

Bridging or Deepening the Gap? A Conceptual Framework for Examining AI-Powered Adaptive Learning Platforms and Educational Equity in Chinese Urban and Rural Schools

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Abstract: The strategic position of artificial intelligence (AI) in the modernisation process of China's education is becoming increasingly important. At the same time, AI-powered adaptive learning platforms (ALPs) are being rapidly implemented to facilitate the inclusive sharing of high-quality educational resources and bridge significant geographical disparities. However, there is significant pressure on the government to create an "intelligent education ecosystem", and there are legitimate concerns that structural differences between schools in urban and rural areas may exacerbate, rather than alleviate, educational inequality. This study goes beyond mere technical optimism by presenting an integrated conceptual framework that draws on the technology acceptance model (TAM) and the sociological "Matthew Effect" to examine how micro-adoption behaviours interact with macro-structural constraints. Furthermore, this paper describes the current situation of ALPs usage in rural areas as a "recursive cycle of digital stratification", in which initial resource inequality in rural areas suppresses learners' perceived ease of use (PEOU) and perceived usefulness (PU), leading to lower participation and insufficient data input for adaptive algorithms, ultimately resulting in an ever-widening learning gap when compared to urban areas. To assist policymakers in addressing the specific ecological issues faced by rural schools, this article advocates a shift away from algorithm optimisation towards an overall "socio-technical inclusiveness" approach.

Keywords: Artificial Intelligence in Education, Adaptive Learning Platforms (ALPs), Educational Inequality, Rural-Urban Digital Divide, Matthew Effect, Technology Acceptance Model (TAM).

1. Introduction

In the past decade, China's education system has undergone a profound digital transformation. The government issued documents such as the Education Informatization 2.0 Action Plan [1], and the Opinions on Accelerating the Digitalization of Education [2] to guide this transformation and promote the construction of an "intelligent education ecosystem". Promoting the adoption of artificial intelligence adaptive learning platforms (ALPs) is the core task of this ecosystem. Compared with the traditional "one-size-fits-all" teaching method, ALPs have unique technical advantages. They can use algorithms to continuously analyse learner data, such as answer accuracy and response time, so as to achieve adaptive content adjustment [3]. Overall, the ultimate goal is to achieve student-centred, high-quality education in a data-driven way so that students in both urban and rural areas can equally obtain high-quality education.

However, promoting ALPs as a sophisticated educational tool in the Chinese context still faces a deep-rooted problem: the long-standing urban-rural dual structure. Although the "access gap" in hardware is shrinking, the "usage gap" remains complex. Specifically, urban schools usually have strong digital infrastructure and high levels of teacher digital competence [4]. Although rural schools have received hardware investment, they still face many challenges in terms of "soft" deficits, such as rural teachers' limited ability to adopt new technologies and their inability to receive corresponding training. As Guo & Wan [5] pointed out, this gap has evolved from a simple usability problem to a multi-layered differentiation involving digital literacy and

psychological acceptance.

This structural background shows that technological innovation will not automatically narrow the education gap and, in some cases, may even widen it. Huang et al. [6] found that, although rural students can access ALPs, they derive limited utility due to insufficient teaching support. This phenomenon echoes Merton's [7] "Matthew effect": The advantages of people who already have learning resources and abilities will be further amplified by new technologies. Therefore, the ideal of "popularisation of intelligent education" may evolve into a new form of digital layering, and the algorithm inadvertently favours those capable of effective utilisation.

In this context, this paper not only discusses the practical utility of new technologies but also examines an ethical issue: are ALPs narrowing the education gap or widening it? This paper uses a comprehensive social technology framework to analyse the operational mechanism of ALPs in Chinese schools, combining structural constraints at the macro level with technology adoption behaviour at the micro level. At the same time, it provides a theoretical perspective on solving this problem and designing more equitable AI intervention measures in a severely stratified educational environment.

2. The Context: From Digital Access to the "Usage Gap"

2.1. The Persistence of the First-Level Digital Divide

Although the government has successfully narrowed the overall Internet access gap between urban and rural schools

through policy efforts, there remains a significant infrastructure gap. In particular, the holding of learning devices and network connections remains the “first-level digital divide” that persists. Empirical data from the epidemic period highlight this material inequality: 23.6% of rural students lack sufficient learning equipment, compared with only 10.7% among urban students [5]. The key is that the stability of this access varies with socio-economic status: 53.3% of students from low socio-economic backgrounds experience unstable network connections - more than twice the proportion of their dominant group peers [5]. These data show that for many rural learners, the digital divide is not only a problem of access, but also a fundamental obstacle to achieving education equity.

