Algorithmic decisions in education governance: implications and challenges

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Perspective

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Abstract
In this perspective article, I explore the implications of artificial intelligence (AI)-enabled algorithmic decisions on education governance. Three main questions are explored: (1) Are algorithmic decisions de facto policy decisions? (2) What distinct features of algorithmic decisions necessitate a re-evaluation of education governance? (3) How should one begin addressing algorithmic decisions in education governance? The analysis suggests, first, algorithmic decisions can indeed be considered de facto policy decisions, as they are often made by private companies with substantial public consequences but little oversight. Second, three distinct features of algorithmic decisions—fast speed of development and implementation, lack of interpretability and transparency, and unpredictable emergence of new capabilities—call for a re-evaluation of education governance. Third, to address algorithmic decisions in education governance, I propose a proactive approach to multilevel social control mechanisms, which includes federal and state legislation, local enforcement, non-governmental organizations, and individual stakeholders. The discussion in this perspective article will stimulate conversations that scrutinize how AI, and algorithmic decisions specifically, challenge traditional assumptions of education governance, including the separation of powers, power distribution between national and local governments, due process, and representative democracy. The discussion aims to shed light on the evolving landscape of education governance in the age of AI.

Keywords Artificial intelligence · Education governance · Education policy · Decision making

Artificial intelligence (AI) has increasingly become part of education. AI-powered tools and platforms have the potential to enhance personalized learning by adapting to individual students' needs and providing real-time feedback. Educators can use AI to streamline administrative tasks, analyze student performance data, and develop more effective teaching strategies [36]. AI can also facilitate remote learning through virtual classrooms and intelligent tutoring systems, which makes education more accessible [18]. In this perspective article, I explore the implications of AI-powered algorithmic decisions on education governance. Three main questions are explored: (1) Are algorithmic decisions de facto policy decisions? (2) What distinct features of algorithmic decisions necessitate a re-evaluation of education governance? (3) How should one begin addressing algorithmic decisions in education governance? Addressing these questions will stimulate conversations that scrutinize how AI, and algorithmic decisions specifically, challenge traditional assumptions

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of education governance, including the separation of powers, power distribution between national and local governments, due process, and representative democracy.

Before diving into the three questions, it is important to define key terms. In this perspective article, *AI* is defined as "the capability of a computer system to show human-like intelligent behavior characterized by certain core competencies, including perception, understanding, action, and learning" (p. 599) [40]. AI encompasses not only humanoid robots with a human-like appearance but also algorithms without a physical form, such as those powering personalized chatbots [1] or screening teaching position candidates and providing hiring recommendations [14]. *Algorithmic decision-making* refers to employing automated systems, often based on machine learning or other AI techniques, to make decisions that were traditionally made by humans. These systems use algorithms to analyze vast amounts of data and offer recommendations or decisions based on that analysis. For example, algorithmic decision-making systems can be used to screen job candidates' resumes and credentials, predict future job performance, track employees' job satisfaction, and recommend compensation [17]. In education, such systems might be used to assess student assignments, predict academic performance, and even tailor learning experiences to individual needs. As a branch of AI and currently a dominant AI method, *machine learning* emphasizes "learning" through building models that allow algorithms to learn from data and gradually improve their performance on specific tasks. As part of this process, the models are trained on massive amounts of data in order to learn patterns and produce reliable predictions or recommendations. Machine learning can assist in creating adaptive learning platforms that tailor content difficulty to student performance. It can also help develop predictive models to identify students at risk of dropping out. This article concentrates on AI-powered algorithmic decisions that are made by algorithms (i.e., automated systems), instead of humans, by using data and computational techniques to analyze and process information and subsequently make decisions based on the outcome of that analysis. Having clarified the terms to be used, the next step is to delve into the three questions raised at the beginning of this perspective article.

This perspective article is structured as follows: First, it explores whether algorithmic decisions function as de facto policy decisions. Next, the distinct features of algorithmic decisions that challenge traditional governance structures are examined. I then propose strategies for addressing these challenges through multilevel social control mechanisms. Finally, the conclusion offers recommendations for policymakers and educators and suggests future research directions.

