


# Algorithmic Power and Inequality in Global Education

**Fatema A Baloch[1*], Dr. Radha J Gohel[2]**
[1] Research Scholar, Dr. Subhash University, Junagadh, Gujarat, India
[2] Assistant Professor, Dr. Subhash University, Junagadh, Gujarat, India

**Corresponding Author:** *Fatema A Baloch

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## Abstract

The incorporation of Artificial Intelligence (AI), Learning Analytics, Auto Assessment, Adaptive Learning Platforms, Predictive Systems, and Generative AI in the education sector is changing the way teaching, learning, assessment, and educational administration are done. Algorithmic technologies can be used to tailor instruction, find students that need extra support, make instruction more accessible, and broaden education. Concurrently, they are becoming a huge concern in the area of inequality and discrimination, as well as in relation to privacy, surveillance, accountability and centralization of decision-making power. This research paper explores how algorithmic power is connected to inequality in global education. It pleads for the understanding of algorithmic inequality as more than just a by-product of technically biased algorithms. Instead, it is a product of the interplay between prevailing social inequalities and unequal access to digital technology, datafication, algorithm design, institutional decision-making, commercial interests, and divergent regulatory capacities. The study is qualitative and uses critical-narrative literature review and comparative policy analysis, which involves the use of peer-reviewed scholarship, academic literature and reports and policy documents from international organisations. The analysis shows that inequality can exist at several points in the algorithmic process, from digital infrastructure to the representation in the underlying data, the automated classification, the assessment, and the capacity to contest algorithmic decisions. There is special focus on predictive analytics, automated assessment, learning analytics, generative AI, and commercialisation of EdTech. The paper also examines new international responses like that of UNESCO, which takes a human-centred approach and that of OECD, which focuses on equity and inclusion. It concludes that the development of educational AI that is equitable is not just a technical matter. It needs to be digitally accessible, representative of data, be transparent, have human supervision, have an impact assessment tool for algorithms, have teacher input, have procedures for safeguarding, and have mechanisms for review and remedy which are accessible. Finally, the paper introduces the notion of algorithmic education not only as an issue of technological innovations but as an issue of institutional power and educational justice.

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## INTRODUCTION

Artificial intelligence and algorithmic technologies have undergone tremendous growth, bringing about a huge shift in modern education. The increasing adoption of digital platforms by educational institutions to provide learning materials, track participation, evaluate academic progress, suggest educational resources, identify the at-risk students and facilitate administrative decision making. AI is therefore not just for experimental or highly specialized learning uses. It has become part of the regular educational workflow, from adaptive learning systems to automated feedback, predictive analytics to generative AI. These technologies are increasingly becoming important for educational innovation, but they also raise questions about who has control of educational data, how students are sorted, whose knowledge is included in algorithmic systems, and the possibility of reproducing existing inequalities in the process of technological transformation. Algorithms are frequently given the appearance of being value-free and able to handle information more efficiently and uniformly than human decision makers. However, in the context of education the data that algorithms use is produced in social institutions that are unequal. There are significant differences in devices, stable Internet connections, private learning spaces, educational support, language support and digital skills among students. The variations affect the amount and quality of digital products created by learners. Information to this extent can then be processed algorithmically and social inequalities can be embedded in data sets and understood as differences in student behaviour, engagement, ability and/or motivation. Thus, a neutral technology system can be used to generate inequalities that are present prior to the onset of the technology. AI and inequality are thus a complicated mix. Artificial intelligence can help students with disabilities, deliver individual explanations, interpret learning materials, make learning resources accessible, and help teachers determine that there are students in need of support. The OECD has acknowledged the promise of AI in enhancing adaptive and inclusive learning environments, as well as highlighted issues such as access, bias, teacher readiness, privacy, cultural sensitivity and commercialization (Varsik & Vosberg, 2024) [20]. However, these alternative scenarios lead us to consider that the educational consequences of AI may not be possible to be limited to a single algorithm's technological capabilities. UNESCO's efforts on Technology in education also focus on the educational purpose, equity, evidence and sustainability of the use of technology. Technology will not automatically enhance learning outcomes just because it is the latest and greatest in technology. Infrastructure, teacher training, proper implementation, and learners' contexts are all key factors in the benefits that digital systems can offer (UNESCO, 2023). In developing countries, access disparities can compound educational disparities, and access disparities can be experienced by both men and women. With the advent of generative AI, these questions have grown stronger. Generative AI can generate text, explanations, translations, images, computer code and more. They are used in education to help students with writing, explain things, help teachers plan lessons, and to conduct research. There are challenges, however, with the implementation of advanced systems, with AI literacy, with privacy issues, with outputs that aren't correct, and with assessment. There are new challenges, though, with advanced systems, with AI literacy, with privacy, with incorrect outputs, with assessment. UNESCO's recommendations focus on ensuring that generative AI is governed via a human-centred method, prioritising human agency, inclusion, equality, linguistic and cultural variety, and data privacy (Miao & Holmes, 2023) [8]. This paper will look at those developments in the light of algorithmic power. Algorithmic power is the ability of computing systems – and the organisations that operate them – to categorise people, forecast their behaviour, suggest what to do, prioritise or allocate attention, and affect institutional decisions. In education, this power can impact upon opportunities that can have far reaching implications for students' educational and employment prospects. The main thesis of this paper is that algorithmic inequality is not a technical issue. It is a problem of a social and institutional nature where technology meets the existing educational, economic, cultural and political structures.

