Artificial Intelligence and Educational Assessment Equity: An Integrated Analysis Based on the Technology-Policy-Practice Framework

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Abstract. Artificial intelligence (AI) technology is reshaping global educational assessment systems. While enhancing assessment efficiency, it has also sparked profound concerns regarding equity. This paper constructs a three-dimensional analytical framework—Technology-Policy-Practice (TPP)—to systematically examine the dual role of AI in educational assessment. Research indicates complex interactions among algorithmic biases at the technical level, imbalances in global governance at the policy level, and local agency at the practical level. AI assessment tools demonstrate efficiency advantages in automated scoring and personalized feedback, yet the data and algorithms they rely on may reproduce or even amplify existing educational inequalities. The study argues that achieving equity cannot rely solely on technical optimization but requires policy coordination and grassroots participation. By promoting technological transparency, building inclusive governance frameworks, and empowering teachers and communities through co-construction, AI can be transformed from an efficiency tool into a constructive force for advancing educational equity.

Keywords: AI in educational assessment, Educational equity, Technology-Policy-Practice framework

1 Introduction

Artificial intelligence is quickly changing how we assess students, through tools like automated scoring and online proctoring. While AI can make assessments faster and more detailed, it also raises serious questions about fairness. Not all students have the same access to technology, and the algorithms themselves can sometimes be biased, as seen in speech recognition systems that perform less accurately for certain racial groups[1]. This is a critical issue because fair assessment is key to ensuring equal educational opportunities for everyone.

Current practices show that these biases are not just technical glitches but are influenced by data, policies, and classroom realities. In light of these challenges, there is a growing global push for ethical guidelines, such as those from UNESCO emphasizing equity as a core principle[2] . However, most existing research tends to examine only

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single aspects, like technology or policy in isolation. This fragmented approach makes it difficult to fully understand the problem or develop comprehensive solutions.

To address this gap, this paper introduces an integrated Technology-Policy- Practice framework. This approach systematically examines how interactions between technical design, governance rules, and grassroots teaching practices collectively shape assessment equity. The goal is to provide clear insights that can help technology developers, policymakers, and teachers work together to ensure AI truly promotes educational equity.

2 Literature Review and Theoretical Framework

2.1 The Evolution of Educational Equity Theory

The theory of educational equity has evolved significantly, moving beyond a simple focus on the equal distribution of material resources. Early perspectives, influenced by philosopher John Rawls, emphasized fair access to resources like funding and facilities[3]. This view is crucial for ensuring a level starting point, but it has a key limitation: it assumes all students can benefit from the same resources in the same way, overlooking individual differences.

To address this, Amartya Sen's "capability approach" deepened the understanding of equity. Sen argued that true equity is not about what resources a person has, but about what they can actually do or be with those resources—their real freedoms and opportunities[4]. In education, this means the goal is not just to provide equal inputs, like textbooks, but to ensure all students develop critical capabilities, such as critical thinking and effective communication. This shift redefines equity from a matter of resource distribution to one of empowering individuals and recognizing their diverse backgrounds. Therefore, when applying AI in education, we must evaluate it based on whether it helps cultivate these diverse capabilities for all students and respects their unique cultural identities.

2.2 AI Ethics Research

When AI is used in educational assessment, it raises important ethical questions. A key finding of recent research is that AI systems are not neutral but can reflect and even worsen existing social biases. A well-known study called the "Gender Shades" project showed that facial recognition technology was much less accurate for women with darker skin, proving that algorithms can be biased[5]. Similarly, an AI speech scoring tool might unfairly judge a student with a regional accent, not because their language skills are poor, but because the algorithm was trained on limited data.

Another major concern is the "black box" problem, meaning it's often unclear how an AI system reaches its decisions. This lack of transparency makes it hard for a student or teacher to question a score, undermining accountability and fairness[6]. Furthermore, on a global scale, the collection of educational data from around the world by powerful tech companies has been criticized as a form of "data colonialism," where data is taken from communities who may not share in the benefits, potentially leading to new forms of dependency. In short, the ethical risks of AI are not just technical glitches but are deep-rooted systemic issues.