1 Question 1: are algorithmic decisions de facto policy decisions?

Education governance is the process through which formal institutions and actors, such as school boards, state education departments, legislatures, governors, and courts, exercise power and make decisions that shape the education system and its outcomes. These decisions influence a wide range of issues, including curriculum standards, teacher evaluation, school funding, and student assessment. Additionally, stakeholders, such as parents, students, educators, and community organizations, engage in education governance by participating in the decision-making process through public comment periods, advocacy, lobbying, and community forums, among other avenues. For example, parents attend school board meetings to voice concerns about school safety or curriculum changes, while educators participate in union activities to advocate for better working conditions. Effective education governance is crucial for creating an educational system that maximizes opportunities for all students and enhances student achievement.

In the United States, education governance is characterized by a loosely coupled structure [39], meaning decision-making power is decentralized and distributed among various levels of governance, including federal, state, and local school districts. This loosely coupled system allows for greater flexibility and responsiveness to local needs. Meanwhile, such a decentralized system leads to substantial variation in educational practices and outcomes. The American educational system is regulated by complex rules and procedures, such as the Every Student Succeeds Act (ESSA), which sets federal guidelines for student achievement and accountability while giving states the autonomy to develop their own educational standards and assessment systems [35]. Moreover, each state has its own education codes and policies, which are further interpreted and implemented by over 13,000 local school districts [23]. This multilevel, loosely coupled education governance structure faces numerous challenges, including incoherent education policies, an overemphasis on standardized testing, funding disparities among districts, and limited stakeholder input [6].

While the loosely coupled systems framework provides a valuable lens for understanding US. education governance, it is important to acknowledge other competing approaches. For example, from the lens of network governance [28], education systems can be viewed as complex webs of interdependent actors, including schools, districts, state agencies, federal departments, and increasingly, private sector entities such as technology companies. However, network governance focuses more on informal relationships, but underemphasizes the formal distribution of decision-making

authority institutionalized in the education governance structure via legislation, rulemaking processes, and hierarchical administrative structures. In comparison, the loosely coupled systems model allows for flexibility without overhauling the entire system [25]. It also provides a buffer against potential failures. If something fails in one part of the education system, such as the collapse of the "Ed" chatbot in Los Angeles Unified School District [10], loose coupling may limit direct operational impacts to that district, rather than causing a debacle across school districts in the entire state or country.

Adding to these existing challenges is the current trajectory of AI development, dominated by large private companies, which signals a seismic shift towards private governance in education. This shift aligns with what Cordelli described as the privatized state, "where the administration of the public is widely outsourced to private actors" (p. 11) [4]. This privatization process undermines the legitimacy of public governance because private actors, driven by profit motives rather than public interest, are not subject to the same accountability mechanisms as public institutions. In education, this privatization trend could lead to what Vergara termed "systemic corruption, a form of political decay that manifests itself as an oligarchization of power in society" (p. 2) [34]. As these private entities gain control over decision-making processes in education governance, the growing concentration of power could marginalize public voices and interests, as well as enable profit-driven motives to overshadow the public good of providing high-quality education.

The use of AI in decision-making processes in education governance also threatens to disrupt the separation of powers by consolidating decision-making power in centralized, privately owned AI systems. Most AI-powered algorithms are proprietary, with their inner workings considered trade secrets and not subject to public scrutiny. This lack of transparency poses serious issues, particularly when the algorithms are entrusted with making life-altering decisions for students (e.g., generating predictive grades and identifying potential abuse or neglect risks) [33], teachers (e.g., hiring screening), and communities (e.g., algorithmic recommendations for school district zoning or school closures). Despite their significant public consequences, the algorithms are mainly developed and managed by private companies and non-profit organizations [24]. As Cordelli argued, the privatization of public functions can lead to a democracy deficit, where citizens lose their ability to collectively shape and control important aspects of their shared social and political life [4]. The lack of transparency and public oversight in the development and implementation of AI-powered algorithms means that stakeholders—including students, parents, educators, and policymakers—often have little to no insight into how decisions are made. This opacity can erode trust in the education system and lead to calls for greater accountability and regulatory oversight.