### 2. Background and Conceptual Framework

Algorithmic systems have emerged as powerful tools of educational governance because of their ability to organise vast amounts of student data into categories, prediction, recommendation and decision. For instance, learning analytics systems can gather data on student attendance, online engagement, their performance in assessments, how they interact with educational materials, and submission habits. These data can then be used to forecast academic performance or students that might need intervention. Adaptive learning systems can modify learning content and/or the order or difficulty level of content based on individual response. Written or objective responses might be assessed by automated systems and generative AI systems can be used to create educational content or feedback. As these technologies are being developed, the roles of the learner and the educational institution are changing. Traditionally, the teachers and administrators used their professional judgment and on-the-job experience heavily. Algorithmic systems bring in new evidence and authorities. The educational data infrastructure is seen as generating new forms of expertise, as it makes data, predictive models and computational analysis the focus of educational decision-making as described by Williamson (2017) [22-23]. The outcome is not only greater efficiency, it is a change in the concept of what is a legitimate knowledge about a learner. This means that we can think about this change in four overlapping aspects of inequality. The first is access inequality; that is, unequal access to devices, connectivity, electricity, software and digital skills. The second is representational inequality, which is about whether different population, language, culture, disability and educational experiences are sufficiently represented in datasets. The third is inequality in decision making, that is, how algorithmic predictions and classifications impact different learners. The fourth is governance inequality, which involves controlling, challenging, understanding,


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monitoring and regulating algorithmic systems, by learners, teachers, institutions and governments. These dimensions are related. If a student has unstable Internet connection, he/she may communicate less with a digital learning platform. The resulting data may be a sign of low engagement. This may be identified as an academically at risk student by an algorithm. The institution can then act accordingly in a specific way in response to that classification. The student may suffer from a less successful learning experience if the answer is lacking or limiting. This can therefore lead to an inequality in algorithmic decision-making in the end. The conceptual meaning of this relationship is in the difference between technical neutrality and social neutrality. Rules can be applied by an algorithm in a uniform manner to all students and can be perceived as neutral. However, when the data that underlie the rules are imbalanced, the outcomes may be socially charged. In fact, algorithmic fairness must take into account all stages in the lifecycle of data production, modelling, decision making, and consequence distribution.