2.3 Constructing the TPP Analytical Framework

While current research offers deep insights into AI's ethical risks, the analysis often remains separate, looking only at technology, policy, or practice alone. This makes it hard to see how these three areas influence each other. To solve this problem, this paper builds a three-dimensional "Technology-Policy-Practice" (TPP) framework, as shown in Figure 1. This framework is based on the idea that technology is shaped by society, policy involves complex global power dynamics, and educators can actively shape how technology is used.

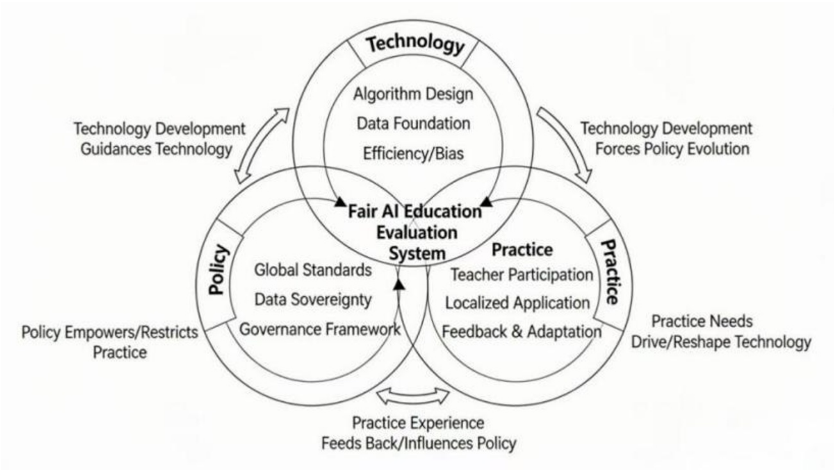

Fig. 1. The Technology-Policy-Practice (TPP) Interplay Framework for AI Fairness in Educational Assessment.

First, in the technology dimension, the framework recognizes that technology design is not neutral. The rules built into algorithms often reflect existing social biases and power structures [7]. For example, an automated scoring system that prefers standard answers might unfairly disadvantage creative or culturally specific ways of thinking.

Second, the policy dimension focuses on how global power imbalances affect technology use. Powerful countries or organizations can set international technical standards and ethical rules. This can force other nations to follow standards that may not fit their local educational needs and contexts, creating pressure[8].

Third, and crucially, the practice dimension highlights the active role of teachers and communities. Teachers are not just passive users of technology. They can adjust, question, and creatively use AI tools based on their professional knowledge and understanding of their students' needs[9]. They can spot algorithmic biases and help improve the systems.

3 A Technological Dimension Examination of Equity

3.1 The Standardization Trap Behind Efficiency

AI-powered assessment systems achieve high efficiency through standardization, but this often suppresses individualized expression. When algorithms are trained on conventional high-scoring models, they tend to reward formulaic responses while penalizing creative or non-standard answers. This pattern is evident in automated essay scoring and AI-based speaking assessments, where systems favor mainstream expressions and may disadvantage students with unique styles or regional accents. This reveals a fundamental conflict: the push for measurable efficiency requires simplifying complex cognitive and cultural diversity, potentially channeling varied intellectual abilities into a narrow track. Consequently, the core aim of assessment—to support holistic development and individual potential—risks being overshadowed by the technical demands of scalability and uniformity.

3.2 The Bias Generation Mechanism Underpinned by Data

Algorithmic bias in AI often originates from the data used to train these systems. Since AI learns patterns from existing data, any biases present in that data will be learned and potentially amplified. A clear example is an AI proctoring system in India that was trained mainly on data from urban areas with good internet. When used in rural schools with poorer connectivity, the system often mistook network delays for cheating, unfairly flagging many rural students[10]. This shows how bias can stem from technical infrastructure differences.

