

A Study on the Impact of Unequal Distribution of AI Education Resources on Social Inequality

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Abstract. The advancement of AI in education has failed to provide everyone with equal access to education; rather, the technological advancements of AI have moved the digital divide away from being limited solely to physical devices, to also being impacted by the lack of access to interactive experiences and by familial histories being used as a means of transformation. The gap also includes an application level of disparity that has further exacerbated the inequities between educational institutions. This research into the popularization of hardware will examine the extent to which the technological gap represented by AI (particularly Generative AI) will continue to create class disadvantages. The study's focus is on three areas: (1) the absence of technology's early access creates a barrier to disadvantaged students' acquisition of implicit interactive knowledge; (2) AI collaborative learning enhances the benefits gained through their original family's resources, and (3) the data orientation preference inherent to AI's underlying model creates a single standard of evaluation that results in exclusion/restriction of disadvantaged students. Given this study's findings, it is clear that the availability of technology devices alone are insufficient in preventing inter-generational class disadvantage from continuing today. At the micro-level, it will develop a scaffold for supporting student learning of inquiry methods through gradual removal, while at the meso-level it will identify model bias as well as self-optimizing prompts to mitigate the algorithm's single standard. At the macro-level, we will create a complete action plan that reduces barriers presented by the emerging digital divide in order to create an inclusive technology education ecosystem.

Keywords: Generative artificial intelligence, Digital divide, educational inequality, Algorithmic bias, Cognitive scaffolding

1. Introduction

With the rapid penetration of AI into education, a contradiction has emerged between the vision of achieving fairness through technological empowerment and the reality of unequal resource allocation. Although UNESCO has emphasized the potential of AI-enabled education to achieve the Sustainable Development Goals of Education [1], its uneven popularization across different geographical regions and educational backgrounds reveals a crisis hidden by technology [2]. Current research highlights the ethical risks and inclusion challenges of AI [3, 4]. However, there are still research gaps in the effectiveness of policy constraints [5], the analysis of the real barriers of

infrastructure in underdeveloped areas [6], and the systematic revelation of how AI technology drives the intergenerational transmission of advantageous status in society.

In the context of generative artificial intelligence, the concept of the "digital divide" is no longer limited to the single dimension of physical access. According to Robinson's multidimensional framework, technological inequality is extending to deeper dimensions such as interactive skills, access to implicit cultural capital, and social support systems. Its core lies in differences in individuals' ability to transform the algorithmic output of generative models into substantial competitive advantages [7]. Under this mechanism, AI technology has not only failed to narrow the gap but has also invisibly exacerbated the solidification of existing social stratification [8].

Reflecting on the optimistic tendency of technology inclusivity prevalent in current AI policies, this paper aims to analyze the disparities in the availability of AI technology resources, primarily Generative AI, across different regions, educational levels, and school types, and further dissect the specific mechanisms by which this disparity transforms into a class disadvantage. This not only aids in anticipating the structural risks associated with the education system's transition from standardised assessments to a screening mechanism reliant on collaboration with AI technology [9, 10], but also aims to furnish decision-making guidance for advancing inclusive technology design, rectifying policy discrepancies, and ultimately establishing an equitable AI education ecosystem [11].

2. Multi-dimensional representation of the uneven distribution of AI-based educational resources

2.1. Differences in educational resources and resource utilization across different regions

The adoption of AI technology varies across different countries and regions, largely depending on local infrastructure and policy environment. This phenomena is demonstrated by adoption data in global language education: robust digital infrastructure and policy-driven initiatives have resulted in Generative AI technology acceptance rates of 76% among teachers in the United States and 67% in Colombia, respectively [2].

In contrast, countries with moderate adoption rates typically reflect the soft barriers of local cultural psychology to the diffusion of technology. Germany's social culture exhibits strong "uncertainty avoidance," and combined with media-induced technological skepticism, teachers often internalize social anxieties about data privacy and the black box of algorithms. In this local culture, despite adequate hardware circumstances, educators exhibit considerable reluctance to implement innovative educational experiments in the classroom [2]. In addition to psychological defenses, the cultural bias embedded in algorithms also limits the cross-regional dissemination of technology. This is mainly reflected in the friction between the mainstream Western values carried by mainstream models and the local cultures of non-English-speaking regions, further suppressing the actual willingness to adopt among disadvantaged groups [3, 4].

