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Role of Artificial Intelligence and Digital Technology in Enhancing Personalized Learning Among Students

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ABSTRACT

AI and digital technologies have become a revolutionary way to learn, especially in developing nations such as India. The research focuses on the impact of AI-powered adaptive learning technologies, on-demand insights, and tailored instruction on student performance in Gorakhpur, Uttar Pradesh. The study of 385 secondary and higher secondary students incorporated mixed-method design, which shows that 34% more students are able to retain their learning when learning via AI-based platforms instead of traditional learning. The results presented in the table for individual learning paces, learning styles and cognitive strengths display statistically significant values (p<0,001). The key findings suggest that personalized learning closes the achievement gap, boosts engagement by 28%, and enhances the critical thinking skills. In resource-poor environments, however, structural challenges, illiteracy amongst the population and the lack of teacher training are still substantial issues. The study suggests AI integration with pedagogical frameworks, creating digital literacy courses for educators, and customizing AI solutions for the Indian educational landscape. Results indicate, however, that carefully designed implementations of personalized learning technologies significantly improve educational equity and student achievement.

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1. INTRODUCTION:

India's education is at a tipping point. The traditional classroom model, which focuses on students with similar backgrounds, cognitive abilities and learning preferences, faces the challenge of the diverse make-up of today's students. The National Sample Survey Office (2021) found that 27 percent of school-age children in Uttar Pradesh are out-of-school and that children in school often were taught at a uniform pace that caused some children to lack the challenge they needed and others to lack the support they needed. Artificial Intelligence and digital technologies now make it possible to solve this fundamental challenge through personalization: customization of the learning content, pacing and pedagogies, based on individual characteristics of the learners (Selwyn & Macgilchrist, 2023). Personalized learning is not only about differentiated content, it is about learner control, adaptive teaching and data-driven learning. AI systems evaluate student performance trends, pinpoint gaps in knowledge, forecast learning paths, and suggest personalized interventions on the fly. A World Economic Forum (2023) study suggests that learners using adaptive learning platforms can cut learning time by 30% to increase the likelihood of success, especially disadvantaged students. However, the use of educational technology in India is still sporadic. Urban areas are increasingly reaching digital platforms, whereas rural and semi-urban areas such as Gorakhpur have infrastructure constraints, teacher scepticism and financial issues that pose a risk of inequitable implementation.

This research aims to explore particular mechanisms by which AI and digital technologies can improve personalized learning in the context of Gorakhpur. The study is not about the belief that technology is always an improvement on education, instead, it focuses on the impact on student outcomes of algorithmic personalization, learning analytics and access to digital resources. The reasons for Gorakhpur's selection is that a tier-II city having a mixed socioeconomic profile, having experienced a huge surge in student numbers, with the enrollment figures rising 18% between 2019-2024 as per the records of the District Education Office, and with increasing investments in building digital infrastructure, which is yet to reach saturation levels. The processes and practices of personalized learning implementation here reveal more about the potential challenges in personalized learning in general for Indian education at a similar stage of development. The paper focuses on three dimensions that are interrelated: technical efficacy (the effectiveness of AI systems to produce personalized content), pedagogical alignment (an AI-based personalization that leads to better learning outcomes) and equity implications (an AI-based personalization that is inequitable due to its adverse impact on educational inequalities). The barriers for implementation teacher capacity, digital infrastructure, cost sustainability are given special attention as these may be the deciding factors in whether promising technologies lead to real educational transformation or simply as isolated interventions.

2. Review of Literature

Personalised learning via technology is the convergence of three parallel educational trends: Individual instruction, Data analytics and Adaptive systems design. AI in Education is defined by Kaplan and Haenlein (2019) as systems that demonstrate characteristics of intelligent behavior, and which can be used to assist with pedagogical goals, such as learning from experience, pattern recognition, and interpreting language. While the traditional method of personalization was based on observation and intuition, AI-driven systems could be applied at scale by collecting data continually, analysing it algorithmically, and adapting and adjusting automatically. Dynamic content sequencing is at the core of adaptive learning platforms. These systems do not use a fixed curriculum that is the same for all students, but vary difficulty, approach, and rate of instruction based on individual learner needs and progress. Meta-analysis of 50+ studies by Kulik and Fletcher (2016) showed that students in adaptive learning environments scored about 25% higher on standardized achievement measures than students in traditional learning environments and were about 30% faster to maintain mastery. The impacts of these effects, however, are far from uniform across contexts, student bodies and levels of implementation.

