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Intelligent Tutoring, Adaptive Learning and Educational Equity: A Conceptual Model of Personalisation, Access and the Risk of a Two-Tier Education System

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ABSTRACT

Adaptive learning systems and intelligent tutors are marketed as a tutor for every child, a promise most persuasive where teachers are scarce, classes are large and foundational learning is weak, as in much of sub-Saharan Africa. Their equity consequences, however, have been theorised far less than their average effects. This conceptual paper addresses that gap. Its objective is to explain when adaptive learning narrows or widens learning gaps and to derive testable propositions and deployment principles. The population is the peer-reviewed literature on intelligent tutoring and adaptive learning, educational equity and the digital divide, and educational technology in low- and middle-income countries. The sample comprises 35 sources: 33 journal articles published 2023–2026, including trials and quasi-experimental and implementation studies from Kenya, Sierra Leone and Tanzania and longitudinal evidence on remote learning in Ghana, and two foundational works. Sources were chosen by criterion-based purposive selection, each verified against its Crossref record and screened for retractions; preprints, reports and conference papers were excluded. Analysis was a conceptual synthesis: empirical sources were coded for what was personalised, teacher involvement, setting of use and the distribution of outcomes, and propositions were derived abductively. The paper distinguishes personalisation of pace, content and pedagogy, and argues that current systems supply the first readily, the second partially and the third rarely, so that the learners who most need responsive teaching receive least of it from software. A three-tier access model then makes the equity effect depend on who gets the technology, who gets the technology plus a teacher, and who gets neither. Seven falsifiable propositions specify when adaptive systems narrow or widen gaps, including the risk that software becomes the education of the poor while advantaged learners keep human teachers. For low-resource, especially African, school systems the paper recommends teacher-complementary design, protected in-school dosage, language and curriculum alignment, low-technology channels and distribution-sensitive monitoring, and it sets a research agenda on the teacher's role, learner motivation and the distribution of outcomes.

Keywords: adaptive learning; intelligent tutoring systems; personalised learning; educational equity; digital divide

Intelligent Tutoring, Adaptive Learning and Educational Equity: A Conceptual Model of Personalisation, Access and the Risk of a Two-Tier Education System

1. INTRODUCTION

Bloom (1984) reported that students tutored one-to-one under mastery conditions performed about two standard deviations above conventionally taught peers, framing the problem that has organised educational technology ever since: how to approach that effect without one adult per child. Intelligent tutoring systems and adaptive platforms, which estimate what a learner knows, select the next task and adjust the route through a curriculum, are the most sustained answer, and generative models now add conversational explanation. The meta-analytic record is broadly encouraging (Wang et al., 2024), and a recent randomised trial found that a carefully designed generative tutor produced more learning in less time than an active-learning class (Kestin et al., 2025).

In many African school systems teachers are scarce and lower-primary classes are large; foundational literacy and numeracy remain low (Piper & Dubeck, 2024), and many children are taught in a language not spoken at home, a mismatch strongly associated with learning poverty (Alkateb-Chami, 2024). There, adaptive software is offered not as enrichment but as a remedy for absent teaching, turning an instructional question into a distributive one: who gets it, on what terms and in place of what?

The equity literature gives grounds for caution. Digital-divide research has long shown that differences in access give way to differences in skills, use and benefit (Scheerder et al., 2017), and a large Australian study found that use of an intelligent tutor appeared to amplify the advantage of affluent urban schools (Hannan & Eynon, 2025). Yet evaluations in Kenya and Sierra Leone report gains that are similar across gender and prior attainment, or even concentrated among lower performers (Major et al., 2026; Zhao et al., 2026). The literature thus holds an equalising and a stratifying story but lacks a model of when each should be expected.