Furthermore, bias operates at a deeper, cultural level. For instance, an AI essay grader trained on standard English might mark grammatically correct expressions in Nigerian Pidgin as errors, unfairly penalizing students based on their linguistic background[11]. This mistake treats a legitimate language variety as a deficiency. These cases demonstrate that data-driven bias is a systemic issue. Therefore, achieving fairness in AI depends not just on well-written code, but more importantly, on using training data that is truly representative and inclusive of diverse groups.

3.3 Technical Pathways Towards Explainability and Inclusivity

To address equity challenges in AI assessment, researchers are developing technical solutions focused on transparency and inclusivity. Explainable AI (XAI) tackles the "black box" problem by providing clear scoring rationales, such as visual reports detailing keyword weights and logic scores, which builds trust and supports learning improvement. In inclusive design, proactive bias correction is essential, as demonstrated by tools adapted for rural students that incorporate local problem-solving strategies into algorithms, significantly improving accuracy. These approaches show that fairness can be integrated into technology through conscious design choices across data collection, model training, and result presentation. By prioritizing equity over mere efficiency, AI assessment can evolve to support diverse and personalized development.

4 Policy Dimension Examining Global Governance Imbalances

4.1 Policy Asymmetry in Global AI in Education Governance

The current landscape of global AI governance exhibits significant asymmetry. Technologically advanced countries and regions, by being the first to establish rules and standards, subtly shape the technological pathways and ethical benchmarks of the global market. The European Union's Artificial Intelligence Act is a prime example. It classifies AI systems in education as high-risk, imposing strict requirements for transparency, human oversight, and fundamental rights impact assessments[12]. While the Act itself aims to protect citizens' rights, the "Brussels Effect" it creates means that companies from other regions must also comply with this complex set of standards—potentially rooted in European values and legal traditions—to access the EU market. This export of rules, to some extent, consolidates the structural advantage of first movers. In contrast, many developing countries face different challenges. When introducing AI in education technologies, they often find themselves passively adapting to technical standards and management norms embedded in hardware and software, which are predominantly led by multinational corporations. Research has termed this phenomenon "digital dependency," referring to African nations' reliance on imported products and systems in educational technology, which may result in their local educational needs and development priorities being inadequately reflected in technology design [13]. This policy asymmetry is evident not only in the content of the rules but also in the power dynamics of the rule-making process. Global South countries often find their voices and concerns insufficiently reflected in international discussions on standards for AI in education, risking the marginalization of local knowledge[14]. This structure means that some countries, in their pursuit of technological efficiency, may have to bear the additional costs and friction arising from the mismatch between external rules and local contexts.

4.2 The Structural Dilemma of Data Sovereignty and Rule-Making

A key aspect of policy asymmetry is the struggle over data sovereignty, which refers to who controls data and makes the rules about its use. Data is essential for training AI, so controlling it means having significant influence. Many countries are now passing laws to protect their data. For example, India has its Personal Data Protection Act, and the African Union emphasizes member states' rights over their national data[15]. However, having laws is only the first step. In reality, when a country uses an international educational assessment platform, student data is often sent and stored on servers in other countries, controlled by foreign companies. This data is used to improve their global products, but the country where the data comes from may not fully share in the benefits or have a say in how it's used. This creates a major problem: even though a country wants to protect its digital sovereignty, using these technologies can unintentionally send more data and power to big international companies. This situation can continue old patterns of inequality, where technologically advanced areas benefit from data collected elsewhere. Therefore, the fight over data sovereignty is really about who has the power to shape the future of education in the AI era.