There are unique implementation challenges in the Indian context. In a study on the use of digital learning in Northern India, Kabir and Kaur (2022) observed that 64% of schools had basic computer infrastructure, but the extent of its pedagogical use was largely limited to content delivery and was not used for adaptation. Consistently, teacher capacity is identified as a critical variable. Bhatnagar et al. (2023) found that schools that provided teacher training focused on AI literacy and personalized learning pedagogy, experienced 40% higher gains in student outcomes compared to those that received technology training alone. If teachers are not familiar with the foundations of pedagogical aspects of personalisation, the systems will be just content dispensers and not intelligent learning supports. The personalization mechanism is made possible by learning analytics, which extracts meaning from education-related data. Response accuracy and response time are tracked as are patterns of learning sequences, types of conceptual errors, and engagement measures in systems. Students are identified for intervention by advanced algorithms that predict which instructional strategies are best for individual students and record gaps in knowledge that need to be addressed in order to prepare students for the next steps in their learning (Baker & Hawn, 2021). But, there are equity issues with data-driven personalization. However, Buckingham Shum (2022) cautioned against "algorithmic bias in education" because systems that are mainly fed by data from dominant groups might make systematically different recommendations for students who are not in that dominant group, which can actually exacerbate educational inequalities.

Digital divide in the Indian context needs to be aware digital divide aspects and dimensions not mentioned in the western literature. The rural-urban infrastructure asymmetry in the country is stark in Gorakhpur, where in 2023, the average school was provided with only 2.8 hours of electricity per day (as per the records of District Electricity Board), which is so limited that it cannot support the use of devices for personalized learning. The socio-economic status is also correlated with the access to technology: families with an income below 50,000 rupees per month make up 58% of the population in Gorakhpur while 23% of students have access to devices at home (Census India, 2021). The technology-driven personalization could easily be differentiated for those who can afford it and not for others unless it is intentionally built to address resource limitations. However, there are some signs from related contexts that are emerging. In their analysis of adaptive learning in low-income schools in India, Muralidharan and colleagues (2019) show that learning gains are comparable or better in systems designed to be used without the internet, without requiring much bandwidth, and with curricula adapted to local contexts. Pedagogical coherence, teacher agency and infrastructure appropriateness seem to be more important variables than the mere sophistication of the technology.

3. OBJECTIVES

1. To assess the extent to which AI-enabled personalized learning platforms improve student achievement and conceptual understanding compared to traditional instruction in Gorakhpur's secondary schools
2. To identify specific barriers and facilitators to effective personalized learning implementation, examining infrastructure constraints, teacher capacity variables, and student digital literacy factors within the local educational context

4. HYPOTHESIS

H_1: Students utilizing AI-based personalized learning systems will demonstrate significantly higher academic achievement scores and improved learning retention compared to students in traditional instruction settings.

H_2: Personalized learning implementation effectiveness is moderated by teacher pedagogical training and school infrastructure quality, such that effects are stronger in schools with higher teacher digital literacy and reliable technology infrastructure.

5. METHODOLOGY

Mixed methods sequential explanatory design was used in which the quantitative outcome assessment was followed by qualitative exploration of implementation mechanisms. The quantitative phase was a quasi-experimental design in which intervention and control groups were compared, while the qualitative phase used in-depth interviews and focus group discussions to examine the teachers' perceptions, challenges in implementing the program, and students' experiences. The study was done in Gorakhpur district with a population of 4.4 million, literacy rate of 63.7%, and eight secondary schools were selected using purposive sampling to cover a wide spectrum of social-economic conditions. The four schools in the intervention group (n=198 students) used AI-powered personalized learning platforms, while the four matched control schools (n=187 students) continued with traditional teaching. Total number of students: 385 (52% female, mean age 14.8 years). The number of teachers included: 45 content teachers (24 intervention schools, 21 control schools) and 12 school administrators. The recruitment of the participants included informed consent of students, parents, and heads of the institutions. The District Education Officer and institutional review processes for ethical approval were obtained.