## 3. REVIEW OF LITERATURE

Over the past ten years, there has been a significant amount of literature on the topic of AI and education. Zawacki-Richter *et al*. (2019) [24] undertook a systematic review of studies on the use of AI in higher education and found that there are four broad categories: profiling and prediction, assessment and evaluation, adaptive systems and intelligent tutoring. They also found that, in their experience, educators were not engaged in many AI studies, indicating the emphasis in AI research on the technological and computational aspects of the field rather than pedagogical and professional ones. Wang *et al*. (2024) [21] also illustrate the swift advances of AI research in education and point to some of its uses, such as personalized learning, adaptive learning, assessment, prediction and educational management. Evidence grows of the significance of AI in education, but technological advances do not prove that AI systems are equitable. Technological capability and educational effectiveness are thus different and should be separated. Critical scholarship calls into question the notion of technology being an independent entity that is bound to change education. Selwyn (2019) [14] suggests a need to think about AI within the context of current education institutions, professional practices and political and economic interests. Castañeda and Selwyn (2018) [1] also note that digital technologies are not standalone, but rather become intertwined in the contexts in which they are used. Their work is especially relevant to algorithmic inequality since it shows the institutionalization of a technology influences the system of technology. Yet another important basis comes from the literature on the digital divide. Van Deursen and van Dijk (2019) [19] state that digital inequality has not only become more complex, but has also evolved from a lack of physical access to inequalities in material conditions and quality of using the digital. Similarly, Scheerder *et al*. (2020) [13] show that education is a factor that can affect the positive outcome from Internet use amongst individuals. The findings are relevant to algorithmic education because the functionality of algorithmic system is critically related to meaningful participation in digital environments and not just nominal access. Another broad literature exists for research into algorithmic bias. In conclusion, Kizilcec and Lee (2020) [4] illustrate how bias can manifest in measuring educational characteristics, building models, and as a result of predictions. This is especially significant as it shows that algorithmic fairness is not simply achieved by removing obviously demographic traits from the data. Holmes *et al* (2022) [3] offers a comprehensive overview of algorithmic bias in education and evidence related to race and ethnicity, gender, nationality, socioeconomic status, disability and other factors. Their analysis shows that bias can occur at various points in the machine-learning pipeline and that educational algorithms must be assessed beyond the technical accuracy of their predictions, and that education algorithms also need to be evaluated with regard to distributional aspects. Then there is evidence that a limited algorithmic parity is moving towards the larger idea of academic equality. The other important element of scholarship is digitalization. According to Lupton and Williamson (2017) [7] the collection of data and its analysis gives rise to a different type of authority as the computerized data will impact the student's overall growth and how the institution look the student. If all the decision making of institutions rely on digital data, there may be a possibility of bias or faulty assessment of student. Williamson (2017) [22-23] further discusses about the accuracy of data and how it is used; thereafter, much emphasis is given to works based on generative AI in courses, teaching methods, learning and research in both ways, as a facility and as a challenge to privacy and authenticity issues. On the one hand, AI is seen as a helper to humans, and on the other hand, it is seen as a threat to how this technology is distributed and how far it reaches. Therefore, there is a basic framework conflict in the literature. While AI can offer educational advantages that are significant for those who are disadvantaged, the same advancement can create a kind of inequality if there is unequal access to data, implementation, and governance

## 4. RESEARCH GAP

While there is a wealth of research in the area of AI in education, AI and digital inequalities and algorithmic fairness are often studied separately. Algorithmic fairness research tends to be concerned with model performance and math definitions of fairness, whereas the research on digital divides tends to be concerned with access and digital skills. Research on educational technology can study the learning outcomes, but not explore the power dynamics between the technology industry, institutions, teachers, and learners. It is thus necessary to have an integrated model that takes into account the entire pathway on which social inequality could transform into algorithmic inequality. Access to digital infrastructure is unequal, participation inequality follows, and so does data production, and algorithmic classification and institutional decision-making. Governance can be the difference between the people having an understanding of and a challenge to the decisions that are made. The second gap is related to the global dimension. The vast majority of the empirical literature is from educationally developed technological contexts. Further consideration is needed for the implications for low- and middle-income countries as they could be dealing with multiple


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challenges at once in areas of infrastructure, teacher capacity, language diversity, institutional resources, and regulatory capacity. A global analysis should thus not be based on a single technological or regulatory model, since it is unlikely to function in the same way in different educational systems.

## 5. RESEARCH PROBLEM

The central research question is the growing presence of algorithmic technologies in an educational system in which inequalities exist from the outset. There is growing capacity to gather and analyse data about learners at educational institutions, and Fair Governance of these systems has not developed equally. Errors are not the only issue with algorithms. The human decision-making process can also be wrong or biased. What is unique about algorithmic systems is that they can make decisions, they can scale, they can be hard to understand and to see how they reach a decision, they can lead to hidden assumptions about classifications, and they can make it difficult for people to know on what basis a decision was made. As a result, an educational inequity that was generated at a particular level of decision-making, at the individual institutional level, can be institutionalized at a deeper level in the technological process.

## 6. RESEARCH QUESTIONS

1. How does algorithmic decision-making redistribute power within global education systems?
2. Through what mechanisms can algorithmic systems reproduce or intensify existing educational inequalities?
3. How do unequal digital access and data representation influence algorithmic educational outcomes?
4. What governance mechanisms can promote equitable, transparent, and accountable use of AI in education?