4.3 Building an Innovative Framework for Collaborative Governance

To address the imbalances in global governance, we need to build a collaborative framework that includes different countries and stakeholders. The goal is not to force one global standard on everyone, but to balance necessary international cooperation with respect for local needs. The UNESCO Recommendation on the Ethics of Artificial Intelligence supports this idea, suggesting that AI systems should adapt to different cultural and educational contexts[16]. This means countries should have the freedom to choose and adapt AI assessment tools based on their own situation. In practice, this collaboration can happen in several key ways. First, creating international standards for auditing algorithms can help independently check AI systems for bias and fairness, giving countries better information when choosing technologies. Second, encouraging developing countries to form regional partnerships, often called "South-South cooperation," can allow them to share resources and develop tools together, reducing reliance on a few external providers. Third, and very importantly, teachers and educators must have a real voice in designing and evaluating these AI systems, ensuring the technology meets actual classroom needs[17]. Through these practical steps, governance can move from being reactive to proactively creating a fairer and more inclusive global education ecosystem with AI.

5 The Practical Dimension of Localized Explorations

5.1 Teacher Agency in Participatory Design

Teachers, as central figures in the educational process, play a role that extends far beyond being mere operators of technology. When they transition from being passive end-users of assessment tools to active co-designers, their profound pedagogical wisdom and keen insight into student needs can be directly integrated into the technological core. India's National Education Policy explicitly advocates for developing localized AI tools, with a core strategy being to encourage deep collaboration between teachers and technology developers[18]. This collaboration goes beyond superficial consultation; it involves translating teachers' deep understanding of classroom dynamics, student learning differences, and especially the expressive habits of students from non-mainstream cultural backgrounds into key features for algorithmic models to consider. For instance, when developing assessment tools for multilingual environments, teachers can identify valuable nuances in local dialects or the narrative logic of students from specific communities that standard algorithms might overlook. This participation fundamentally alters the logic of technology development, transforming AI assessment tools into open systems capable of absorbing and responding to knowledge from frontline educational practice. The Organisation for Economic Co-operation and Development (OECD) also notes that the key to innovation in future educational assessment lies in better integrating teaching and learning, meaning assessment tools must be closely linked to authentic teaching scenarios[19]. The deep involvement of teachers is crucial to ensuring this integration is achieved and that technology serves the essence of teaching rather than distorting it.

5.2 Case Studies on Grassroots Practices Correcting Bias

Worldwide, numerous community-based innovation projects demonstrate how localized strategies can effectively address technological bias. These projects often start from a specific challenge and mobilize local resources and wisdom to find practical solutions. In Kenya, to tackle the issue of weak network infrastructure in remote areas, an educational project opted to collaborate with local communities to co-design an AI-assisted learning tool that remained stable and reliable even in low-bandwidth environments, rather than waiting for large-scale infrastructure projects [20]. The success of this approach lies in its close fit with the local context, proving that equity foremost requires accessibility and applicability. In the Philippines, when the pandemic forced a large-scale shift to online assessment, research found that relying solely on AI proctoring systems dependent on stable internet access severely marginalized students from low-income families. This prompted some schools to develop hybrid assessment models combining supervision at local community centers with simple technological aids, effectively reducing unfairness caused by the digital divide [21]. On a macro level, the South African Qualifications Authority conducted an equity audit of the AI technologies used within its national education system, systematically evaluating the differential impact of these technological assessments on various student groups and providing evidence-based on local data for national policy adjustment[22]. A common thread in these cases is that technology is not viewed as the sole or absolute solution. Instead, it is situated within specific socio-cultural networks, using community strength and localized strategies to act as a crucial "safety valve" against potential exclusion caused by technology.