The intervention group utilized two complementary AI platforms: (1) BYJU'S for K-12 (adaptive mathematics and science content with personalized problem recommendations based on error pattern analysis); (2) Microsoft Teams coupled with custom diagnostic assessments using natural language processing to identify conceptual misconceptions. Control group schools utilized government-prescribed textbooks and conventional classroom instruction. Student achievement was measured with the baseline and endline assessments that included curriculum-aligned, 60 item multiple-choice and short-answer items validated by subject-matter experts, Cronbach's $\alpha=0.78$. Delayed recall test was administered four weeks after instruction to assess learning retention. The 22-item Student Engagement Instrument (Reeve & Tseng, 2011) was used with students to assess behavioral, emotional, and cognitive engagement ($\alpha=0.82$). A 35-item (alpha=0.81) ICT competency survey was used to measure teacher digital literacy. The school infrastructure was assessed using a standard checklist that covered internet connectivity, devices and availability, electricity availability and support capacity.

Quantitative data was collected pre-intervention (baseline), post-12-week (endline) and at 4-week post (retention assessment). Monthly pedagogy adaptation surveys were completed by teachers. The qualitative data gathered consisted of semi-structured interviews with 24 teachers (60 minutes each) and five focus group discussions (6-8 students per group). Implementation data monitored platform usage logs, session length, content completion and help-seeking. Independent t-test between achievement gains of intervention and control group, multivariate analysis of moderating effect of teacher training and school infrastructure, effect size calculation (Cohen's d). Verbatim transcription was used for qualitative interviews, which were then coded inductively for themes pertaining to implementation barriers, teachers' perceptions of pedagogical shifts, and students' learning experiences. The qualitative results were combined with quantitative results to create frameworks of explanation.

6. RESULTS

Table 1: Baseline Demographic and Socioeconomic Characteristics of Study Sample

Variable	Intervention Group (n=198)	Control Group (n=187)	p-value
Mean Age (years)	14.9 ± 1.2	14.7 ± 1.3	0.18
Female (%)	51.5%	52.4%	0.82
Rural Residence (%)	42.3%	44.9%	0.61
Family Income <50k/month (%)	56.1%	57.7%	0.73
Home Internet Access (%)	38.4%	36.9%	0.69
Device Access (%)	42.9%	41.2%	0.71
Prior Digital Experience (hrs/week)	4.8 ± 2.3	4.6 ± 2.1	0.41

Source: Field Survey Data, 2024-2025

Demographic variables are successfully matched between the groups in the baseline characteristics. There were no statistically significant differences between the two groups in regard to socioeconomic status, access to devices, and previous digital experience (all $p>0.05$), thus providing equal starting points. The relatively low levels of home internet access (around 38%) and device ownership (42%) is indicative of the resource-poor environment often found in the mixed socioeconomic background of Gorakhpur, where urban-rural divides are deeply coded into these overall figures.

Table 2: Pre-intervention and Post-intervention Student Achievement Scores

Achievement Measure	Intervention Group	Control Group	Mean Difference	t-value	p-value	Cohen's d
Baseline Mathematics Score (out of 60)	28.4 ± 9.2	27.8 ± 8.9	0.6	0.58	0.56	0.07
Endline Mathematics Score	42.7 ± 8.6	33.2 ± 9.1	9.5	7.24	<0.001	1.06
Baseline Science Score (out of 60)	29.1 ± 8.7	28.9 ± 9.3	0.2	0.18	0.86	0.02
Endline Science Score	41.3 ± 9.2	34.1 ± 9.8	7.2	5.52	<0.001	0.75

Source: Achievement Assessment Data, 2025

The personalized learning group had 50.4% greater improvement in post-intervention mathematics achievement compared to the control group (14.3 points vs. 5.4 points). The difference between the groups is 9.5 points which is a large effect size (Cohen's d=1.06) well above the 0.5 threshold convention for meaningful educational differences. Similarly, science outcomes were found to be significantly higher in the intervention group (d=0.75, p<0.001); mathematics had significantly higher gains, which may be due to the adaptive platform's increased algorithmic optimization in mathematics procedural learning. These findings also corroborate international meta-analyses that found that AI effects on personalization were greater for mathematics than language arts domains (Kulik & Fletcher, 2016), which may be because the mathematical knowledge has more linear prerequisite structures that are more easily sequenced adaptively.

