

Digital Marginalization and Educational Inequality in the Age of Artificial Intelligence

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Abstract— The rapid integration of artificial intelligence (AI) into educational systems is generally presented as a means of enhancing efficiency and access to learning. However, these technological developments also risk intensifying existing social inequalities. This study examines digital marginalization and educational inequality in the age of artificial intelligence, arguing that AI-driven educational tools can function as mechanisms of exclusion rather than inclusion. Drawing on critical pedagogy and digital studies, the research addresses digital marginalization evident in an unequal access to technology. There appear to be structural and cultural exclusions embedded within algorithmic systems. The study also explores how data disparities in digital education contribute to algorithmic discrimination and unequal learning outcomes. Through discussion of marginalized learner groups, the educational consequences of AI-mediated instruction and assessment are highlighted. The analysis also addresses the ethical implications of surveillance and institutional responsibility in AI-driven education. Ultimately, the study proposes pedagogical strategies aimed at fostering more inclusive and socially just AI design and implementation. Situating AI within broader educational relations, students of different social and cultural background can benefit and better use AI tools.

Keywords— Artificial Intelligence (AI), inequalities, digital divide, marginalization, exclusion, pedagogy, algorithm, discrimination, ethical, assessment.

Introduction

Artificial intelligence (AI) has quickly become an integral part of modern educational infrastructure. This includes adaptive learning systems and automated grading systems in addition to predictive analytics and learning management systems. AI technologies are increasingly informing the ways in which knowledge is distributed, tracked, and measured. Educational institutions around the world have turned to AI-enabled solutions in the interests of efficiency, personalization, and scalability. They have positioned these solutions as neutral tools that can be used to improve learning outcomes and expand educational access. These trends have been fueled by the growth of digital learning spaces and the increasing use of data-driven environments in educational settings.

However, technologies are embedded in existing social, political, and economic contexts. They

necessarily embody the values and assumptions of the contexts in which they are developed and used. While AI enables personalized learning and objective assessment, it also enables new forms of surveillance, standardization, and algorithmic regulation of learning paths. Consequently, education is increasingly mediated not only by human educators and social norms but also by computational systems whose logics are inaccessible to most users. Despite claims that AI can reduce educational disparities, its implementation often reproduces and intensifies existing inequalities. Digital marginalization extends beyond unequal access to hardware and internet connectivity to encompass structural, linguistic, and cultural forms of exclusion embedded in algorithmic design. Learners who lack technological infrastructure, digital literacy, or stable connectivity are systematically disadvantaged in AI-driven educational environments. Furthermore, algorithmic systems that are based on

dominant linguistic datasets and cultural norms are in danger of marginalizing students who do not speak the dominant language (Blodgett et al., 2020). They may also have non-standard accents, or not conform to dominant cultural norms. The current study argues that educational AI systems may serve as a gatekeeping tool instead of an equalizing tool. Through data bias and automated assessment AI systems are capable to label, track, and restrict students in ways that are seemingly objective but are, in fact, heavily mediated by social hierarchies of class, language, geography, and power. Eubanks (2018) demonstrates that digital systems operate within political and social structures that reproduce inequality and injustice. Digital marginalization, therefore, is not only a socio-technical issue, but also a socio-political condition that is constructed at the interface of technology, inequality, and social justice.

On the other hand, AI can improve educational accessibility by helping learners overcome linguistic, physical, or technological barriers. AI-powered speech-to-text and text-to-speech technologies, for example, can support students with hearing, visual, or reading difficulties. Similarly, automatic translation and language-support tools can make educational materials more accessible to students who are studying in a second or foreign language. In EFL contexts, AI can provide explanations of difficult vocabulary, grammar, and texts at a learner's proficiency level, reducing some of the barriers that may prevent students from fully participating in the learning process.

This study is significant both theoretically and practically. Theoretically, it contributes to critical debates in digital studies and educational theory by situating AI within broader frameworks of power, inequality, and social reproduction. By drawing on critical pedagogy and algorithmic critique, it challenges dominant assumptions that technological innovation is inherently progressive and neutral. The research also expands the concept of the digital divide to include algorithmic and cultural dimensions of exclusion, thereby offering a more nuanced understanding of digital marginalization.

Practically, the study holds implications for educators and technology designers. By exposing the ways in which AI may exacerbate educational inequality, it calls for more ethically grounded and socially aware approaches to educational technology. The findings aim to negotiate policies that prioritize equity over efficiency and pedagogies that foreground human agency over algorithmic authority. In an era increasingly shaped by AI governance, this research underscores the urgent need to align technological

development with principles of social justice and inclusive education.