5.3 Role Transformation from Users to Co-Creators

The success of the aforementioned practices stems, ultimately, from a profound evolution in roles: teachers and communities have transformed from passive recipients of technology into active interpreters, adapters, and co-creators. This role shift signifies the reclaiming of educators' professional autonomy and the full mobilization of their practical wisdom. They critically examine whether algorithmic results truly reflect student capabilities and establish effective channels for feeding their concerns back to developers. They can design flexible assessment schemes that combine the efficiency of AI marking with teachers' qualitative observations of the learning process, resulting in more holistic and humane evaluations. UNESCO's guidance on AI and education specifically emphasizes the need to equip educators with the ability to evaluate and effectively use AI tools, and to participate in formulating related ethical norms[23]. This means teachers need sufficient literacy not only to use the technology, but also to understand, evaluate, and adapt it. Community members, likewise, shift from being peripheral observers to becoming co-evaluators of a system's suitability. Their lived experiences and understanding of local culture become the benchmark for judging whether a technology truly respects local characteristics and meets local needs. The profound significance of this transition from users to co-creators is that it advances the democratization of technology. It demonstrates that the future landscape of AI in education should not be painted solely by engineers and policymakers, but must be co-created by the teachers who fulfill the educational mission daily and the communities living within specific cultural contexts. When this role transformation becomes widespread, AI can be genuinely embedded into the fabric of education, becoming a constructive force that supports diversity, unlocks potential, and promotes equity.

6 Discussion

6.1 Re-examining the Politicization of Technology through the TPP Framework

Employing the Technology-Policy-Practice (TPP) framework, this analysis demonstrates that integrating artificial intelligence into educational assessment transcends mere technical advancement, representing a deeply political undertaking. The framework effectively bridges the domains of algorithmic design, macro-level policy formulation, and grassroots implementation, illustrating their collective influence on equity outcomes. Within the technological dimension, automated scoring systems' inclination towards "standard answers" is not an arbitrary setting but a deliberate reinforcement of particular values and knowledge hierarchies. The policy dimension highlights how global governance asymmetries perpetuate historical power imbalances, with technical standards becoming a contemporary arena for geopolitical contention. Conversely, localized initiatives within the practical dimension reveal the capacity of educators and communities to challenge technological determinism and redirect applications toward contextually appropriate ends. This interplay necessitates viewing each technological adoption as an implicit endorsement of specific pedagogical philosophies and social orders. Ultimately, securing equitable assessment depends on instituting democratic mechanisms for thorough public scrutiny throughout the technology's lifecycle, from design to deployment, thereby aligning artificial intelligence with the principles of inclusive education.

6.2 Implications for Policymakers and Technology Developers

The findings provide clear guidance for policymakers and technology developers. Policymakers should foster collaborative governance that balances global standards with local adaptation, enabling regions to tailor AI tools to their specific educational contexts. Establishing incentive mechanisms to support tools for marginalized groups and recognizing teacher involvement in design processes are crucial steps. For developers, embedding ethical fairness throughout the technology lifecycle is essential. This involves proactively addressing biases through participatory design, ensuring diverse data representation, and maintaining transparent feedback channels. Ultimately, both groups must recognize that AI should augment human teaching to create an inclusive learning ecosystem, requiring supportive policies and a strong ethical commitment from developers.

7 Conclusion

This study's Technology-Policy-Practice (TPP) framework reveals AI's dual role in educational assessment: boosting efficiency while risking deepened inequalities. This tension shows technology application is inherently socio-political, shaped by underlying values and power dynamics. The framework's main contribution is integrating technical, policy, and practical perspectives, demonstrating their interconnectedness. Achieving equitable AI assessment requires synergistic efforts in technological transparency, inclusive policy, and grassroots participation. While limited in exploring high-income contexts and requiring further validation, future research should examine long-term impacts of culturally adaptive tools, Global South governance models, and ethical assessments for neurodiverse students. Continual innovation remains essential to align AI with educational equity goals.