The International Baccalaureate controversy serves as a cautionary tale. In response to the COVID-19 pandemic, the International Baccalaureate Organization (IBO) canceled spring exams on March 23, 2020, and decided to evaluate 170,000 students from nearly 150 countries using an algorithm that used both historical and present-session data to generate grades. These grades would contribute to each student's overall Diploma Programme results and be used for college admission and scholarship applications [16]. On July 6, 2020, the IBO released the algorithm-generated, predictive final grades, sparking international outrage. Many students received lower grades than their teachers had expected, resulting in lost scholarships and uncertainty about how to pay for college. Others feared losing provisional acceptances to universities. As a response to the uproar, the IBO offered only the standard appeals process or retaking exams in November, both of which require fees [30]. However, the algorithm's exact workings were not disclosed, leaving the model's fairness unclear. Without algorithmic details, students were unable to effectively contest the grades. The IBO controversy highlights that algorithmic decisions were not subject to the same scrutiny and criticism as traditional governance decisions.

Teacher evaluation is another policy area that highlights the issues associated with the use of AI and proprietary analytic systems. States and school districts increasingly rely on an array of analytical systems to generate predictive models for governing decisions, such as teacher evaluations, bonuses, and terminations. One notable example is the City of Houston's use of the Education Value-Added Assessment System (EVAAS), proprietary software developed by a private software company, to rate teacher effectiveness [26]. EVAAS aimed to measure teacher performance by analyzing student test scores and predicting future student achievement based on past performance. However, the system faced scathing criticism for its lack of transparency and accountability. Teachers and their representatives argued that the proprietary nature of EVAAS meant that the criteria and algorithms used to evaluate their performance were not disclosed, making it difficult to understand or challenge the ratings [13].

This issue reached a critical point in the court case Houston Federation of Teachers v. Houston Independent School District (2017) [12]. The Houston Federation of Teachers filed a lawsuit against the school district, claiming that the use of EVAAS violated teachers' due process and equal protection rights. Teachers argued that the opaque nature of the algorithm and its reliance on student test scores did not fairly or accurately reflect their performance, leading to unfair evaluations, bonuses, and even terminations. The case reached a settlement in which the school district agreed

to discontinue its contract with the vendor providing EVAAS and pledged not to use the system in the future. This legal battle underscored the potential risks of relying on proprietary AI systems for high-stakes decision-making in education without adequate oversight and transparency.

In all of these cases, algorithmic decisions made by private and non-profit companies can have substantial public consequences. As such, they can be seen as de facto policy decisions that have implications for education governance. These decisions can shape policies related to student performance, teacher evaluations, resource allocation, and more. However, current regulations and accountability mechanisms for these companies are nearly nonexistent, which creates a glaring gap in oversight and public protection. Contemporary AI frontrunners, such as Facebook, Google, and other tech giants, have histories of engaging in problematic practices. For example, it took a whistleblower to expose Facebook's questionable practices about how the company prioritized profit over public safety and integrity [7]. Similarly, school districts have had to file lawsuits to hold companies like TikTok, Snap, Meta, YouTube, and Google accountable for contributing to the youth mental health crisis through their platforms' addictive and harmful content [21]. The public's protection currently relies heavily on "faith" in the technical abilities of private company employees and confidence that these companies will adopt best practices. However, the track records of these companies have not built a compelling case for taking that leap of "faith."

OpenAI, the company that developed the Generative Pre-trained Transformer (GPT), was initially established as a non-profit with the goal to "advance digital intelligence" (para. 5) [19] for the benefit of humanity. However, it has since transitioned into a for-profit company with the revised goal to "advance digital intelligence in the way that is most likely to benefit humanity as a whole, unconstrained by a need to generate financial return" (para. 5) [19]. Despite this stated mission, OpenAI is now "heavily constrained by the need to generate a financial return, working around Microsoft's goals, with far less emphasis on the admirable humanitarian goals in their initial charter" (para. 5) [19]. This shift not only raises concerns about trusting private companies to prioritize public good over profit, but also casts doubt on the efficacy of punitive measures to inspire ethical behavior.