With an interdisciplinary theoretical framework that draws on critical pedagogy, critical digital studies, and social theory, the perspectives presented allow for an analysis of artificial intelligence in education not merely as a technical innovation but as a socio-political system embedded in relations of power, inequality, and knowledge production. Combining educational theory with critical approaches to technology, the framework foregrounds questions of domination, exclusion, and resistance within AI-mediated learning environments.

Conceptualizing Digital Marginalization

Digital marginalization can be understood as the processes by which individuals and groups are denied effective participation in digital spaces. This marginalization is not merely concerned with issues of inequality in access to technological resources such as computers and internet connections. Recent arguments have highlighted that such inequality continues to exist even after basic levels of access have been gained. Digital marginalization, therefore, is concerned not only with issues of material lack but also with issues of differential ability to make use of, interpret, and benefit from digital technologies.

Traditionally, the notion of digital divide has emphasized a division between those who are connected and those who are not. However, this dichotomy has failed to adequately address the complexities involved in contemporary digital divides. Instead, researchers are now using notions such as multiple levels of digital divides, including skill divides, usage divides, and outcome divides. Hargittai introduces the concept of a second-level digital divide, emphasizing inequalities in skills and patterns of technology use rather than access alone. (Hargittai, 2002) In the educational sphere, these divides are reflected in learning opportunities, differential participation on digital platforms, and levels of institutional support. Digital marginalization has, therefore, led researchers to focus on the socio-technical conditions surrounding digital participation.

Digital marginalization is created by the intersection of economic, linguistic, and cultural factors. Structurally, the education system is situated within a global power hierarchy that favors some regions, institutions, and people over others. Institutions in more wealthy settings have a better chance of being equipped with sophisticated digital infrastructure and AI-enabled learning technologies, while less well-funded institutions struggle to provide even basic technological support. Economic marginalization

further exacerbates these conditions by depriving learners of access to devices, reliable internet, and additional digital support.

The linguistic and cultural factors have an equally decisive role to play. Most of the educational technologies driven by AI have a design bias towards dominant languages and cultures, and often they have a Eurocentric or Global North bias. For those who speak minority languages there is a systematic disadvantage when they use speech recognition technologies, feedback and assessment technologies. Similarly, those who have different cultural norms of learning, communicating, and assessing are also marginalized if they are different from the dominant culture embedded in the technology. Digital marginalization is, hence, also a question of symbolic power, where certain ways of speaking, knowing, and being are rendered visible and legitimate whereas others are excluded or misrecognized.

The current forms of digital marginalization are being influenced by algorithmic systems that regulate access to information, evaluation, and learning opportunities. While digital divide in the past focused on hardware and connectivity, current digital divide is being influenced by data-driven mechanisms that classify, predict, and regulate learners' behavior. Exclusion by algorithm refers to exclusion that is caused by algorithmic systems that disadvantage learners in particular groups. For instance, algorithmic tools can monitor the progress of students, offer suggestions on what to study, and identify those who qualify for educational support. Although algorithmic tools are often portrayed as objective and efficient, they can also perpetuate social stratification, as they reflect the inequalities of the past. O'Neil explains that algorithmic systems are shaped by historical data and institutional biases, allowing inequality to be reproduced under the appearance of objectivity (O'Neil, 2016). Students who belong to disadvantaged groups are likely to be labeled as low-achievers or risk-takers. They are denied opportunities to engage with advanced content. Algorithmic exclusion, therefore, marks a transition from overt barriers of access to hidden mechanisms of control.

This transformation represents a shift from technological inequality to epistemic inequality, wherein some learners are systematically misrepresented or erased within digital systems. Digital marginalization in the age of AI is not only a question of being offline but also one of being misread, misclassified, or erased by digital systems. Conceptualizing digital marginalization in this manner allows for a more critical understanding of how power works through educational technologies and

underscores the importance of interrogating not only who has access to AI but also who has a presence within it.

Artificial Intelligence and Contemporary Education

Artificial intelligence has been integrated into a variety of educational technologies, transforming the manner in which education is arranged, delivered, and assessed. Adaptive learning systems, for instance, use algorithmic models to arrange educational content based on the performance of the learners (Kulik & Fletcher, 2016). Such systems have the capability of offering customized learning processes since they can constantly change the levels of difficulty, offer suggestions, and predict the learners' future requirements. Automated assessment systems also mark the expansion of artificial intelligence since they can grade assignments, assess written and spoken content, and offer performance analytics. Such systems are used to oversee a number of learners and assist human instructors.