This paper offers such a model. Its central claim is that the equity effect of adaptive learning cannot be read from its average, because it depends on what personalisation a system delivers and what human teaching surrounds it: systems personalise pace readily, content partially and pedagogy rarely, an asymmetry that matters most for the children with least access to responsive teachers. Combined with unequal access to teachers, it creates a specific risk: that adaptive software becomes the education of the poor while advantaged learners keep human teachers and use software as a supplement. The question matters because buying software in place of teachers or alongside them is a budget decision that such a model can inform before rollout.

The paper aims to decompose personalisation, model how access to technology and teachers shapes the distribution of benefits, and derive testable propositions and deployment principles for African school systems. Four research questions follow. RQ1 asks what personalisation consists of and which of its components adaptive systems supply; RQ2, how configurations of access to technology and to teachers shape the distribution of benefits; RQ3, under what conditions adaptive systems narrow or widen learning gaps; and RQ4, what principles should govern deployment in African school systems and what research is most needed on the teacher's role, learner motivation and the distribution of outcomes. Being conceptual, the study tests no hypotheses; in their place it advances seven testable propositions.

2. LITERATURE REVIEW

2.1 CONCEPTUAL REVIEW

"Personalised learning" is used so loosely that it can describe almost any digital product, so a useful start is the distinction between teacher-driven and technology-driven personalisation. Van Schoors et al. (2023) observed teachers implementing a digital personalised learning track for programming with 12- to 14-year-olds and found that, although the technology-driven personalisation was the same across cases, teachers enacted different personalisation strategies and relationships with the

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software, which the authors call a teacher–technology nexus. They note that teacher-driven personalisation is hard to facilitate in large heterogeneous classes, the very condition that motivates technology-driven alternatives in low-resource systems.

Wang et al. (2024) coded adaptive systems by their sources of adaptation (cognitive, affective and behavioural learner data) and their targets (navigation through material and assessment). In higher education, du Plooy et al. (2024) found that pre-knowledge quizzes were the most common trigger for adaptive content. Both reviews describe systems that mainly decide what comes next and when a learner may move on: valuable, but narrower than what a skilled teacher does when she changes the explanation, representation, language or emotional register for a particular child.

Attempts to automate that deeper adaptation have often relied on weak constructs. A systematic review of machine-learning approaches to adaptive learning found growing effort devoted to detecting learners' "learning styles" from behaviour (Essa et al., 2023), although a recent meta-analysis concluded that benefits from matching instruction to learning styles are too small and infrequent to justify widespread adoption (Clinton-Lisell & Litzinger, 2024). Generative models, which can vary explanations in conversation, change the picture, yet pedagogical adaptation still depends on design: a tutor built on research-based pedagogy outperformed active learning (Kestin et al., 2025), while an unguarded chatbot improved practice performance and then lowered unaided examination scores once access was withdrawn (Bastani et al., 2025).

Equity is meant distributively: the concern is how learning outcomes are spread across socioeconomic, geographic, gender, language and ability groups, not only whether averages rise. Following Scheerder et al. (2017), the digital divide is treated as layered, from access through skills and use to outcomes. The two-tier risk named in the title is that the form of schooling itself, human-led or software-led, becomes stratified by social position.

2.2 THEORETICAL REVIEW

Three bodies of theory frame the argument. The first is the mastery-learning tradition that Bloom (1984) summarised, whose core mechanism is corrective feedback and additional time until a criterion is met. It translates naturally into software, which explains why pace and item selection are the most mature forms of adaptation. Bloom's tutors, however, also diagnosed and re-explained, and the two-sigma result concerns that whole package.

The second is the layered account of digital inequality. Scheerder et al. (2017) showed that research had moved from access to skills and uses but had paid little attention to the third level, the tangible benefits people derive, and that the determinants identified at every level were mostly socioeconomic and sociodemographic. Applied to adaptive learning, it predicts unequal benefit even from universal provision if skills, support and usage differ. Hannan and Eynon (2025) interpret their Australian findings through the related idea of a Matthew effect, in which initial advantage is compounded by more effective use.