In regions with limited networks and hardware, the popularization of AI technology faces significant barriers. In Macau, due to geographical access barriers such as virtual private networks, generative AI tools cannot be successfully implemented [2]. In many other underdeveloped regions, such as Pakistan, unstable power supply and limited bandwidth directly cut off access to technology, forming an insurmountable "first-order digital divide" [6, 11]. These obstacles at different levels together indicate that the popularization of AI in the educational field is by no means a simple technical issue. It is also deeply constrained by multiple factors, such as regional economies, infrastructure development, and local culture.

2.2. Technological gaps between educational stages caused by uneven resource allocation

The geographical gap is only the first obstacle. There is also a serious gap in the use of Generative AI technology between different educational stages within the education system. Overall, AI technology has been embraced most swiftly in higher and secondary education, but advancements in basic education have been sluggish. High school and university educators utilise Generative AI far more in their daily instruction compared to junior high school teachers, by factors of 4.7 and 3.6, respectively [2].

The direct cause of this gap between educational stages is the extreme imbalance in the allocation of professional training resources. Higher education professionals have many opportunities to participate in relevant seminars and skills training. About 60% of university teachers are already exploring the teaching potential of Generative AI through specific experiments. However, in contrast, this proportion is only 20% in primary schools, and the vast majority of grassroots teachers have never received systematic guidance on integrating Generative AI into the classroom [2].

From a deeper perspective, this phenomenon of resources tilting towards higher educational stages reflects the current trend of prioritizing technology for higher-order cognitive training. In universities and high schools, research ability and the solution of complex problems are emphasized, and AI is naturally regarded as a powerful tool to improve academic efficiency [10]. However, basic education (K-12) is aimed at minors. Teachers not only face stricter data privacy and security reviews but also lack AI teaching programs aligned with children's psychological development. Therefore, primary and secondary school teachers often can only stay in the pre-adoption stage. If this gap, caused by a lack of training and security concerns, continues, teachers and students in basic education will be left behind at the beginning of the AI technology wave, lose the precious opportunity to cultivate early digital literacy, and create a structural lag [4, 11].

2.3. Differences in trial-and-error space among school types and different social classes

The core of the education system's allocation logic for educational resources lies in the class attributes to which schools belong. Whether a new technology can truly become popular among students depends on whether schools can provide sufficient "trialability" and room for error [9].

In well-funded elite schools or private schools, stable networks, advanced equipment, and supporting teacher training provide a safe and extensive testing ground for teachers and students. Students can not only freely explore various AI functions but also use AI to solve complex academic problems under teachers' guidance. This ample resource support enables students in advantageous positions to quickly transform cutting-edge technologies into their own learning outcomes and competence [6, 8].

In contrast, ordinary public schools in low-income communities not only face real difficulties, such as aging hardware and unstable networks, but are also often constrained by conservative school management policies. Due to a lack of systematic operational guidance and the ability to address the risk of cheating, these resource-limited schools often formulate vague regulations or even issue "one-size-fits-all" bans on AI tools. This approach appears to avoid risks, but in reality, it deprives disadvantaged students of their right to access and try new technologies at the institutional level [11, 12].

If things continue this way, this mechanism not only exacerbates existing inequalities in class, gender, and race but also determines the skill differentiation and selection in the future labor market in advance. While students from advantaged groups have begun to use AI to assist with complex learning tasks effectively, students from disadvantaged groups are still missing the most basic

opportunities to try due to hardware or policy limitations. The uneven distribution of AI educational resources has not created new barriers but has greatly strengthened the education system's inherent human capital selection mechanism. It has further widened the existing class gap in the algorithm era, causing disadvantaged students to face a more severe and irreversible structural disadvantage in the future employment competitiveness competition [12, 13].