Apart from teaching and evaluation, there is also the use of artificial intelligence as a tool of surveillance and behavioral monitoring. For instance, there is the use of learning management systems that monitor attendance, engagement, and interaction, as well as the use of facial recognition, proctoring, and other biometric technologies aimed at detecting cheating and lack of engagement. Williamson shows how learning management systems and AI-based tools track attendance, engagement, and interaction, and how biometric and proctoring technologies are increasingly used to monitor and control students (Williamson, 2017). All this creates a kind of educational environment that is constantly engaged in the extraction of data, with the student as a kind of data subject.

The most common argument that advocates for AI in education use is that it is able to personalize learning. However, it has also been argued that such a form of personalization conceals underlying inequalities that are inherent in technology. Firstly, it is important to recognize that personalization assumes that the student has access to technology, has access to the internet, and has a learning environment that allows for interaction with technology. Such factors are not always guaranteed for students in disadvantaged groups.

Furthermore, the notion of personalization depends on data-driven profiling, wherein students are classified based on specific parameters of success and ability. Such classifications may result in essentializing students' identities and may lead to false perspectives

of learning, particularly for those whose linguistic, cultural, and learning styles may be different from the dominant ones. Instead of freeing students from the constraints of standardization, AI may actually result in a further standardization of education by reducing complex human capabilities to data-driven parameters. Exclusion, in this sense, may also be understood as a function of the ways in which students are refigured as algorithmic subjects whose opportunities may be curtailed by predictive calculations.

The use of AI in the educational sector mirrors the global power relations between the technology-producing and the technology-consuming countries. Most educational AI technologies are produced in the economically powerful countries of the world and then exported to different educational settings with little modification to suit the diverse educational contexts. The global exchange of educational technologies carries the potential of imposing universalized educational models that disregard linguistic differences, cultural nuances, and socio-economic variations. In the Global South, regarding the education of refugees and poor communities, AI-based solutions are being promoted as an ideal solution to the difficult learning environments there. However, the producers and code writers of this technology are likely sitting in relaxing and fulfilling environments that do not allow them to conceptualize the stress and even threats in the targeted education-environments.

Locally, the impact of AI is affected by institutional practices, teachers' training, and infrastructural capabilities. Educational institutions, such as schools and universities, differ greatly in their procedure in the ethical and effective integration of AI. In some places, AI contributes to the development of teaching innovations and resource accessibility, while in other places, it contributes to the problems of overcrowding and underfunding. The tension between global technology standardization and local education realities underscores the need for contextual analysis of the impact of AI in education. The impact is thus viewed as a socio-technical system in the context of the complex global and local power relations.

Critical Pedagogy and the Politics of Education

Critical pedagogy, as conceptualized and advanced by Paulo Freire, can be seen as a foundational theory that informs and guides our understanding of education as a site of struggle and not merely as a neutral process of knowledge transfer. Freire argues that education is never neutral but is always embedded in relations of power and struggle (Freire, 2000). In fact, Freire's critique of the "banking concept" of education

highlights how dominant pedagogical systems maintain and reproduce social inequalities by locating learners as mere recipients of knowledge. This idea also underscores the danger of an AI-based education potentially increasing the intensity of educational domination. For instance, an AI-based education can potentially follow the banking model of education, in which the student is treated as a mere collector of data and knowledge is treated as a commodity to be delivered. However, what is of critical concern is not what is taught to the students with the help of AI, but rather the manner of teaching and learning. For instance, an AI-based education with its focus on maximum efficiency can potentially undermine the dialogical nature of education and create a hierarchy of technology and students.

Critical digital studies is an extension of this analysis into the technological sphere, which seeks to illustrate the ways in which social values and inequalities are embedded within digital systems. Critical digital scholars argue that algorithms are not neutral entities but are instead sociotechnical constructs based upon historical data sets and assumptions. Kitchin argues that algorithms are not neutral or objective but are sociotechnical systems shaped by human values, assumptions, and the data on which they are trained (Kitchin, 2017). Algorithmic bias can be defined as the ways in which digital systems systematically disadvantage particular social groups.