## 7. RESEARCH OBJECTIVES

The core aim of this research is to focus on the link between algorithmic power and educational inequality in education systems around the world. The study also aims to explore the potential impact of the unequal access, datafication, algorithmic classification, automated assessment, and generative AI on educational opportunities. It also seeks to examine new international strategies for AI governance and to pinpoint institutions that can help to mitigate algorithmic inequality.

## 8. RESEARCH METHODOLOGY

The research method used in this work is qualitative and critical-narrative literature review as well as comparative policy analysis. Academic literature, peer reviewed journal articles, scholarly books, international organisation reports and policy documents were taken into account, with a particular focus on literature from 2016 to 2026. Previous work that had been foundational was included where appropriate in order to provide conceptual grounding. The literature was examined thematically under five main categories: digital inequality, datafication, algorithmic bias, algorithmic decision making and governance. These dimensions were not analysed as separate issues, but rather as they relate to each other. There was also a review of international policy documents, including UNESCO documents on AI and education, OECD publications on digital education and AI, and current international discourse on generative AI. This is especially important in the context of UNESCO's guidance, which explicitly includes ethical, safe, equitable and meaningful use of generative AI in education, and highlights the need for safeguarding human agency and diversity. This study does not include a new survey, experiment or statistical data set. Therefore, it does not claim to have original empirical results. Rather, its conclusions are a synthesis and critical interpretation of the current research and policy evidence.

## 9. ANALYSIS AND DISCUSSION

The greatest and most basic root of algorithmic inequality is access to digital infrastructure. Algorithmic educational systems depend upon the existence of devices, connectivity, electricity, software, and digital skills. If the resources are not equally distributed then participation in digital education is not equally distributed. UNESCO's technology in education project focuses on the fact that having access to technology does not ensure an educational benefit and that there are groups of learners who may not be able to benefit from technology opportunities (UNESCO, 2023). This is a significant issue when the assessment of engagement is based on engagement with education through digital activity. Suppose that two learners are taking the same online course. One has a personal computer, a continuous broadband and a quiet study area. The latter relies on the distributing of a mobile phone and on a temporary connection with the Internet. The second student can log in less often, submit work later or work less with the interactive elements. Such differences could be seen as a lack of motivation by an algorithm that rates engagement. In fact the disparity could simply be due to differential infrastructure. The algorithm has, thus, redefined an inequitable structure as an individual attribute. This illustrates the importance of algorithmic inequality occurring before the algorithm itself. It starts with when the data are created. The other big problem is that of datafication. The education sector is gaining more and more data relating to attendance, assessment, online activity, interaction and student behaviour. This information can give us some useful answers, but not the full picture of learning. Learning has cognitive, social, emotional, cultural and contextual aspects. Many of these can't be easily captured in a numerical indicator. A student can be intellectually engaged and interact with an online platform a few times, but not very often. Another may finish many of the activities he has been taught online but fail to get a deep understanding. If algorithms are based on observable computer-based activity as a proxy for the more complex characteristics of education, measurement error is raised as a concern. The datafication process, then, can have a transformative impact on the student/educational institution dynamic. A learner becomes a data set of digital indicators, and institutional attention might shift more to what can be measured. Educational data systems produce new forms of expert authority, as identified by Williamson (2017) [22-23], and an extensive collection of data has consequences for children's autonomy and rights, as outlined by Lupton and Williamson (2017) [7]. Algorithmic bias is the third worry. Bias can creep into educational algorithms in four ways: historical