What is missing in algorithmic decision-making in education governance is the active public voice necessary for a democratically accountable governance model. Consider a scenario where a school district adopts an AI-powered system to allocate resources based on predicted student enrollment and school performance. If this system is developed by a private company without input from educators or the community, it may overlook critical factors such as unique local needs. Without a countervailing voice from education stakeholders, algorithmic decision-making in education governance risks becoming dominated by private interests. This brings us to the second line of inquiry, which concerns the challenge that governance institutions and actors face in responding to algorithmic decisions made by the private sector in education governance.

2 Question 2: what distinct features of algorithmic decisions necessitate a re-evaluation of education governance?

Distinctive features of AI-powered algorithms make them a poor fit for top-down, prescriptive regulation and traditional education governance. In this section, I explore three unique features of algorithmic decisions that merit rethinking education governance: fast speed, lack of interpretability and transparency, and unpredictable emergence.

2.1 Fast speed

The rapid development and highly specialized technical nature of AI-powered algorithms present a formidable obstacle to rebalancing the locus of control away from the private domain. The development and implementation of such algorithms implicate speed in at least two significant ways [31]. First, the development of algorithms may occur at a pace that outstrips previous cycles of innovation. Unlike traditional industries such as manufacturing, construction, transportation, agriculture, and energy, the process of software production necessitates relatively fewer up-front physical resources and infrastructure. For example, creating a new manufacturing process often requires extensive investment in machinery, materials, and facility upgrades. By contrast, developing a new algorithm can be achieved with comparatively modest resources—computing resources, skilled programmers, and access to data.

Second, algorithms can be rapidly adjusted and modified due to the fluid nature of machine learning, which is the dominant approach to AI. Through machine learning, statistical models "learn" to recognize patterns by analyzing training data, and these observed patterns are then applied in a "working algorithm" that predicts outcomes based on new

data. Importantly, to ensure the accuracy and relevance of the algorithm, algorithm developers must continuously make decisions about how to optimize the model using the latest data. This dynamic, ever-changing nature of algorithms contrasts sharply with the regulatory aspects that are typically more slow, bureaucratic in nature, a fact that poses ongoing regulatory challenges [31]. Even if a specific algorithm is formally approved for a particular use, its outputs are bound to change as new data are introduced, prompting a new round of regulatory approval. This is why regulating ever-changing algorithms is more challenging than regulating fixed entities like molecules, which are subject to more stable regulatory frameworks like those of the Food and Drug Administration.

2.2 Lack of interpretability and transparency

AI-powered algorithms often lack transparency, which makes it difficult for humans to understand and interpret how they work. Instead of following straightforward instructions (like "If X happens, then do Y"), these algorithms learn from large amounts of data. They adjust their internal processes based on the patterns they find in the data, which can make their decision-making procedures difficult to explain. Even algorithm developers may struggle to elucidate how the output is derived [5], similar to the challenge of articulating human decision-making. Neural networks, inspired by the human brain, amplify this mystery with their interconnected nodes that process information and adapt through learning, yet their interpretation remains elusive to humans [9].

When contrasted with the cause-and-effect reasoning that undergirds the scientific method, the non-intuitive manner in which these models connect data and identify patterns can be disconcerting. Consider, for example, a neural network charged with the task of differentiating between images of wolves and dogs. Instead of grasping the biological distinctions between the canines, a neural network model discerned that wolves were consistently pictured on snow, while dogs were portrayed on grass [8]. These non-intuitive yet rationalizable correlations might elude human perception or be dismissed as insignificant, but machine learning often uncovers such concealed connections.

Algorithmic decisions in education governance raise concerns about fairness, transparency, and accountability [29]. These concerns become particularly pronounced when trying to attribute responsibility in scenarios where outcomes are unfavorable. In cases where a student fails to meet proficiency levels, it can be challenging to determine who is accountable. Is it the technology company that developed the personalized learning algorithm, the teacher who facilitates the learning process, the administrators who recommend the algorithm, or the school board that approves its purchase? Machine learning's interpretability issue is particularly problematic in the context of opaque computational models. This can raise concerns over procedural justice (i.e., applying procedures consistently across people and across time in organizations) [3] and difficulties in proving discrimination or discriminatory intent [22]. If a job applicant believes that a school district's resume-screening algorithm is discriminatory, what evidence would be required for the US. Equal Employment Opportunity Commission (EEOC) to pursue charges? The applicant would need to demonstrate that the algorithm systematically disadvantages certain groups. However, proving this can be challenging when the inner workings of the algorithm are not transparent, and the data used to train it are not disclosed.