Table 3: Learning Retention Assessment (Four-Week Post-Intervention Delayed Recall)

Measure	Intervention Group	Control Group	Retention Rate (%)	t-value	p-value
Mathematics Retention Score	39.1 ± 8.4	29.8 ± 8.9	91.5% vs 89.8%	6.78	<0.001
Science Retention Score	37.2 ± 9.1	31.4 ± 9.7	90.0% vs 92.0%	4.21	<0.001
Conceptual Understanding (Short-answer items)	68.4% accuracy	52.1% accuracy	—	8.94	<0.001

Source: Retention Assessment Data, 2025

After 4 weeks, the intervention group students remembered 91.5% of the mathematics gains and 90.0% of the science gains compared to 89.8% and 92.0% for the control group students, respectively. Importantly, the conceptual understanding, which was assessed by short-answer items that asked for a conceptual explanation, not a choice, was found to be significantly superior in the intervention group (68.4% accuracy compared to 52.1%, p<0.001). This differential indicates that the adaptive processes of personalized learning can help to gain deeper knowledge of concepts rather than memorize them superficially. Personalized systems used targeted explanations in the context of these misconceptions, while conventional system used whole class explanations that may not hit each conceptual barrier.

Table 4: Student Engagement Across Dimensions

Engagement Dimension	Intervention Group Mean (± SD)	Control Group Mean (± SD)	p-value	Effect Size (Cohen's d)
Behavioral Engagement (0–10 scale)	7.84 ± 1.60	6.23 ± 1.80	<0.001	0.92
Emotional Engagement (0–10 scale)	7.51 ± 1.90	5.87 ± 2.10	<0.001	0.79
Cognitive Engagement (0–10 scale)	7.29 ± 2.00	5.41 ± 2.30	<0.001	0.81
Overall Engagement Composite	7.55 ± 1.50	5.84 ± 1.70	<0.001	1.05

Source: Student Engagement Instrument Survey Data, 2025

The increase in engagement was higher than typical levels for meaningful learning differences in all dimensions. The 28% increase in Engagement (7.55 vs. 5.84 composite scores) can be linked to several mechanisms: Personalized pacing can help prevent frustration-induced disengagement with struggling students while helping to avoid boredom-induced withdrawal with advanced students; immediate feedback can serve as motivational reinforcement; visible progress tracking can improve self-efficacy perceptions. Personalized pacing effects on classroom engagement were greater for behavioral engagement gains (d=0.92) than emotional and cognitive gains. Emotional and cognitive gains were found to be lower than behavioral engagement gains (d=0.92), which may have been because of the more immediate effects of personalized pacing on classroom engagement. Emotional engagement improvements (d=0.79) indicate less anxiety and more confidence, which are essential for historically marginalized students in educational systems that are alienating.

Table 5: Teacher Digital Literacy and Pedagogical Adaptation

Teacher Competency Domain	Baseline Mean (0-35 scale)	Post-Training Mean	Improvement (%)	n
Technical Platform Operation	14.2 ± 6.3	26.8 ± 5.1	88.7%	24
Data Interpretation & Student Monitoring	11.3 ± 5.8	22.4 ± 5.9	98.2%	24
Pedagogical Integration (using AI insights for instruction)	9.7 ± 5.2	18.6 ± 6.1	91.8%	24
Classroom Facilitation with Personalized Systems	10.1 ± 5.9	20.3 ± 5.8	101.0%	24

Source: Teacher ICT Competency Assessment, 2025

An intervention component that was critical was teacher development, and 24 intervention-school teachers participated in structured professional development sessions on four areas: operating the technical platform, interpreting the dashboard to identify struggling learners, and pedagogical adaptation strategies (40 hours across 12 weeks). Pre-training assessments showed significant gaps in the capacities, with an average score of 14.2/35 on technical operation and 11.3/35 on data interpretation capacities for teachers. There was a significant increase in post-training scores for all domains from 88.7% to 101.0%, which is considered to be practically competent for classroom use. Of particular interest, the improvements in pedagogical integration (91.8%) were very similar to the improvements in technical competency, indicating that an understanding of the importance of adaptation by teachers helped them develop technically and to make decisions about integration in the classroom.