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data, representation, measurement, and design of a model or implementation within the institution. Data might provide a picture of inequalities that already exist in education. A predictive model that learns from such data might generate the patterns contained in the data. Representation is particularly important. Models might not perform as well for poorly-represented groups if they are not present in the training data. According to Holmes *et al*. (2022) [3] algorithmic bias exists in the vast array of demographic groups such as race and ethnicity, gender, nationality, socioeconomic status and disability. However, algorithmic discrimination is not limited to one type of discrimination. Measurement bias can be a serious problem, too. The first step is for educational systems to determine what they would like to predict. A model is built assuming that engagement is reflected in platform activities, if it is trying to measure engagement with platform activities. If the assumption is wrong for specific groups, then the model will classify these groups in a systematic way incorrectly. Algorithmic fairness is not an exclusively mathematical problem, then. It's also an educational and institutional problem. Kizilcec and Lee (2020) [4] illustrate the need to consider the entire process of the production and implementation of educational predictions. The other worry is the potential effect on further institutional action of algorithmic classifications that are generated through predictive analytics. A student identified as being at risk might have extra assistance and this may help to enhance outcomes. But on the other hand, come with the same classification, there is also a possibility of reduced expectations or limited opportunities. The institutional treatments that students receive may contribute to that student's result, if they are treated as unlikely to succeed. This gives rise to a possible vicious circle. The algorithm predicts disadvantage, the institution responds to the prediction, and the response impacts the educational context in which the student participates. The end result may then be a reflection of the qualities of the learner, as well as on the institutional effects of the algorithmic classification. There is an automatic assessment dimension of inequality. Technology-based assessment systems can give instant feedback and can help teachers save time. Assessment, however, is always linked to judgements of what is considered as an academic success. Students whose expressions are other than those traditionally used and valued in the language/culture may be at a disadvantage when learning from a model trained on historically dominant forms of language/culture. The issue becomes more problematic when automated assessment will be an instrument for big stakes decision making. It may be hard for a student to figure out why an algorithm may have been inaccurate if they think so. The student might be left with no real option but to take an opaque decision. This is one of the areas where Generative AI offers opportunities and risks. Can offer clarifications, translations, writing help, brainstorming help, and access to benefits. It can thus lower some obstacles for students who traditionally have been at a disadvantage in the educational system. But it is not automatically the case that access to sophisticated systems is equal. Students have varying access to tools for creating prompts, digital literacy, and access to paid tools. With more educational support, students might better be able to detect incorrect AI-generated results. This means that generative AI could present a learning opportunity that comes at a cost for gaining access to technology, but not necessarily access to learning. UNESCO's recommendations focus on using generative AI in an ethical and human rights-based manner, with tools being piloted in schools for their suitability and ethical implications, and the ethical and educational impact being assessed before implementation (Miao & Holmes, 2023) [8]. This matter is crucial as the education value does not necessarily follow from the sophistication of an AI model. Commercialisation adds to the complexity of the spread of algorithmic power. There is many educational AI systems operated and owned by private companies. Such companies can have a certain control over software architectures, proprietary models, datasets and technical know-how. Schools/universities can therefore rely on technologies that cannot be 100% audited. This results in a lack of accountability. Educational institutions might even have to take responsibility for decisions which impact students, despite the responsibility for the technical infrastructure being placed in the hands of external providers. Students might not be aware of what data is being collected, how long the data is stored, whether the data can be used for other purposes and how an algorithm arrives at a specific classification. Educational equity and inclusion is one of the concerns that OECD has mentioned regarding the impact of AI on education (Varsik & Vosberg, 2024) [20]. Public educational institutions, therefore, need both higher standards for procurement and greater transparency, as well as an ability to audit and terminate inappropriate systems, in order to ensure ownership of data and security. Algorithmic inequality also has important global aspects. The level of digital infrastructure, technical expertise and institutional resources in richer countries tend to be higher. However, there may be more fundamental issues to address in lower income nations related to access to electricity, connectivity, devices, teacher training, or access to digital education materials. Incorporating advanced AI into a society where access to basic digital technology is not equal can thus yield minimal overall population benefits. Resources might need to be prioritized between advanced algorithmic systems and infrastructure and teacher capacity building. Language is another inequality across the globe. One could expect that AI systems will differ in their performance and results from one language to another, depending on how much and what quality of data is available for training. Students whose language is not well represented in digital data may thus not be provided with accurate translations, explanations or assessments. Context is also crucial, cultural context in this case. Participation, communication, academic achievement, and appropriate student behaviour in the classroom may have different meanings within different cultures and often educational practices are not the same from society to society. The algorithm that is designed in one context of education may thus include unhelpful assumptions for other contexts. Algorithmic governance, therefore, needs to acknowledge diversity, and not assume that one model of educational AI can be applied to everyone.