2.3 Unpredictable emergence

A uniquely intractable characteristic of AI is emergence, a phenomenon where complex systems (i.e., systems comprising multiple, interdependent components that interact with one another) display properties or behaviors not directly attributable to or predictable from the behavior of their individual components or subparts in isolation. Simply put, the whole can transcend the simple aggregation of its parts, and new, unexpected abilities emerge from such a complex system. To illustrate, when discrete components, such as GPT, Language Model for Dialogue Applications, and Pathways Language Model, interact with one another, they collectively give rise to new, unexpected abilities. This interaction is similar to the way traffic patterns emerge from the behavior of individual cars or how brain function cannot be fully understood by examining individual brain cells. The collective abilities of current large language models (LLMs) arise from the interactions among the models themselves, giving rise to emergent properties that are more complex and difficult to predict by examining each model independently.

An example of emergent behavior in AI can be seen in LLMs like GPT-3. Initially, GPT-3 was designed to generate human-like text based on input prompts. However, it began to exhibit capabilities such as completing complex arithmetic problems and even generating programming code—abilities that were not explicitly programmed but emerged from the intricate interactions of its vast number of parameters and training data. GPT-3 has 175 billion parameters. It is estimated that GPT-4 may have around 170 trillion parameters, which is significantly larger and more complex than

its predecessor, GPT-3 [27]. A study by Wei et al. reported that LLMs exhibited emergent abilities such as understanding nuanced contexts, generating creative content, and solving problems in ways that were not anticipated during their development [38]. Thanks to emergence, AI systems can develop capabilities that go beyond the intentions and expectations of their creators [37].

In certain instances, emergent properties may even embody an entirely novel form of intelligence [15]. Google's DeepMind developed AlphaGo, an AI that mastered the game of Go. While AlphaGo's individual components were designed to process moves and evaluate board positions, its overall strategy and ability to defeat human champions emerged from the complex interactions between its neural networks and extensive training. AlphaGo's emergent capabilities included innovative moves and strategies that surprised even expert Go players.

Emergent properties are not necessarily detrimental. An AI system designed to assist with personalized learning might unexpectedly develop the ability to diagnose disabilities more accurately than current methods. A considerable portion of the creative, desirable potential of AI-powered algorithms originates from their capacity to respond to inputs in a manner that would be unforeseeable to humans [41]. Nevertheless, in the context of education governance, any policy intervention must grapple with AI's emergent abilities, which are inherently unpredictable.

The above three distinctive technical challenges and the private sector's dominance in AI investment and development present formidable obstacles for the public sector to participate in regulation and collaboration. However, inaction paves the way for governance by the private sector and ultimately undermines the very principles of education governance, including the separation of powers, power distribution between national and local governments, due process, and representative democracy. This raises the question: How might we effectively confront these challenges?

3 Question 3: how should one begin addressing algorithmic decisions in education governance?

With the increasing use of algorithmic decisions, addressing the challenges it presents becomes increasingly crucial. To navigate this new algorithmic landscape, a proactive approach to education governance is recommended to exert multilevel social control. Drawing on McDonnell and Elmore's alternative policy instruments, this multilevel social control can be understood through the policy instruments of mandates, inducements, capacity-building, and system-changing measures [20]. Social control refers to the mechanisms and means by which individuals or groups express their concerns or grievances and attempt to enforce normative behavior [11]. It is an umbrella term for practices that contribute to maintaining social order. Social control can be exercised through various formal and informal mechanisms. Formal social control mechanisms include legal proceedings and sanctions, which function as what McDonnell and Elmore termed "mandates" [20]. For example, if a school district adopts an algorithmic system for evaluating teacher performance that is suspected of being biased, teachers or teachers' unions might initiate legal action to challenge the system's fairness and transparency. Legal proceedings such as cease-and-desist orders can be employed to halt the use of such systems until thorough investigations and modifications ensure they comply with fairness standards. By contrast, informal social control mechanisms include negotiations, peer pressure, and advocacy efforts, which often operate as "inducements" [20]. Parents and community members can organize to voice their concerns about the use of AI-powered student assessment tools. Through public forums, petitions, and meetings with school administrators, they can exert pressure to ensure algorithmic decisions are made transparently and fairly.

