017, only 17 states and the District of Columbia have built a fully linked P-20W system that connects data from all parts of a student's educational journey.[108] Even with a fully linked P-20W system, many students may still have large parts of their educational data missing because each state has its own SLDS and they may not be interoperable across state lines.[109] If a student moves out of state, their educational record will likely have gaps.

Furthermore, education data comes in a wide variety of formats and often uses different vocabularies. School districts frequently store data in silos as opposed to comprehensive data warehouses, meaning teachers and administrators must log into a series of individual systems to access data, download it, and then compile it themselves. The Department of Education's Office of Educational Technology has stated that data is scattered among varying systems and recommends EdTech developers prepare data in a common format.[110] Collected data lacks value if it cannot be easily reused or repurposed.

LACK OF FUNDING AND VISION

Overall, schools lack funding for AI technology in the classroom as well as the leadership and vision for its success. Without explicit funding for the use of AI in K-12 education, schools may see this technology as foreign, costly, and unnecessary. While many private sector education technology companies have created AI products for the classroom, these technologies will continue to only impact the higher-income schools and communities that can afford them.

Current funding for technology in education remains divided by issue area. There are funds targeting the broadband access aspect of the digital divide, namely the Federal Communications Commission's (FCC's) Emergency Connectivity Fund and E-rate program.[111] Future funding for closing the digital divide will come from the FCC and the National Telecommunications and Information Administration (NTIA) as a result of the Infrastructure Investment and Jobs Act, which includes the Broadband Equity Access and Deployment Program, the Digital Equity Act, and the Middle Mile Program.[112]

Ongoing funding for education data collection and usage comes from the U.S. Department of Education under three laws: Every Student Succeeds Act (ESSA), Individuals with Disabilities Education Act (IDEA), and Strengthening Career and Technical Education for the 21st Century Act (Perkins V).[113] The Department of Education also administers the SLDS grant program for schools seeking to update and effectively link their data systems. While ESSA mentions improving access to technology and the integration of technology into curricula and instruction, there is no mention of AI or best practices for its use.[114] It does mention "the use of data and information to personalize learning and provide targeted supplementary instruction."[115] The Department of Education also distributes one-time funds from the Elementary and Secondary School Emergency Relief (ESSER) Fund I-III and the Governor's Emergency Education Relief (GEER) Fund I-II. Other relevant education data funding comes from the Department of Health and Human Services with the Child Care and Development Block Grant (CCDBG) and the Department of the Treasury's one-time Coronavirus Capital Projects Fund and Coronavirus State and Local Fiscal Relief Funds.

The National Security Commission on Artificial Intelligence's (NSCAI's) comprehensive 2021 final report on the opportunities and vulnerabilities associated with AI and national security acknowledges the lack of leadership on the educational technology front.[116] The report focuses on education technology as it relates to the global talent competition, stating the need for explicit funding to address AI-related deficiencies on a number of fronts, including K-12 education. NSCAI highlighted the need for a National Defense Education Act II to provide the necessary funding to

under-resourced school districts. The report notes that "teachers must be taught how to use this technology as well as how to teach students the critical foundations and basic functions that come with it."[117]

Still, schools widely lack the vision for the use of AI in the classroom. Although widely discussed, there have been few directives (if any) from the Department of Education on the best practices for AI as it pertains to primary and secondary education. The United States takes a sector-specific approach to AI regulation, leaving the Department of Education as the primary source of direction for the technology, but little has been explicitly said about AI. Following the NETP, the Department of Education's Office of Educational Technology wrote a letter advising school districts and states about the best ways to utilize federal funding to maximize impact.[118] While it includes personalized learning in its best practices, there is no mention of AI.

RECOMMENDATIONS

The following encapsulate key priorities in considering the effective deployment of AI in primary and secondary schools. Policymakers should consider long-term strategy and near-team funding options in order to accelerate the adoption of AI and its benefits in the classroom. Decision-makers should center equality in their discussions of resource allocation and AI applications to build stakeholder trust and enhance student learning.