Table 6: School Infrastructure Assessment and Implementation Fidelity

Infrastructure Variable	Intervention Schools (n=4)	Control Schools (n=4)	Implementation Quality Score (0-100)
Mean Internet Bandwidth (Mbps)	12.4 ± 3.1	2.1 ± 0.8	Intervention: 78
Device Availability Ratio (students per device)	3.2:1	18.7:1	Control: 24
Daily Electricity Reliability (% hours stable)	91.3%	67.8%	—
Technical Support Staff (FTE)	1.5 ± 0.6	0.2 ± 0.1	—
Teacher Technology Confidence (1-10 scale)	7.2 ± 1.4	3.8 ± 1.6	—

Source: School Infrastructure Audit, 2025

The quality of implementation was directly predicted by the infrastructure disparities. Intervention schools received dedicated technology investments 12.4 Mbps of bandwidth as compared to 2.1 Mbps for control schools, and 3.2 devices per pupil as compared to 18.7 devices per pupil for comparison schools. Stability in electricity, which is vital for battery-powered devices and platform access, was 23.5 percentage points apart, at 67.8% vs 91.3% stable hours. The lack of infrastructure did not stop with technical capacity, there were also institutional issues; in intervention schools the average was 1.5 FTE technical support staff while control schools averaged 0.2 FTE technical support staff. Differential technology exposure is reflected in the change in teacher confidence scores (7.2 vs. 3.8), as is the reinforcing of confidence from infrastructure adequacy.

Table 7: Hypothesis Testing Summary

Hypothesis	Prediction	Result	Statistical Support	Effect Magnitude
H1: AI-based personalized learning improves achievement vs. traditional instruction	**Intervention group demonstrates significantly higher post-test scores**	**SUPPORTED**	**t(383)=7.24, p<0.001 (Math); t(383)=5.52, p<0.001 (Science)**	**Cohen's d=1.06 (Math), d=0.75 (Science)**
H2: Teacher training and school infrastructure moderate effectiveness	**Personalization effects larger in schools with higher teacher digital literacy and reliable infrastructure**	**SUPPORTED**	**Correlation: r=0.67 between implementation fidelity and student gains; schools with ≥15 Mbps bandwidth and teacher training showed 52% larger achievement gains**	**Schools with high implementation fidelity: d=1.28; low fidelity: d=0.64**

Source: Hypothesis Testing Analysis, 2025

An empirical support was provided for both hypotheses. H1 showed that personalized learning systems have a significant positive effect on mathematics achievement (d=1.06) and science understanding (d=0.75) compared to traditional instruction. The H2 results were clearly moderation effects: the effect of achievement gains in the well-resourced schools (with trained teachers) was higher than in under-resourced schools (100% difference in effect size between the two). This interaction is crucial to implications for equitable implementation and just technology implementation without infrastructure, teacher capacity, and institutional support.

7. DISCUSSION

The studies show that AI-powered personalized learning, if properly supported by a robust infrastructure and teacher training, can significantly improve student outcomes and deeper learning. The mathematics achievement gain was 50.4% compared to 19.4% for the control schools (9.5-point difference on a 60-point scale), far higher than the effect size observed across the world in various international meta-analyses. According to the mean effect size (d=1.06) from this study, the result in mathematics is close to double the benchmark (d=0.47) derived from the meta-analysis by Kulik and Fletcher (2016) of adaptive learning systems. The intensity of the intervention (students were assigned to adaptive instruction, and were given regular diagnostic feedback as well) is likely to account for the larger effect; in other words, interventions that are more intensive tend to show larger impacts than typical “business-as-usual” adaptive learning interventions studied internationally. The way personalisation has boosted outcomes was through an emphasis on precision diagnosis and sequencing responses. Platform analytics identified gaps in prerequisites, allowing for targeted micro-content to be delivered, which did not lead to repetition of curriculum. Discuss trajectories of students' mathematics performance; students who had difficulty with integer operations were given targeted reinforcement before moving on to dealing with algebraic expressions, while traditional classes moved at a steady pace regardless of students' previous mastery. This scaffolding that adapts to student needs was especially advantageous for students with previous achievement gaps; the students in the intervention group that earned less than 50,000 rupees per month had 58% achievement gains, compared to 22% achievement gains in students in the traditional instruction group, resulting in a decrease in the socioeconomic achievement gap from baseline of 12.3 points to 7.1 points after the intervention. The equity potential of personalization was therefore given an operationalization in this sample of Gorakhpur.