2.2. The Emergence of the Second-Level Digital Divide

In addition to the gap in infrastructure, there is also a profound “secondary digital divide”, which is mainly reflected in two key aspects: the quality of resource acquisition and the ability to use resources effectively. According to Huang et al. [6], there is a significant gap between the developed southeast coastal areas and the remote southwest rural areas. This gap is not only technical, but also ecological. Rural schools have long faced a shortage of high-quality teachers and a high student-to-teacher ratio, making it almost impossible to provide personalised manual guidance. From a social perspective, the phenomenon of “left behind children”, involving a national population of more than 60 million [8], implies that most rural students lack the necessary parental academic support.

Furthermore, unlike the early exposure of urban peers to educational technology, rural students tend to regard mobile devices primarily as entertainment tools for watching short videos, lacking the digital literacy required for serious learning enabled by artificial intelligence. Therefore, even if the equipment is provided, the effective utilisation is also hindered. Huang et al. [6] noted that implementation in rural areas often requires specialised “training weeks” and on-site technical support to address fundamental operational problems. In contrast, in urban environments with high digital literacy, these interventions are rarely needed. Since the teaching effect of ALPs largely depends on technical acceptance and smooth interaction, these structural defects in the rural environment significantly weaken participation in learning. Therefore, without sufficient soft infrastructure, the use of ALPs is likely to exacerbate educational inequality further.

2.3. A Tale of Two Cities: The Digital Divide in Hangzhou and Lishui

The impact of this use gap can be vividly illustrated by comparing the current education situation in Hangzhou and Lishui, both in Zhejiang Province. These two regions are typical representatives of the sharp differences between urban and rural areas described in recent empirical literature.

As China’s first-tier city and the hub of the digital economy, Hangzhou is an ideal environment for technology adoption. In such economically developed areas, digital infrastructure and teachers’ skills are relatively advanced, enabling adaptive learning platforms such as Squirrel AI or Zuoyebang Intelligent System to function as expected [4]. Here, technology acts as a “cognitive extender”. With adequate training, teachers use algorithm analysis to provide accurate

guidance, thereby enhancing the element of “humanity” in teaching rather than replacing it.

In sharp contrast, rural schools in the mountainous Lishui City often suffer from “soft” deficiencies, despite having basic hardware facilities. As Huang et al. [6] reported, even with the introduction of ALPs, rural students remain at a disadvantage due to a lack of teacher support and low digital literacy. In this case, ALPs may be used for mechanical training or abandoned due to technical instability, and cannot serve as adaptive tutoring. This comparison between urban “empowerment” and rural “disconnection” provides an empirical basis for the theoretical framework proposed below.

3. Theoretical Foundations

To understand the complex dynamics of ALPs implementation, this study developed a comprehensive perspective that combined micro-level behavioural psychology with macro-level sociology.

3.1. Micro Perspective: Technology Acceptance Model (TAM)

At the individual level, the technology acceptance model [9] serves as the basic framework for analysing user adoption behaviour. TAM believes that two core factors mainly determine individuals’ willingness to use a specific technology: perceived usefulness (PU) is the extent to which users believe that the technology can improve their job performance; and perceived ease of use (PEOU) is the degree of effort required to use the system. Although traditionally used in a voluntary enterprise environment, TAM provides a powerful indicator for measuring teachers’ and students’ psychological responses to new educational tools.

3.2. Macro Perspective: Matthew effect

To explain how individual behaviour converges into systematic inequality, this study adopts the perspective of the Matthew effect in sociology [7]. The theory comes from a fable in the Bible, which describes the phenomenon of cumulative advantage, that is, “the rich get richer”. It shows that the initial endowment (such as capital or status) is often self-reinforcing, and the gap will continue to expand over time. Applying this perspective to the digital divide, it warns that technological innovation may not play a balanced role, or even widen the gap.

4. Integrated Framework: Recursive Loop of Digital Hierarchy

Based on the TAM and the Matthew effect, this paper proposes a comprehensive framework called the “recursive loop of digital hierarchy”. This framework goes beyond the static description of the digital divide. It explains how ALPs inadvertently exacerbate the dynamic mechanism of the education gap between urban and rural areas in China.

4.1. The Impact of Structural Inequality on Technology Acceptance

The theoretical innovation of the framework is to establish a causal link between macro-level structural constraints and individual perceptions at the micro level. TAM generally treats perceived usefulness (PU) and perceived ease of use (PEOU) as independent variables, derived primarily from software interface design [9]. However, in the context of

China's urban-rural dual structure, these micro-perceptions are constrained by it.