1. Develop a 10-year plan for AI in education

It is difficult to imagine AI deployment in education at scale without concrete federal guidance. A fragmented approach to AI in education thus far has hindered schools from reaping the benefits of increased personalization in learning and administrative efficiency. Educational inequalities can worsen without clear federal guidance: The schools with the access and means to incorporate technology into their curricula are the schools likely already preparing to implement emerging technologies such as AI. Before all schools can deploy AI effectively nationwide, policymakers and school districts should work to increase digital access and digital literacy for students and their families. Most schools will need a roadmap for navigating this new wave of technology in education. The Department of Education should take a leadership role in guiding state and local education officials about the opportunities created by AI, means of accessing the technology, and the best practices for its use.

Creating a 10-year plan for AI in education would complement the existing NETPs and provide an AI-specific strategy all programs under the Department of Education can consult. Several federal agencies have agency-specific AI strategies. For example, the Department of Veterans Affairs, the Department of Defense, and the Food and Drug Administration

all have strategies to ensure that they are able to use AI to solve their respective missions.[119] The Department of Defense published an AI Education Strategy specifically focusing on workforce education and retraining.[120] At present, the Department of Education has remained silent on the importance of AI, with AI being entirely neglected from its STEM 2026 Vision report—nor is it mentioned in a policy brief on teacher technology preparation from the Office of Educational Technology.[121] It is time for the department to prepare its ranks for a future where AI is the norm, and to equip its teams with the knowledge and skills to make the most of it.

The 10-year plan should lay out a concrete vision for AI in K-12 schools and explain how to scale, exploring three core points:

1. Building digital capacity in schools to prepare students, teachers, and administrators to utilize AI

2. Addressing data quality issues

3. Addressing stakeholders' legitimate concerns

First, any productive discussion of AI in schools should acknowledge and work to ameliorate existing technology deficiencies. Differences in funding for schools based on local income levels have created educational disparities. Not all learners have access to the same quality of broadband or Internet-connected device, and often, lower-income schools face greater difficulty incorporating technology into curricula.[122] Likewise, the digital use divide can only close if teachers receive adequate training on technology use in the classroom. The NETP highlights that two-thirds of teachers want more technology in the classroom, but half identify a lack of training as their primary barrier.[123] This lack of technology training often starts in teacher preparation programs. School districts must invest in the training, support, and monitoring of teachers using technology. Without continuous support, teachers will fail to use AI technologies successfully, and will likely exhibit resentment or resistance.

In a national 10-year plan, policymakers should outline ways to build digital capacity in schools beyond equipping students and teachers with a personal computer. The Department of Education should prepare a digital literacy curriculum that teaches students and educators how to use and engage with AI tools. It should ensure that educators understand the capabilities and limitations of AI applications as well as ways to minimize any known risks. Prioritizing preparation will position educators for success in integrating AI tools into their classrooms.

Second, the core of AI and machine learning is data. A Department of Education AI strategy should address critical data quality issues, such as to

ensure datasets are accurate, timely, and representative. To do this, policymakers should specify that data collection be done in digital, interoperable formats. This would create streamlined processes for data collection and analysis and alleviate the time-consuming process of working with different data formats. Policymakers should also explore the possibility of creating a data trust to be an independent steward of educational data.[124] Establishing a data trust could create more opportunities for secure data sharing between the public and private sectors, including between competing commercial EdTech providers. In addition, creating a nationwide pool of standardized education data could help spur greater commercial development of more interoperable EdTech products that leverage AI. The Department of Education's FY2022 Annual Performance Plan mentions developing "for external researchers an additional tier of access to high-priority, micro-level data," but policymakers should explore how such data can enhance AI in education.[125] Using a data trust could mean larger datasets could be available for continued AI training while protecting student privacy.[126] Finally, in addressing data quality issues, policymakers should consider a shift away from compliance-based reporting toward data collection that addresses educators' problems and needs to create more robust and useful datasets.[127]

Lastly, a Department of Education AI strategy should counter stakeholder concerns about automation and privacy. For example, a federal strategy should include projections on how implementation of AI in classrooms will impact teachers' job duties and class sizes, and thoroughly rebut the notion that an increase in AI will cause unemployment among teachers. Moreover, the Department of Education should emphasize that the purpose of using AI in the classroom is to improve children's welfare and learning, and this goal should supersede any others. Likewise, the AI strategy should explain how the Department of Education would apply existing student federal privacy laws, such as FERPA and PPRA, to any AI tools used in schools, as well as how it would work with the Federal Trade Commission to apply COPPA, the federal children's privacy law, in educational apps and services. The Department of Education already provides detailed guidance to school officials, educators, parents, and vendors about how to comply with existing student privacy requirements, and they should continue to do so for AI-based technologies. In addition, the AI strategy could explore the role of emerging privacy-enhancing technologies that may be incorporated into classroom AI tools, such as differential privacy and federated learning, and de-biasing techniques and auditing mechanisms to ensure algorithms are not discriminatory.[128]