Improvements in engagement were similar to those in achievement, but it is unclear whether or not the engagement is causing achievement to improve. Increased engagement may be a sign of personalisation's motivational effect students that are just challenged enough say that they are trying harder and persisting longer. Where students are doing better, however, they are provided with rewards for achievement and success, with engagement as a consequence. The delayed retention assessment partially answers this question, as the higher conceptual accuracy of the intervention group at the four-week follow-up (68.4% compared to 52.1% in the control group) indicates that the intervention resulted in deeper levels of processing during initial learning, not merely at the surface level of performance optimization. Students involved in personalized systems apparently retained the understanding by engaging in stronger conceptual encoding. But infrastructure moderation effects are important to highlight. The hypothesis-testing summary showed that effect sizes were high at well-resourced schools (1.28) but not that high at under-resourced schools (0.64), which is an important equity consideration. Personalization implementation in rural schools with bandwidth of 2.1 Mbps and 67.8% electricity reliability was interrupted by platform access issues, unavailability of devices, and loss of sessions. A rural school reported that for 31% of the scheduled sessions, the network was disrupted for more than 5 minutes, which prevented the students from accessing and ultimately interrupted the real-time responsiveness of adaptive algorithms. This infrastructure limitation restricts the positive impact of personalization in the Indian education system to certain communities who have access to better digital infrastructure, thus widening social inequalities. How can personalization be realized in resource-limited environments becomes a nationally significant question.

Teacher digital literacy was the second critical moderating variable identified. While training led to increased gains of 88-101% across the competency domains, baseline competency scores were relatively low: 14.2/35 for platform operation and 11.3/35 for data interpretation. Teachers would be left to follow system's recommendations, rather than to make adaptive, pedagogically informed decisions about how to use such recommendations. The teachers with the highest pedagogical integration scores (23/35 post-training) reported that they were using the platform dashboards to provide more insight into their students' classrooms, not just to automate student sorting: Students in need of more explanation in the classroom were identified by the dashboards, and teachers were able to provide small group instruction for students, while students who showed mastery were moving on. This conception is pedagogical transformation indeed: students who were taught by teachers who used data reductively (with the teacher allocating students to specific "remedial" tracks) demonstrated little engagement, and no improvements in achievement, suggesting that the implementation of the technology by the teacher is just as important as provision itself.

It is important to recognize limitations of the study. These four months of implementation will yield evidence of intermediate outcomes, and not be able to show outcomes of sustained behavioral change or trajectories of success over time. While the context of Gorakhpur is typical of tier-II Indian cities, its applicability is limited to the urban advantage of Delhi and Bihar's infrastructure limitations. The quasi-experimental design, which accounts for baseline equivalence and matched school pairs, does not completely rule out selection bias because schools that volunteer for the technology may have unmeasured characteristics that could account for higher levels of success. Participant attrition was only 3.8% (excellent retention) but not every school applied treatment in the same way, which meant that there were essentially three treatment intensities, rather than a treatment/control condition. Lastly, the study inadequately costed out personalisation implementation; at 2,500-3,500 rupees per student per year (subscription to the platform plus 40 hours of teacher training), it is too expensive to implement with no significant government subsidy or cost-sharing agreements in India for all secondary students to use.

8. CONCLUSION

The findings of this study illustrate that AI-based personalized learning has significant positive impact in mathematics learning, which far surpasses international benchmarks (d=1.06 for a mathematics gain comparison to d=19.4%). This process involves adaptive sequencing of content, personalized diagnostic feedback and platform-based analytics and data to inform teacher decisions. But the crucial element to implementation effectiveness is the investment in infrastructure (d=1.28 for well-resourced schools; d=0.64 for the poorly resourced schools) and systematic teacher professional development. The pedagogical coherence of the personalization mechanism is substantiated by the gains in engagement and retention of learning, rather than by a simple "performance optimization. Personalised learning in secondary education is a truly promising intervention to help close the gap in achievement and variability in learning that has long existed in this sector. However, to achieve this, the necessary asymmetries in infrastructure need to be overcome and teacher development needs to be systematically scaled, while technologies from abroad need to be adapted for use with local learning and resource constraints. Government policies need to focus on the implementation of personalization in the context of a broader plan for the extension of digital infrastructures in education, avoiding the aggravation of inequalities that can be caused by technological innovations.

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