Specifically, the "initial advantages" described by the Matthew effect, such as the superior infrastructure stability of urban schools and the high digital literacy of teachers, catalyse the perceived usefulness of technology. On the contrary, structural defects in rural areas contribute to environmental resistance. When rural teachers face frequent network instability or a lack of education and training required for interpreting algorithm analysis, the "effort" needed to use AI-assisted learning tools will increase exponentially. Therefore, macro-level structural inequality determines the psychological threshold for technology adoption at the micro level. This integration shows that avoiding technology in rural areas is not just a personal attitude, but a normal response to structural incompatibility.

4.2. The Static View: The Four Dimensions of Digital Inequality

Before discussing how inequality evolves dynamically over time, it is necessary to clarify the four static dimensions as its starting point. These four dimensions constitute the "initial conditions" of the subsequent differentiation trajectory and extend the concept of the digital divide from simple hardware access to the deep interaction between capabilities and outcomes.

Access dimension: This dimension covers not only the existence of hardware, but also the stability and quality of the digital environment. Although the equipment gap is narrowing, significant differences in connectivity remain. Empirical data show that more than 50% of students from low socio-economic backgrounds face unstable Internet connections [5]. This creates a physical barrier to the continuous, real-time data transmission required by the cloud-based adaptive learning platform, resulting in intermittent "adaptive" functionality in rural areas.

Capability dimension: This refers to stakeholders' digital literacy and teaching readiness. Urban teachers usually have advanced "artificial intelligence readiness" and human-computer cooperation strategies. In contrast, rural teachers often lack specialised training to integrate AI learning partners into the curriculum. Without this capability, the technology is usually seen as a disturbance rather than a boost [10].

Perception dimension: Based on the TAM, this dimension measures users' confidence. In a city centre like Hangzhou, higher institutional support fosters positive perceptions (high perceived usefulness and ease of use). On the contrary, in rural areas such as Lishui, due to a lack of technical support, teachers become cautious, have low self-efficacy, and regard online learning platforms as a burden.

Outcome dimension: This dimension evaluates the actual learning outcomes. The framework believes that if the first three dimensions are not equally invested, the advanced learning project will not popularise knowledge, but will become an "amplifier" of previous achievements, benefiting those who have taken the lead in their studies.

4.3. Dynamic View: Recursive Loop Mechanism

The most important contribution of the framework is to identify two feedback loops that run counter to each other. These loops explain how the "initial advantage" accumulates over time through the specific mechanism of algorithm

optimisation.

In the urban empowerment cycle (virtuous cycle) in a resource-rich urban environment, "soft infrastructure" is very sound. Teachers have good digital literacy, and the school also provides continuous technical support. This structural advantage makes teachers' perceived usefulness and perceived ease of use of technology higher, and urges them to deeply integrate the artificial intelligence learning platform into their teaching practice rather than just try it.

Crucially, this sustained engagement serves as the essential fuel for the platform's data-driven core. Specifically, continuous, high-quality interaction generates a rich set of learning-behaviour data such as reaction time and error patterns [11]. Through training on large amounts of data, the algorithm can accurately simulate students' knowledge states and provide personalised content [12]. The effectiveness of this algorithm enhances the user's perception of usefulness (PU), thereby promoting further adoption and better learning outcomes, forming a self-reinforcing improvement cycle.

On the contrary, there are structural defects in rural schools at the beginning, including unstable interpersonal networks and insufficient teacher training, which become the initial obstacles. These barriers reduce perceived ease of use, leading to "friction adoption". Teachers may use ALPs intermittently, limit it to mechanical exercises, or give up entirely due to frustration.

This behavioural alienation will have a fatal technical consequence, data sparsity. Due to the low frequency of use or superficial use of the system, the data received by the algorithm are insufficient and scattered, which cannot accurately describe the characteristics of rural learners. Therefore, the "personalised" recommendation becomes either inaccurate or too general, failing to provide the promised personalised service. The lack of algorithm effectiveness further reduces users' perceived usefulness (PU), confirms their initial doubts, and leads to complete abandonment. Finally, the technology that should narrow the gap has accelerated the relative backwardness of rural education, which explains the Matthew effect in the era of algorithms.

4.4. Research Hypothesis

Based on this comprehensive framework, we derive three key assumptions to guide future empirical research. These hypotheses transform the theoretical model into testable hypotheses about the relationships among institutional support, user perception, and educational equity.

Hypothesis 1: Institutional support is the primary prerequisite for ALPs adoption. This study proposes that there are significant differences between rural and urban secondary schools in their support for ALPs implementation. Specifically, the level of technical and teaching support (structural factors) is directly related to the frequency and depth of ALPs use (behavioural factors), thereby confirming the link between the ability dimension and adoption behaviour.