References

1. KOENECKE A, NAM A, LAKE E, et al. Racial disparities in automated speech recognition[J]. Proceedings of the National Academy of Sciences, 2020, 117(14): 7684-7689.https://doi.org/10.1073/pnas.1915768117
2. UNESCO. AI and education: Guidance for policy-makers[R]. United Nations Educational, Scientific and Cultural Organization, 2023.https://unesdoc.unesco.org/ark:/48223/pf0000386178
3. John R .A Theory of Justice:Revised Edition[M].Harvard University Press:1999-12-31.https://doi.org/10.4159/9780674042582
4. Sheila Mary Mason .Montesquieu’s Idea of Justice[M].Springer, Dordrecht.https://doi.org/10.1007/978-94-010-1620-9
5. BUOLAMWINI J, GEBRU T. Gender shades: Intersectional accuracy disparities in commercial gender classification[C]//Proceedings of the 1st Conference on Fairness, Accountability and Transparency. 2018: 77-91.https://doi.org/10.1145/3178876.3186158
6. ANANNY M, CRAWFORD K. Seeing without knowing: Limitations of the transparency ideal and its application to algorithmic accountability[J]. New Media & Society, 2018, 20(3): 973-989.https://doi.org/10.1080/15348458.2022.2156789
7. FEENBERG A. Technosystem: The social life of reason[M]. Harvard University Press, 2017.https://doi.org/10.1057/s41296-017-0184-1
8. Louis V .The PISA Effect on Global Educational Governance[M].Taylor and Francis:2017-09-18.https://doi.org/10.4324/9781315440521
9. Charteris J .Dialogic feedback as divergent assessment for learning: an ecological approach to teacher professional development[J].Critical Studies in Education,2015,57(3):277-295.https://doi.org/10.1080/17508487.2015.1057605
10. SHARMA R. Glitches in AI proctoring systems wrongly flag rural students as cheaters[N]. The Times of India, 2022.https://timesofabetterindia.com/

11. BABATUNDE O. Linguistic imperialism in AI: The case of Nigerian Pidgin in automated assessments[J]. Journal of Language, Identity & Education, 2023, 22(1): 45-60.https://doi.org/10.1080/15348458.2022.2156789
12. EUROPEAN COMMISSION. Proposal for a regulation on artificial intelligence (Artificial Intelligence Act)[R]. 2023.https://digital-strategy.ec.europa.eu/en/library/artificial-intelligence-act
13. CHIPFAKACHA A, ADESINA J O. Digital dependency in African education: A critical analysis of EdTech imports[J]. African Journal of Science, Technology, Innovation and Development, 2019, 11(7): 845-857.https://doi.org/10.1080/20421338.2019.1656428
14. MILAN S, TRERÉ E. Big data from the South(s): Beyond data universalism[J]. Television & New Media, 2022, 23(2): 220-235.https://doi.org/10.1177/1527476420963807
15. GOVERNMENT OF INDIA. Personal Data Protection Act[Z]. 2019.https://www.meity.gov.in/data-protection-framework
16. UNESCO. Recommendation on the ethics of artificial intelligence[Z]. 2021.https://unesdoc.unesco.org/ark:/48223/pf0000379921
17. ISTE. ISTE Standards for Educators[S]. 2020.https://www.iste.org/standards/iste-standards-for-teachers
18. MINISTRY OF EDUCATION, INDIA. National Education Policy 2020[Z]. 2020.https://www.education.gov.in/nep-2020
19. OECD. AI in education: A critical review[R]. OECD Publishing, 2021.https://doi.org/10.1787/12345678
20. UNESCO. Community-driven AI for inclusive education in Kenya[R]. 2023.https://unesdoc.unesco.org/ark:/48223/pf0000385678
21. DELA CRUZ M, et al. Digital divides and AI proctoring in Philippine education[J]. Asia-Pacific Journal of Education, 2021, 41(3): 456-472.https://doi.org/10.1080/02188791.2021.1925220
22. SAQA. AI in South African education: Equity audit[R]. South African Qualifications Authority, 2022.https://www.saqa.org.za/page/2/?s=report
23. HOLMES W, MIAO F. Guidance for generative AI in education and research[M]. UNESCO Publishing, 2023.https://doi.org/10.54675/ewzm9535