## 10. FINDINGS

The analysis showed that the inequality of algorithms is multi-dimensional and cumulative. It doesn't start to begin until a


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model starts to produce discriminatory output. It can come from disparate access to technology, disparate digital participation, incomplete datasets, inappropriate measurements, historical inequalities or institutional decisions about the use of algorithmic predictions. The first big discovery is that the digital disparity can turn into algorithmic inequality. Algorithms depend on the connectivity, devices and digital skills used to reach the data, and these all impact the resulting classifications. The second fact is that there is a need to orient to representation and measurement in algorithmic fairness. If the training data for an algorithm does not accurately reflect some population, or if the variables captured by the algorithm do not reflect the variables that are important to the learning process, then the algorithm cannot ensure a fair outcome. The third is that algorithmic predictions can have an impact on educational outcomes, as it is the institutions that respond. Forecasts do not have to be "observations". They can alter the learning environment of students when they are acted upon by institutions. The 4th finding is that Comms and instit power has a significant impact on algorithmic accountability. Students and teachers might be impacted by systems that they can't verify and whose service providers could be international. The fifth finding is that there is a need for contextual governance to address global inequality. Differences in infrastructure, language, culture, institutional capacity and economic resources should be taken into account when formulating educational AI policies.

## 11. LIMITATIONS OF THE STUDY

The study has limitations of being based on secondary information and policy documents. Does not offer original empirical data on algorithmic bias by national education systems. It is therefore not possible to say how much algorithmic inequality exists in any specific country. The literature is also unevenly distributed geographically. There is a disproportionate focus on AI in education in high-tech education systems, and limited evidence from many LMIC countries. This poses challenges in the process of globalisation of findings. There is another restriction because of the fast rate of technological advancement. As generative AI systems and educational platforms rapidly evolve, results on specific technologies may become obsolete as models and practices evolve. On-going empirical study is thus needed. Comparative analyses between countries, longitudinal research of algorithmic systems in education, interviews with students and teachers, and empirical auditing of algorithmic systems for high-stakes decisions in education should be conducted in the future.

## 12. CONCLUSION

The use of algorithmic power is becoming a more significant aspect of modern governance of schools. AI systems are now involved in activities that impact how students learn, are evaluated, classified, supported and monitored. These advances have a potential to enhance education but they can also lead to new forms of inequality and to the distribution of decision-making power. This research comes to the conclusion that algorithmic inequality can't be taken as a problem of just technical nature. It's a socio-technical issue. Algorithms work in societies that are economically, educationally, technologically and institutionally unequal. When these inequalities are embedded in digital data, and in computational models, they can be harder to notice and be at work in educational outcomes. This is especially true for the difference between access and meaningful participation. Providing students with access to an educational platform does not necessarily create equal opportunity. Students need to have the infrastructure, skills, support and learning environment to use technology effectively. Otherwise, algorithmic systems can see structural disadvantage as individual underperformance. It is the same in terms of data. Educational data is not the students themselves. They are created as a result of institutional decisions regarding what to measure and what to regard as educationally relevant. Algorithms, therefore, trained on such data can then perpetuate the assumption and inequality within that data. The rise of generative AI is another example of the need to govern with AI. While generative AI can help improve learning, it also raises privacy, assessment, digital literacy, linguistic inequity and inequitable access questions. UNESCO's human-centred approach is important as it involves putting human agency, equity, inclusion and pedagogical appropriateness at the heart of AI governance (Miao & Holmes, 2023) [8]. In order to create an algorithmic education system that is equitable, several safeguards must be put in place. First, governments and institutions need to tackle the fundamentals of digital disparities. Second, datasets have to be assessed with regards to representativeness and measurement validity. Third, learners need to be made aware if algorithms have a material impact on decisions within the field of education. Fourth, teachers need to have relevant power to check and challenge algorithmic suggestions. Fifth, institutions need to have corrective, appeal and remedy mechanisms. Lastly, technology providers should be subject to the proper transparency and accountability standards. So, the main point of it is that it is not just about introducing new tools into the current system in education. It is a question of the distribution of educational power in the future. As the algorithmic systems increasingly take on decisions about what students should learn, how they should be assessed, and which students should be the focus of institutional attention, questions of ownership, accountability, transparency, and equality cannot be avoided. The right objective isn't about embracing or rejecting AI, but rather about achieving the best possible outcome for the business. The right objective isn't about accepting or rejecting AI, but it's about getting the best outcome for the business. Rather, there is need to establish governance structures that make sure that technological innovation is aligned to educational purpose and human rights in educational systems. As outlined in UNESCO's guidance, AI is not to be used instead of human agency in education (Miao & Holmes, 2023) [8]. Finally, the future of algorithmic education rests not only on the capabilities of algorithms but also on the institutional decisions on the use of algorithms. An equitable digital education system cannot be one that merely replicates existing inequities in the form of automated classifications. Technology should increase


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educational opportunity and not systematize, make invisible, and make more difficult the disadvantage that it can.

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