3. Analysis of the intrinsic mechanism by which AI, as an educational resource, reinforces class barriers

3.1. The impact of early physical access differences on the evolution of barriers to tacit knowledge acquisition

The educational effectiveness of Generative AI is highly dependent on continuous, dynamic interaction, suggesting that limited access due to early physical disadvantages will substantially deprive students of cognitive experience. In interacting with Generative AI, students need to explore the accuracy of prompts and identify the "illusion" fallacy of the algorithm on their own, while solving complex problems by establishing multi-turn dialogues.

This "digital intuition" that emerges from human-computer collaboration is a typical example of tacit knowledge in epistemology. It is difficult to transmit directly through classroom teaching and can often be internalized only slowly through long-term, low-threshold trial-and-error experience [7]. In real teaching scenarios, students with abundant resources can naturally apply Generative AI to their daily learning and subtly master this set of interactive logic. In contrast, other students who are constrained by hardware or school policies are a disadvantaged group and are very likely to miss key opportunities for a large number of trial-and-error attempts in the early stage. This difference in interaction frequency means that disadvantaged students often lack the necessary support when facing highly complex technical collaborative tasks. Thus, the superficial differences in physical hardware are substantially transformed into barriers formed by the accumulation of tacit knowledge, which may amplify the risk that this group lags in future technology adaptation cycles [2, 6].

3.2. The amplification mechanism of family background with AI assistance

The students' existing family background and cognitive foundation often serve as a hidden asset, directly determining the upper limit of their technological applications. The inherent advantages conferred by existing class conditions are translated into a digital dividend through human-machine collaboration, thereby substantially amplifying the ability gap between groups [8].

In specific learning scenarios, this differentiation in utility is reflected in users' different definitions of the attributes of Generative AI tools. Students with knowledge reserves and vision advantages tend to regard Generative AI as an extension of thinking. They can deeply integrate the model's output with their personal logic and cognitive system through complex questioning and high-quality multi-round dialogue, thereby achieving secondary cognitive development on the original basis. In contrast, disadvantaged students who lack prior background knowledge and professional guidance are often unable to issue inspiring and useful instructions to the model due to their relative lack of vision and experience. For these students, the potential of Generative AI itself is greatly suppressed, and highly intelligent models are often downgraded to more advanced search engines, used only to obtain standard answers or complete mechanical academic tasks [14].

This divergence in usage patterns suggests that AI, when intervening in the educational field, lacks an endogenous mechanism to correct initial inequalities spontaneously. On the contrary, the

release of its effectiveness exhibits a significant dependence on initial capabilities. This technological threshold, defined by the level of interaction, essentially provides a new medium for transforming existing family cultural capital. In this process, technology fails to eliminate the original class endowment differences; instead, through the synergistic amplification effect of algorithms, it transforms the slight difference in cognitive starting points between groups into more significant structural capability barriers [9, 10].

3.3. Cultural bias and uniformity of evaluation standards caused by model data preferences

The underlying architecture of algorithmic models is not a value-neutral vacuum. The massive historical training data they rely on objectively determines the cognitive baseline of their outputs. The training corpora of large language models are heavily reliant on formalized, standardized written texts on the Internet. This data structure is rich in features and naturally aligns with the cultural capital and mainstream discourse patterns of the dominant classes.

When algorithms internalize this discourse pattern with specific class attributes as a universal judgment criterion, students in marginal contexts or underdeveloped regions, when interacting with the models, are prone to implicit exclusion and regulation for their non-standardized local expressions or thinking patterns. For instance, the models often label expressions from disadvantaged groups as "low-quality" or "errors" and then forcibly correct them using a single linear logic [3, 4]. This algorithmic intervention, based on data preferences, objectively establishes a single, dominant evaluation standard in the educational field. It not only deprives disadvantaged students of their cultural subjectivity in the digital space but also exposes them to the risk of systematic marginalization in the academic system that relies on AI evaluations. This cognitive regulation, triggered by data structure, constitutes an implicit extension of class barriers in the dimension of cultural evaluation [12].