The social control of AI in education governance raises questions about who is responsible for regulating and controlling AI-powered algorithms. Decentralized social control requires engaging a broad range of actors, including government agencies, non-government organizations, labor groups, and individual stakeholders. Effective regulation will require coordination and collaboration among multiple stakeholders to ensure ethical and responsible practices. Transparency and accountability will be ensured by notifying the public about egregious practices, investigating and punishing them to the fullest extent of the law, with consequences like fines or legal prosecution.

At the federal level, the legislative branch can pass laws and regulations to exert social control over AI in education governance. In the United States, the White House Office of Science and Technology Policy published "The Blueprint for an AI Bill of Rights: Making Automated Systems Work for the American People" in October 2022 [32]. This Blueprint, described as "a bill of rights for an AI-powered world" (p. 4) [32], laid out five principles: (1) safe and effective systems, (2) algorithmic discrimination protections, (3) data privacy, (4) notice and explanation, and (5) human alternatives, consideration, and the fall back. These principles are recommended to be integrated into the reauthorization and rulemaking of the Elementary and Secondary Education Act and the Individuals with Disabilities Education Act. Suppose an AI tool

is developed to identify students who may need special education services based on their academic performance and behavioral data. By incorporating algorithmic discrimination protections from the AI Bill of Rights, the tool would be required to undergo thorough bias testing to ensure it does not disproportionately misidentify students from minority backgrounds as needing special education.

In addition to educational laws, the Blueprint for an AI Bill of Rights' principles should be incorporated into broader legislative and executive initiatives aimed at making amendments and implementing related laws, such as the Family Educational Rights and Privacy Act (FERPA) and Title IX of the Education Amendments Act of 1972. FERPA, which governs the privacy of student education records, could be updated to include specific provisions on the handling and protection of data used by AI systems, ensuring that students' personal information is safeguarded against misuse. Under an updated FERPA, schools using AI-powered tools for personalized learning would be required to obtain explicit consent from parents before collecting and processing students' data. Additionally, parents would have the right to access and review the data used by the AI system to ensure its accuracy and fairness. Moreover, the updated FERPA would need to address the role of third-party vendors who develop and manage these AI-powered tools. These vendors often require access to vast amounts of student data to train and refine their algorithms. The regulation would mandate strict data privacy and security protocols to protect students' information from unauthorized access and misuse. Similarly, employment laws such as Title VII of the Civil Rights Act of 1964 and the Age Discrimination in Employment Act (ADEA) could be amended to address the use of AI in hiring and employment practices. These amendments could ensure that AI-powered hiring tools are designed and used in ways that prevent discrimination based on race, gender, age, and other protected characteristics.

State and local entities can enforce social control too. At the state level, actors like state education agencies, state attorney general offices, and departments of consumer protection regulate corporate practices involving AI-powered algorithms in education governance. At the city level, actors like city councils, neighborhood associations, and community-based organizations enforce social control. New York City (NYC) implemented a local law called "Automated Employment Decision Tools," which took effect on July 5, 2023 [2]. The law requires employers to conduct a bias audit on any automated employment decision tool used for making employment decisions. Employers must disclose the job qualifications and characteristics the tool will use to evaluate the candidate or employee at least 10 days before using the tool. The law also requires employers to notify candidates or employees residing in NYC about the tool's use and post the results of the most recent bias audit on their website. Violations of the law can lead to a civil penalty. The law is not perfect, but it is at least one effort to ensure that AI-powered algorithms are used fairly and transparently.

Non-governmental organizations, such as professional associations, watchdog organizations, and labor groups (e.g., teachers' unions), can contribute to the social control of AI-powered algorithms in education governance. For example, the Institute of Electrical and Electronics Engineers (IEEE) has developed a set of principles for ethical AI that emphasize transparency, accountability, and human-centered design. These principles provide a framework for developing and deploying AI systems in ways that prioritize human well-being and fairness. By promoting these standards, IEEE and similar organizations can influence how AI is integrated into educational settings, ensuring that these technologies enhance, rather than undermine, educational outcomes. Moreover, watchdog organizations can monitor the deployment of AI in education and call out practices that violate laws, civil liberties, and shared norms. These organizations can conduct independent audits of AI systems, publish reports on their findings, and advocate for policy changes to protect students and educators.