In the context of education, algorithmic bias is evident in automated grading systems, predictive analytics, and adaptive learning systems. They classify and sort students based on normative standards. These systems are based on data from dominant populations and, therefore, misrecognize linguistic minorities, culturally diverse students, and those from marginalized socio-economic groups. Critical digital studies, therefore, allow for an understanding of the ways in which education-based AI generates new forms of stratification under the title of objectivity. This is evident in the ways in which digital technologies naturalize inequalities by presenting social constructions as technical necessities.

In order to shed more light on the ways in which digital marginalization works, we can discuss works of various theorists, including Pierre Bourdieu, Michel Foucault, and those of the postcolonial studies movement. The concepts of economic capital, cultural capital, and symbolic capital, as set out by Bourdieu, are relevant when analyzing the distribution of digital resources and competences. Bourdieu conceptualizes economic, cultural, and symbolic capital as key resources that structure social inequalities, making his framework relevant for analyzing unequal access to

and use of digital resources and competences (Bourdieu, 1986). Digital literacy can be seen as a type of capital that provides educational benefits, while the recognition of certain linguistic and cultural practices is a type of symbolic power in the context of AI systems. Students who do not possess the dominant type of capital required by educational technologies are at a structural disadvantage.

Foucault's concept of power/knowledge offers a lens to examine the role of AI systems in regimes of classification and normalization. By constantly collecting and assessing data, educational technologies discipline students by determining what constitutes success, risk, or deviation. Algorithmic surveillance can be seen as an extension of disciplinary power, turning learning spaces into sites of constant visibility and control. Knowledge generated by AI systems is prescriptive, not just descriptive, and determines student learning paths and institutional reactions to them. Postcolonial theory further situates these dynamics within the global relations of inequality. The development of educational AI technologies is largely the product of economically hegemonic regions and is subsequently transferred to other cultural settings, often without significant adaptation. Such a phenomenon has the potential to inscribe epistemological hierarchies whereby Western learning and knowing practices are universalized, while indigenous knowledge systems are marginalized or erased. From a postcolonial perspective, digital marginalization signifies not only technological exclusion but also the continued colonial patterns of domination in digital form.

These perspectives offer an encompassing view for an analysis of digital marginalization in AI-based education. Critical pedagogy focuses on the political and ethical implications of education. Social and postcolonial theory contextualizes these issues within broader structures of capital and power. This comprehensive view allows for multidimensional analysis of AI's implications for education and its inclusion and exclusion dynamics. This analysis can then transcend the technology-based causes of inequality and move towards an understanding of AI as an intersection of pedagogy, power, and technology.

Educational Inequality in AI Systems

Data bias is one of the key ways in which AI systems perpetuate educational inequality. Artificial intelligence works by identifying patterns from large data sets, but these data sets are not objective representations of the world. They are instead a reflection of historical inequalities, social norms, and

institutional practices. When biased data are used to train educational algorithms, the algorithms perpetuate these inequalities. For instance, algorithms that predict student performance may have been trained on data that has been influenced by socio-economic disadvantage, linguistic marginalization, or disadvantaged learning conditions. Williamson and Eynon argue that educational algorithms are shaped by the data used to train them, which often reflects existing socio-economic inequalities and disadvantaged learning conditions, thereby reproducing structural bias in predictive systems (Williamson & Eynon, 2020). This means that students who come from marginalized groups are more likely to be labeled as low-performing.

Algorithmic discrimination is when these biased classifications lead to discrimination. Automated systems may deny people access to advanced content or institutional support based on algorithmic predictions instead of human judgment. These systems appear objective but mask their social construction. The inequality in educational systems is a product of data-based rationality instead of injustice. This makes inequality harder to argue against because algorithmic discrimination is often unclear and cannot be questioned.

Language and culture represent other important dimensions of inequality in the context of AI-mediated education. Many educational AI technologies, such as speech recognition technology, writing evaluation technology, and chatbots, are often developed based on standardized language models that favor dominant language forms. Students whose language varieties are not dominant or are spoken in the minority, such as regional or non-native language speakers, are likely to suffer misrecognitions or mis-evaluations. In this sense, AI systems are not merely testing knowledge but enforcing cultural conformity by favoring certain forms of expression over others. Noble demonstrates that algorithmic systems are embedded in dominant cultural assumptions and tend to privilege certain linguistic and cultural forms while marginalizing others, meaning they do not merely assess information but enforce normative patterns of expression (Noble, 2018). So, linguistic and cultural bias function as means by which symbolic power is exercised, transforming difference into deficiency, and diversity into deviation.