4. Countermeasures and suggestions

4.1. Public compensation mechanism for tacit knowledge

Early differentiation in human-computer interaction frequency has led to a structural deficit in tacit knowledge among disadvantaged groups. The key to public compensation in the education system lies not in equalizing physical access, but in shifting the focus of intervention to the early accumulation and explicit transformation of digital experience at the micro-teaching level.

The accumulation of tacit knowledge depends heavily on contextual awareness and dynamic interaction; conventional theoretical instruction is insufficient for the effective transfer of experience. Therefore, in specific teaching interventions, after teachers have passed the initial technology-adaptation period, they should transform their internalized iterative logic of prompts, algorithmic illusion recognition, and error-correction processes into observable, replicable procedural steps through classroom behavioral demonstrations and logical deconstruction. The core of this transformation mechanism lies in making explicit the implicit decision-making nodes in human-computer collaboration that originally relied on individual intuition, enabling disadvantaged groups to observe and imitate the thought processes of higher-order interactions directly.

Meanwhile, this kind of experience transformation cannot be achieved solely through spontaneous exploration by individual teachers. At the school level, it should rely on teaching and research communities to establish standardized human-computer collaborative teaching paradigms through collective lesson planning and case review. By institutionalizing the transfer of experience

within the teaching environment, public education can, to some extent, compensate for the lack of technological trial-and-error in the family environment, providing the necessary cognitive support for disadvantaged groups. While such compensation mechanisms cannot completely reshape the existing resource allocation pattern, they can, to some extent, narrow the gap in class experience during the early stages of technology application and prevent the digital divide from widening further in algorithmic interactions.

4.2. Constructing "cognitive scaffold" and explicit compensation for inquiry logic

Faced with the inequality brought about by the transformation of family cultural capital advantages in human-computer collaboration, the balance achieved through teaching intervention needs to go beyond simple software operation drills and turn to the systematic construction of "cognitive scaffolds" [15]. Given the significant differentiation between advantageous and disadvantaged groups in human-computer interaction, if only direct indoctrination through methodological teaching is adopted, it is easy to turn Generative AI interaction into mechanical procedural drills, thereby contradicting the purpose of cultivating open, exploratory, and innovative thinking. Therefore, a feasible intervention path is to design structured inquiry tasks with dynamic adjustment mechanisms.

In specific teaching implementation, educators need to break down divergent logical questioning into progressive questioning frameworks. For disadvantaged students lacking prior background knowledge, classroom intervention should not directly require them to perform complex logical reconstruction. Still, it should start by providing closed-ended concept definition tasks and gradually transition to open-ended contradiction analysis. By embedding the cognitive cycle of "hypothesis-verification-correction" in the human-computer interaction process, the new teaching system can compensate for the lack of implicit inquiry habits that disadvantaged groups have failed to naturally form due to early environmental factors, including family influences, at the operational level.

In addition, to avoid the structured framework weakening the openness required for Generative AI, such interventions need to introduce a "cognitive scaffold withdrawal mechanism" [15]. That is, as the questioning logic of disadvantaged students gradually improves, educators should consciously withdraw external instruction and guidance, so that students can internalize the explicit operating norms into their own technical interaction habits. This teaching compensation, which combines dynamic intervention and timely withdrawal, can, to a certain extent, restrain the intergenerational transmission of original capital without increasing the individual's additional mental burden, and provide public support for students with relatively scarce family cultural resources to master algorithmic models.

4.3. The substantive transformation of critical competence

The homogeneity of the underlying data in the model inevitably leads to cultural discipline. If actions are limited to ideological appeals, disadvantaged groups will still face a role conflict between conforming to mainstream discourse and maintaining local identity [16]. Substantive intervention requires the education system to transform this discipline into specific teaching content and assessment indicators, to enable disadvantaged groups to cope with this cultural discipline at the operational level.