Private companies can also play a role in the social control of AI in education governance when their interests are at stake. For instance, technology companies may develop their own AI regulations to safeguard user privacy and mitigate ethical concerns. However, these efforts by private entities could face challenges as they might potentially compromise profits. This contested nature of the motivations behind private companies' self-regulation underscores the need for greater oversight and regulation to ensure that ethical standards and procedural justice are upheld.

Furthermore, individuals can act as agents of social control by boycotting companies with unethical practices or blowing the whistle on corporate wrongdoing. Parents, community members, and human decision-makers in school districts and state education agencies can collectively exert social control by choosing to boycott products or algorithms that they perceive as harmful or unethical, such as those algorithms that racially discriminate against certain groups and punish the poor [10]. Citizen activism can put pressure on companies and governments to take action on AI-related issues.

In summary, the social control of AI will require a collective effort from a wide range of actors to ensure democratic accountability and the preservation of ethical and moral values in the development and implementation of AI technologies. However, the three distinct features of algorithmic decisions—fast speed, lack of interpretability and transparency,

Table 1 Recommendations and Actionable Strategies

Recommendations	Actionable strategies
1. Implement transparency standards for AI systems used in education	• Require AI developers to provide clear documentation on how their algorithms work and make decisions • Establish regular auditing processes for AI systems to ensure fairness and accuracy • Create mechanisms for students, parents, and educators to appeal algorithmic decisions to ensure procedural justice • Introduce mandatory notification systems to inform stakeholders when and how AI systems are used in decision-making processes • Protect the right to reject algorithmic decisions by offering alternative, human-centered decision-making processes
2. Ensure stakeholder involvement in the development and implementation of AI tools	• Establish advisory boards comprising educators, parents, democratically elected student government leaders, and AI experts to guide AI implementation in schools • Create formal channels for advisory recommendations to be considered in institutional governance structure • Conduct public feedback collection and discussions before introducing new AI systems in educational settings • Provide training for educators and administrators on understanding and effectively using AI tools
3. Develop regulatory frameworks that keep pace with AI advancements	• Create flexible, adaptive regulations that can evolve with technological progress • Establish cross-sector collaborations between education departments, technology companies, and legal experts to address emerging challenges • Implement ethical guidelines for AI use in education by drawing from frameworks like the Blueprint for an AI Bill of Rights

and unpredictable emergence—pose significant challenges. Given the discussion in this perspective article, policymakers and stakeholders are recommended to (1) implement transparency standards for AI systems used in education, (2) ensure stakeholder involvement in the development and implementation of AI tools, and (3) develop regulatory frameworks that keep pace with AI advancements. More detailed actionable strategies for each of these recommendations are presented in Table 1.

4 Conclusion and future possibilities

As AI becomes increasingly woven into our education, economic, and social fabric, the risks it poses will grow. The impact of AI on fundamental education governance principles is complex and depends on how AI is designed, implemented, and regulated. This perspective article highlights the potential for algorithmic decisions to become de facto policy decisions—primarily made by proprietary algorithms owned by a few private companies. This article aims to initiate conversations that scrutinize how AI, and algorithmic decisions in particular, challenge traditional assumptions of education governance, including the separation of powers, power distribution between national and local governments, due process, and representative democracy.

The social control proposed above is by no means perfect. No single policy instrument is sufficient for addressing complex educational challenges [20]. The choice and combination of instruments must consider the existing institutional capacity, available resources, political feasibility, and implementation timeline. It is crucial to discard the notion that there exists an ideal governance that, if adopted, will automatically propel American schools and students to higher levels of performance, especially in the era of AI. Like any complex issue, simple solutions are rarely effective. Hopefully, this perspective article serves as a starting point for discussion on AI-powered algorithmic decisions in education governance.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Competing interests The authors declare no competing interests.

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