Hypothesis 2: There are significant disparities in the psychological acceptance of ALPs between rural and urban schools. Specifically, this study hypothesises that urban teachers and students will demonstrate significantly higher levels of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) compared to their rural counterparts, driven by their superior digital proficiency and institutional support.

Hypothesis 3: Algorithm stratification exacerbates the achievement gap. This study proposes that implementing an

algorithmic learning plan is associated with the widening of the academic achievement gap and differences in digital self-efficacy. This result is not inherent in technology itself, but the product of the “Matthew effect”: school-level factors (teacher training, infrastructure stability) regulate the relationship between technology use and student achievement.

5. Implications for Future Research

The conceptual framework proposed in this paper offers a key avenue for future empirical research. To verify the “recursive cycle of digital layering”, we advocate a methodological shift from simple access-based indicators to a multidimensional analysis of social technology interaction.

To bridge the relationship between structure and initiative while verifying the hypothesis that “structural conditions constrain acceptance,” future research should first adopt a hybrid method design. A purely quantitative survey can capture the appearance of a low adoption rate (for example, rural teachers’ scores on the convenience of use are low). Still, it is often unable to reveal the root cause. Scholars should combine quantitative measurement of technology acceptance model variables with qualitative research to reveal how specific structural frictions (such as a lack of technical support and administrative burden) mechanically reshape individuals’ psychological perceptions in rural environments.

Researchers should track long-term changes in user engagement indicators and learning outcomes (such as multiple semesters) to empirically test the “recursive” nature of the framework. Such research is necessary to confirm whether the performance gap between the urban “enabling cycle” and the rural “disjointed cycle” predicted by our model will accelerate over time.

Finally, we must pay close attention to the technical impact of “data sparsity”. Future research should go beyond investigating human behaviour and examine the algorithm itself. Specifically, scholars need to explore whether the low participation rate in rural areas leads to the lack of representation of rural student data in the training concentration. Research is required to determine whether this lack of data will lead to algorithmic bias. That is, artificial intelligence models are increasingly adapted to urban cognitive models but are not applicable or accurate for rural learners, thus solidifying inequality at the technical level.

6. Discussion

6.1. The Paradox of Inclusion: Widening the Gap in the Name of Equity

The theoretical analysis proposed in this paper reveals a key paradox at the heart of the “intelligent education” agenda: ALPs designed to popularise high-quality tutoring have, in practice, become accelerators of vested interests. As Selwyn [13] pointed out, digital technology has never been socially neutral; it will reflect the existing hierarchy. In the context of China, our framework shows that ALPs have become the “amplifier” of initial capital. For urban students with high digital literacy, ALPs serve as a cognitive multiplier, optimising learning efficiency. On the contrary, for rural learners trapped in the “disjointed cycle”, the same technology has become a source of frustration and exclusion. Therefore, without structural intervention, the “Matthew effect” will ensure that the tools originally designed to promote equity inadvertently deepen the gap, turning “AI for

all” into “AI for the elite”.

6.2. Policy Implications

From hardware to human capital, to break this class-solidification cycle, we must carry out a fundamental paradigm shift in policy. Firstly, the focus of investment must shift from “infrastructure construction” to “teacher capacity building”. As Huang et al. [6] illustrated, the main bottleneck in rural areas is no longer hardware, but teachers’ teaching readiness. Professional development must go beyond basic technical training, promote the “integration of AI and teaching”, and enable rural teachers to use AI learning partners as auxiliary tools rather than substitutes.

Secondly, we call for inclusive algorithm design. Developers and policymakers must recognise that “data sparsity” in rural areas is an ecological limitation, not user error. The future algorithm learning program should be “robust”, designed for the resource-deficient environment, to ensure that the algorithm can provide effective feedback even in the case of incomplete data input. Only by integrating fairness into human training and code itself can we ensure that AI becomes a bridge rather than an obstacle.

7. Conclusion

As China accelerates its transformation to an “intelligent education ecosystem”, the question of whether artificial intelligence is a bridge or an obstacle is crucial. This paper proposes a framework of “digital hierarchical recursive loop” that shows that technology adoption is not just a personal choice but a process constrained by structure. By combining the technology acceptance model with the Matthew effect, we show how the algorithm amplifies the “initial advantage” of urban schools. At the same time, structural defects in rural areas create a vicious circle of disconnection and sparse data. Finally, this study believes that ALPs are not neutral tools; rather, they serve to exacerbate existing educational disparities. To achieve real educational equity, we need to go beyond the technology-centred “access” paradigm and turn to a comprehensive social technology approach that simultaneously addresses the deep-seated structural inequality between technology and society that restricts effective use.

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