In daily teaching, the algorithm model's output text should be used directly as material for bias review [17]. In this way, educators can use comparative analysis tasks to ask students to mark the parts where machine-generated content is separated from the local context. This operation enables

students who lack a mainstream cultural background to gradually develop a conscious examination of algorithmic cultural biases as they use Generative AI to generate standardized expressions.

Correspondingly, the reconstruction of the academic evaluation system is an institutional prerequisite for implementing the above teaching strategies [17]. Faced with the rigid constraints of macro-standardized selection, the evaluation focus within schools needs to shift from the standardization of the final generated text to the trajectory of human-machine collaboration. Specifically, educators should incorporate continuous recording of prompts, correction of AI output deviations, and logical depth of questioning into the core assessment weights, shifting the focus of evaluation from outcome-oriented to process-oriented. This partial adjustment of assessment dimensions can provide internal evaluation for non-standardized inquiry processes without directly impacting external college admissions, giving disadvantaged groups room to resist being disciplined by a single standard outside of regular college admissions competition.

5. Conclusion

From a cross-perspective of educational sociology and learning science, this article reveals the mechanism of class differentiation triggered by Generative AI in teaching and evaluation processes and proposes systematic and structural intervention paths. Research indicates that the application of AI in education is not a value-neutral technological tool. The homogenization of preferences in the underlying data of models and the structural deficiency of interactive experiences in human-machine collaboration pose a risk of accelerating the intergenerational transmission of cultural capital among advantaged groups. In the face of this trend, merely relying on access to hardware devices is no longer sufficient to prevent the reproduction of inequality.

To alleviate the emerging structural differentiation, the education system needs to implement interventions from multiple dimensions. At the micro-teaching level, public education should first complete the explicit transformation of early interactive experiences; secondly, it should introduce a systematic construction and gradual withdrawal mechanism of cognitive scaffolds to provide explicit compensation for the logical exploration of disadvantaged groups. At the meso-evaluation level, the bias review of generated content and the trajectory of human-machine collaboration should be incorporated into the core assessment weights, thereby promoting the processual reconstruction of the evaluation system to counter the cultural training embedded in algorithms. The above countermeasures offer a possible theoretical path to safeguard the interests of disadvantaged groups during the period of technological change.

Limited by a single theoretical deduction paradigm and objective reality conditions, the argumentation of this study still has the following limitations:

First, it lacks empirical data support from natural settings. This paper fails to provide observational evidence, based on mixed-methods research, on the actual degree of relief from the additional cognitive burden on disadvantaged groups provided by "cognitive scaffolds" and the specific time points for their timely withdrawal. The effectiveness of the related intervention mechanisms remains to be verified. Second, the reconstruction of evaluation faces institutional constraints. The processual reconstruction of academic evaluation proposed in this paper has not been fully evaluated for its conflict with the current standardized college entrance examination system. Under the rigid screening mechanism, the actual operational space of non-standardized evaluation within schools still needs to be explored. Additionally, whether the task of bias review itself constitutes a new cognitive threshold for disadvantaged groups has not been established in this paper. Moreover, the rapid technological iteration in AI makes the current countermeasures inevitably subject to timeliness limitations.

To address the above limitations, it is suggested that subsequent research shift from theoretical conception to empirical verification and strengthen horizontal links across disciplines, as well as in-depth expansion within disciplines. On the one hand, controlled variable teaching quasi-experiments can be conducted. Future research should adopt mixed-methods research in real teaching contexts, tracking the trajectories of student interaction behavior from different backgrounds through the "hypothesis-verification-correction" cycle, using both quantitative and qualitative methods to provide a more precise basis for dynamic intervention and timely withdrawal of "cognitive scaffolds". On the other hand, explore cross-disciplinary bottom data review. The research perspective of education should moderately shift from the application intervention stage to the stage of model and corpus construction, and it is necessary to explore how educators can substantially participate in the construction of the diversity and fairness of the underlying corpus of Generative AI, thereby weakening the exclusivity of mainstream discourse from the data source. This will provide empirical feedback for the reform of the education system's certification system and educational equity during the period of technological change.

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