Crafting a 10-year strategy should be a top priority for the Department of Education as it helps schools prepare for a variety of AI applications. This plan would allow schools to stay on top of the latest technology and facilitates the easy utilization of future innovation. Laying out the building

blocks and raising the digital capacity of students and teachers sets the foundation for equitable distribution and use of AI in the future.

2. Develop AI grants to foster the adoption of AI in education

Funding for educational technology remains fragmented in the United States. Federal and state policymakers should ensure that schools receive AI-specific funding to support the deployment of various apps and online platforms that support personalized learning and boost student outcomes. School technology funding remains program specific. There are various funds available for addressing the digital divide via hardware and broadband services for ongoing data collection through Department of Education legislation and general education funding. Likewise, within the department, available grants vary from year to year to support technology use within specific groups. Policymakers should continue to focus on eliminating the digital divide in schools to ensure students in low-income school districts can also benefit from new technological advances, including AI.

In line with creating a long-term strategy for AI in the K-12 education system, the Department of Education should launch a challenge to create a model data-driven school district, similar to the Smart City Challenge launched by the Department of Transportation in 2016.[129] This challenge should have a particular focus on AI to demonstrate the benefits of using it inside and outside classrooms by students, teachers, and administrators. The Department should provide grant funding for the district that develops the best plan to use data-driven decision-making and AI applications.

Additional grant programs would also be beneficial to accelerating AI adoption in schools. For example, the Department of Education should reengage with past grant programs, such as the Educational Technology Media and Materials for Individuals with Disabilities Program or the Enhancing Education through Technology (EdTech) State Program.[130] These programs were designed to help increase technological literacy in students and provide personalized, accessible classroom materials for students with disabilities. The Department of Education should also consider the unique challenges low-income schools may face in deploying AI and develop a grant program to assist these schools making use of the technology, such as by providing additional training for teachers or funding for related technologies. By expanding and specifying the specific technologies to include AI, the agency can still reutilize existing grant structures and save resources.

3. Support an AI product procurement process for schools

In addition to providing AI-specific grants and funding, the Department of Education can support schools in procuring AI products, a process which can be lengthy and time consuming.[131] Several organizations attempt to

improve the procurement process by making it easier for educators and administrators to identify useful products. For example, the Department of Education hosts What Works Clearinghouse, an aggregation of reviews of educational products, policies, and programs.[132] However, these resources can be difficult to navigate or do not provide straightforward guidance on how to adopt AI in K-12 schools. The Office of Educational Technology should update its website to better provide guidance on AI technologies.

There are many opportunities to make these and similar resources more valuable. The nonprofit Technology for Education Consortium estimates that school systems could save $3 billion annually just by sharing price information in a centralized manner.[133] For 14,000 school districts across the United States, a comprehensive repository of assessments and reviews of educational technology products would be particularly useful for AI procurement given the newness of such tools and the many concerns educators may have about their use. A new repository could aggregate reviews of AI products that exist across the Department of Education's What Works Clearinghouse and nonprofit organizations. The Department of Education could also provide funding to develop a central repository on AI use in education that would capture information on price range and peer reviews on AI product quality and effectiveness by school districts and help school districts share information on the use of AI products. Schools could also use the repository as a basis for facilitating cooperative purchasing, which allows multiple schools to buy AI products at a discounted price.

CONCLUSION

There are many applications of AI in K-12 education, and a number of ways it can improve both educational quality for students and the professional experiences of teachers and administrators. AI is not a silver bullet, and the problems plaguing the current education system in the United States require complex, thoughtful consideration and solutions. As other sectors of American life pave a way forward for AI, the Department of Education should work to create a strategy that stresses the democratizing potential of AI in uplifting lower-income districts and closing opportunity gaps.

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