This is because educational inequalities are also heightened by inequalities in access to technology and digital literacy. AI-based education is based on the assumption of access to internet connectivity, the functionality of devices, and the ability to access digital platforms. Digital literacy is also a crucial

factor that determines educational outcomes. The capacity to operate platforms, decode automated feedback, and control digital identity is a type of cultural capital that is not evenly distributed among different social classes. Students who do not have prior experience with digital technology are put at a disadvantage not because of their cognitive abilities but due to social positioning. As a result of making educational success contingent on digital literacy, social inequalities in education, income, and language are mapped onto digital inequalities. This serves as the material basis for algorithmic inequality, connecting technological exclusion with social stratification.

Marginalized Learners in the Age of AI

Marginalized learners' experiences with AI-driven education are complex and contradictory, depending on their geopolitical, economic, and cultural positions. In the Global South, for example, there has been a common phenomenon where educational AI is introduced as a solution for a lack of teachers and learning materials. However, these technologies are based on infrastructures that are often unreliable or insufficient. Thus, learners in these regions experience interrupted connectivity, insufficient device compatibility, and reliance on external platforms that are neither locally curriculum-oriented nor culturally relevant. With regards to refugee groups and displaced students, such technologies also place students in positions where they are subject to increased surveillance and data extraction, especially in cases where technologies such as biometrics are used. Such refugee students are placed in positions where they are assessed by AI technologies without their clear consent, making them data subjects as opposed to active participants in their own education.

In addition, low-income communities are characterized by structural barriers that impede the efficiency of AI-based learning tools. There is an issue of representation by the algorithm-based system, which often assumes inconsistent usage as a lack of ability and interest. Minority language groups are also characterized by multiple levels of marginalization, especially because AI-based learning tools are designed with dominant language norms and expectations. The feedback mechanisms are designed with assumptions of correct grammar, regional accents, and monolingual norms, which are all translated into deficiency and lack. This indicates that marginalization is not absolute but is based on the intersection of technology and inequality.

The educational outcomes of marginalization through AI are thus felt not only at the policy or program levels but also in the lives of learners. Learners who are

classified by an algorithm may begin to think of themselves as deficient or at risk, and this may affect their own understanding of themselves and their educational goals. Linguistic misrecognition and cultural misfitting may create a sense of alienation among learners, and this may affect their engagement with their learning. Cummins argues that when students' linguistic and cultural identities are devalued or misrecognized in educational contexts, they may experience alienation, which negatively affects their academic engagement and participation (Cummins, 2001). For learners who are already vulnerable, the promise of personalization may be one of fragmented and impersonal learning experiences.

These lived consequences are not limited to academic achievement but also encompass aspects such as belonging, and agency. When students are treated as data profiles, their complex identities and social worlds become invisible. Here, educational AI contributes to the creation of unequal subjectivities, where students are recognized as adaptable subjects, while others are constructed as problematic or deficit subjects. Digital marginalization is not only a state but also an experience, which shapes students' self-perception as they navigate these systems. The importance of examining AI not only as an innovation but as a social practice that has tangible impacts on human lives should be highlighted. The understanding of how inequality is experienced and navigated in AI-mediated education is crucial for the development of interventions that value equity over efficiency and human development over optimization.

Ethical and Pedagogical Implications

The increasing use of AI in education creates ethical issues of surveillance, autonomy, and informed consent. Learning platforms using AI technologies are constantly collecting students' performance and behavioral data, making the educational setting a surveillance setting. Proctoring software, facial recognition technology, and predictive analytics not only monitor students' academic activities but also their bodily presence and learning styles. This blurs the line between support and surveillance. The increasing scope of surveillance also impacts the autonomy of the learner, as they have a reduced ability to behave beyond the parameters set by the algorithm. As a result, the student may change their behavior to conform to the parameters set by the machine rather than engage in any meaningful way with the learning process. The issue of consent also becomes a nominal concept rather than a genuine one, as the student may be forced to engage in AI-mediated education. The

student is also not made aware of the parameters set by the algorithm and its impact on the learning process. The ethical issue, therefore, becomes not only one of data protection but also the right of the learner to autonomy, dignity, and participation in the digital learning environment. Floridi et al. argue that the ethical evaluation of AI systems must go beyond data protection to include respect for human dignity, autonomy, and the capacity for individuals to meaningfully participate in sociotechnical systems (Floridi et al., 2018).