The third is critical scholarship on the political economy of educational technology. Selwyn (2024) argues that statistical modelling can capture only part of what happens in education, that AI risks reinforcing disadvantage for minoritised students, and that reorganising education into machine-readable forms carries losses. Bulathwela et al. (2024) call the belief that technology can quickly fix complex educational problems techno-solutionism and argue that, without deliberate design, AI may deepen inequality and misdirect resources. Komljenovic et al. (2026) show how venture investors promote visions of the educational future and legitimise their influence through impact metrics. Together these accounts suggest that substituting software for teachers is a commercially and politically attractive narrative, not only a technical possibility, especially where public systems are under fiscal strain. Khan et al. (2024) add a development perspective: leapfrogging is plausible only where foundational capacity already exists, and elsewhere absorptive capacity must be built first.

No one tradition explains why the same system can equalise in one setting and stratify in another: mastery theory predicts gains, digital-divide theory unequal uptake, and critical theory substitution pressures. The model below joins them by treating personalisation as decomposable and access as configurational.

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2.3 EMPIRICAL REVIEW

The average effect of adaptive systems is positive but less certain than enthusiasts suggest. Wang et al. (2024) report a medium-to-large effect (g = 0.70) across 45 studies relative to non-adaptive interventions, with significant moderation by publication type, study origin, student level, discipline, duration and design. Létourneau et al. (2025) reviewed 20 K–12 studies with 2,853 students; most were quasi-experimental, half were very short, and the advantage of intelligent tutors shrank when the comparison was a non-intelligent tutoring system rather than ordinary teaching. A Campbell review of mobile devices in primary classrooms found positive effects on literacy and numeracy across 18 randomised trials, but rated every study as raising some concerns or at high risk of bias (Dorris et al., 2024).

Several findings bear directly on teachers. In log data on about 139 million mathematics problems solved by some 194,000 students in Germany and the Netherlands, Bardach et al. (2026) found that students whose problems were assigned by teachers dropped out later, stayed active for more weeks and completed more problems per week than those who chose their own. A Kenyan randomised trial of digital personalised learning with 1,955 pre-primary learners in 291 government schools, where teachers could adapt the sequence to their own judgement, found an effect of 0.534 standard deviations over 13 months, similar for boys and girls and across class sizes, without clear differences by prior achievement; effectiveness declined after the midline, which the authors attribute to suitable content running out (Major et al., 2026). A companion A/B/C test across 4,487 Kenyan schools found that teacher-dashboard design changed both learner usage and literacy results (Sun et al., 2026), and a three-year design-based study concluded that pedagogical factors, above all curriculum alignment and classroom management, and the teacher's own personalising work shaped whether the technology took hold (Daltry et al., 2025).

The distributional evidence is mixed in ways that configuration of use helps explain. Hannan and Eynon (2025), studying 66,451 students in 304 Australian schools, found that students in more affluent urban schools began using an intelligent tutor earlier in their schooling, used it for more years and had higher outcomes; usage mediated, and modestly amplified, the association between school advantage and achievement. In Ghana, remote-learning engagement and resources during school closures were associated with better outcomes in 2021 and 2022 but not in 2024; children with average or higher prior mathematics scores appeared to benefit at trend level while those below average did not, though household socioeconomic status and school type did not significantly moderate the associations (Do et al., 2026). Across seven sub-Saharan African countries, better-off, more educated and urban households engaged children in a wider range of learning activities during the pandemic (Dang et al., 2025). Where use was discretionary and home-based, then, social advantage shaped engagement and prior attainment appeared to shape benefit.

Programmes delivered under structured conditions, by contrast, reported equalising patterns. In Sierra Leone, two personalised modalities of a lower-primary intervention appeared to have equalising effects for girls and lower performers, although the authors caution that such interventions may not be as cost-effective as other personalised interventions (Zhao et al., 2026). A Kenyan adaptive SMS literacy platform, needing neither smartphones nor internet, produced gains that were equitable by gender and location even though engagement varied along the same lines (Jordan et al., 2025). In 172 remote Tanzanian villages, the apps that produced the largest gains for out-of-school children shared features of autonomous learning, motor skills, task structure, engagement, language demand and personalisation (Huntington et al., 2023). A meta-analysis of interventions in conflict and protracted crisis found that software with academic games produced strong, consistent gains in literacy and numeracy (Diazgranados & Thuo, 2026). A three-round panel survey in Tamil Nadu, India, found that a state television channel broadcasting classes during school closures had been effective in addressing the rural–urban divide (Jafar et al., 2023). Barriers persist even in structured programmes: Sierra Leonean teachers identified English as the language of instruction and access for children with special educational needs as key issues for an EdTech intervention (Lurvink & Pitchford, 2023).

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This evidence has plain weaknesses. Most African studies evaluate a few programmes, often by teams connected to their implementers; outcomes are almost all foundational test scores, and follow-up rarely extends beyond a school year. Cost data are also thin (Diazgranados & Thuo, 2026). Fairness research on educational algorithms has dealt mainly with prediction and classification, and calls to extend it beyond gender and race to other demographic attributes remain largely unmet (Idowu, 2024). End users are seldom involved in design (Alfredo et al., 2024), and South African reviewers could locate no African studies of AI in special needs education (Saal et al., 2025). The literature can show that adaptive software raises foundational scores under supervised conditions, but not yet what happens to the full distribution of outcomes when software replaces teachers at scale.

3. MATERIALS AND METHODS

3.1 RESEARCH DESIGN

The study is a theory-building conceptual synthesis: it estimates no effects but constructs a model whose propositions others can test.

3.2 POPULATION AND SAMPLE

The population is the peer-reviewed literature on intelligent tutoring and adaptive learning, educational equity and the digital divide, and educational technology in low- and middle-income countries. The purposive sample comprises 35 sources: 33 journal articles published 2023–2026 and two foundational works (Bloom, 1984; Scheerder et al., 2017).

3.3 INCLUSION AND EXCLUSION CRITERIA

Inclusion required a peer-reviewed journal article published 2023–2026 with a working DOI and a Crossref record of type journal-article showing no retraction. Preprints, working papers, NGO and multilateral reports, book chapters, conference proceedings, editorials, items without an obtainable abstract and items whose venue or methods fell below a basic quality bar were excluded, which removed several prominent African AI-tutoring studies available only as working papers or preprints. The two pre-2023 works were admitted because the theories they introduced cannot otherwise be attributed.

3.4 DATA COLLECTION PROCEDURE AND TOOLS

Searches ran in October 2026 through the OpenAlex and Crossref APIs, publisher pages and targeted web searches of journals in educational technology, learning sciences and international education, combining terms for intelligent tutoring, adaptive and digital personalised learning, generative AI tutors, digital divide, equity, fairness and Matthew effects with terms for low- and middle-income and named African countries. Bibliographic details were copied from Crossref unaltered, and at least the abstract of every source was read (via OpenAlex, publisher or repository pages, or RePEc) before citation.

3.5 DATA ANALYSIS

Analysis proceeded abductively in three passes. First, each empirical source was coded for what the system adapted (Section 3.8), whether and how a teacher was involved, the setting of use (school or home, scheduled or discretionary) and reported differences across learner groups. Second, the codes were grouped into the pace–content–pedagogy decomposition and the three access tiers, and anomalies, such as tutors equalising in Kenyan classrooms but stratifying in Australian schools, were examined. Third, propositions were drafted.

3.6 BASES OF JUDGEMENT

Evidence was weighted by design (randomised over correlational), scale, duration, independence from developers and relevance to low-resource systems. A proposition was written wherever two or more sources converged on a mechanism or conflicting findings implied a moderator; where one rests on the paper's own inference, it says so.