Toward Inclusive and Equitable AI-Driven Education

To achieve equity in AI-driven education, there is a need for policy frameworks that privilege social justice over technological efficiency. Governments and educational authorities need to recognize that digital inequality is not only a technical problem but a structural problem caused by economic, linguistic, and geopolitical differences. Therefore, policy initiatives should address both access and power. Investment in digital infrastructure is a necessity but it is incomplete without parallel investments in linguistic diversity, data security, and institutional accountability. In addition, there is a need for policies to ensure transparency in the use of algorithms in decision-making, especially in assessment, placement, and tracking.

There is also a need for learners and educators to be able to access information regarding the process of educational outcome generation and for them to be able to contest any discrimination and inaccuracies in the use of algorithms. There is also a need for public monitoring of education by AI service providers, which is essential in avoiding the use of commercial interests instead of pedagogical and ethical considerations. Policies regarding AI use in education should be made at an international level, especially for the purpose of avoiding the use of AI tools generated from dominant contexts for marginalized contexts. Educators have a key role to play in mediating the impact of AI by emphasizing a critical engagement with technology rather than its consumption. Pedagogical approaches to equity in AI-driven education include the development of dialogical and participatory learning environments in which students are encouraged to critically engage with AI-driven feedback. Instead of seeing AI-driven feedback as a definitive judgment, teachers can use it as a starting point for critical discussion.

Moreover, equitable pedagogy must be sensitive to linguistic and cultural diversity. The pedagogy must be designed in a way that accommodates different

modes of expression, rather than relying on standardized communication. The teachers must be equipped with the knowledge of how algorithmic systems may misrepresent students belonging to marginalized groups and must be able to act when the algorithmic assessment is at variance with the contextual knowledge of the students' lives and capabilities. In a way, pedagogy acts as a space of resistance against algorithmic authority, where the role of human judgment is upheld as a moral corrective against algorithmic classification.

Equity, therefore, must be built into the very design of the AI system itself. Designing an AI system with social justice in mind requires engaging diverse contributors, such as educators, students, and linguistically and culturally marginalized populations in the design process. This could enable diverse learning and teaching practices to be represented in educational technology, rather than dominant ones being imposed. Similarly, there is a need to critically audit data sets used to train educational AI systems for representational imbalance and bias, and to explore alternative models of evaluation that value diversity rather than conformity. This also means a shift in the goal of educational technology, away from optimization towards recognition. Rather than predicting failure or sorting students into risk groups, it is possible to design AI systems with a goal of supporting human agency. This is a challenge to the logic of surveillance and control that is often at the heart of much of what exists for educational technology. It is a challenge to think of AI as a tool of empowerment, rather than as a tool of governance. Policy reform, equitable pedagogy, and socially conscious design constitute a foundation for a more inclusive and AI-driven educational future. Rather than abandoning technology, this entails a commitment to reimagine its purposes and limits. Rather than seeing learners as data to be optimized, an equitable vision for AI in education should see learners as subjects whose dignity, voice, and social conditions remain paramount. In so doing, AI becomes not a site of exclusion but a site for inclusion for educational justice.

Conclusion

Artificial intelligence in education cannot be viewed as a technological development alone but needs to be studied as a socio-political system within the existing framework of power, language, and capital. AI applications in learning, from adaptive learning systems to automated assessment and surveillance, transform learning experiences in ways that tend to marginalize already disadvantaged groups of learners. The Global South, refugees, poor communities, and

language minorities have experienced and negotiated inequality. AI is a technology of control and a potential site of resistance, depending on how it is designed, governed, and pedagogically mediated. Digital marginalization in the age of AI is a process that works through both visible and invisible mechanisms of inequality. Developing a unified framework of analysis that combines critical pedagogy, algorithmic critique, and social theory can be the solution that addresses marginalization. Rethinking policy, pedagogy, and design in AI education should be taken into consideration. The ethical dangers of surveillance and autonomy in AI education policy and practice should be noted also. There are possibilities for more equitable education by focusing on the role of educators as ethical mediators, the need for transparency and accountability in education policy, and the necessity of social conscious AI design. Programmers should seek an alternative approach based on justice, dialogue, and human dignity.

In conclusion, the future of education in the age of artificial intelligence is not predetermined by technology per se, but rather by decisions and priorities at social and political levels. Ultimately, whether artificial intelligence will help create a fairer education system will depend on how it is thought about, delivered, and contested. By including those who are marginalized, equity, recognition, and human dignity can be maintained.

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