3.7 RELIABILITY AND VALIDITY

Every reference was checked against Crossref twice, at selection and in an independent verification that screened all 35 DOIs for retractions, corrections and expressions of concern. Every citation was independently re-checked against its source abstract and corrected where it overstated the source, and a separate review tested abstract, body, references and notes for consistency. One article carries a published correction, but it concerns only an author affiliation and leaves the cited findings intact. Section 4.2 states what would disconfirm each proposition. Limits remain: synthesis selects and interprets, unexamined

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literature could alter the model, and the African evidence centres on a few programmes, mostly Kenyan and Sierra Leonean, so the propositions are conjectures for testing, not findings.

3.8 VARIABLE MEASUREMENT

Personalisation was operationalised by the target of a system's adaptive decision: pace (timing, repetition, progression), content (selection of items, topics or remediation) or pedagogy (explanation, representation, language, scaffolding or motivational stance). Tier is defined by whether the learner uses the technology and whether a teacher assigns, monitors and adapts that use; equity, by outcome differences across socioeconomic, geographic, gender, language and ability groups. Each proposition names measurable indicators, such as the share of logged decisions by type (P1) or subgroup and quantile effects (P2, P4, P5).

3.9 AVAILABILITY OF MATERIALS

All sources are listed with DOIs in Section 7. The verification log and coding notes are available from the corresponding author on request, and no restrictions apply.

3.10 AI USAGE DISCLOSURE

Generative AI tools assisted literature retrieval, drafting and formatting under the authors' direction. The authors verified all sources against publisher and Crossref records and take full responsibility for the content.

3.11 OTHER DISCLOSURES

The study involved no human participants, so ethical approval was not required. It received no external funding, and the authors declare no conflict of interest.

4. RESULTS AND DISCUSSION

4.1 RESULTS

The pace–content–pedagogy decomposition. Personalisation of pace adjusts when a learner moves on along a fixed path; of content, which items, topics or remedial units a learner meets in light of estimated knowledge; and of pedagogy, how something is taught (Table 1).

Table. 1. Three components of personalisation and their supply by current adaptive systems

Component	What is adapted	Main signals used	Supply by current systems	Illustrative evidence
Pace	Timing, repetition, progression through a fixed sequence	Correctness, response time, mastery estimates	Readily supplied; the core of most platforms	Bloom (1984); Wang et al. (2024)
Content	Choice of items, topics, remediation and difficulty	Pre-tests, knowledge-state models	Partially supplied; limited by item banks, curriculum fit and language	du Plooy et al. (2024); Daltry et al. (2025)
Pedagogy	Explanation, representation, language, scaffolding, motivation, relationship	Affective and behavioural data, dialogue	Rarely supplied well; often based on weak constructs, or unguarded	Essa et al. (2023); Clinton-Lisell & Litzinger (2024); Bastani et al. (2025)

The components are analytically distinct but interact. A system that holds a struggling learner on easy items is personalising content but in effect slowing her pace, and if the loop continues it becomes tracking within the software. Generative tutors blur the content–pedagogy boundary, since a re-worded explanation is a pedagogical act, yet without the child's language, history and mood it lacks the relational information that guides a teacher. The decisive point is the asymmetry: systems are strongest where a teacher's absence costs least and weakest on pedagogy, the dimension most needed by children with low prior attainment, a home language that differs from the language of instruction, special educational needs or weak motivation (Alkateb-Chami, 2024; Lurvink & Pitchford, 2023). In a small adaptive-algebra study, prior knowledge shaped how learners responded to motivational agents and which strategies they adopted, so even the effects of

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pedagogical design depend on what learners already know (Su et al., 2025).

The three-tier access model. Adaptive learning reaches learners in three configurations (Table 2): the technology alone, used instead of a teacher (Tier A); the technology plus a teacher who assigns work, reads the data and supplies the pedagogical adaptation the software cannot (Tier B); and neither adequate technology nor adequate teaching (Tier C).

Table. 2. Three-tier access model of the equity effects of adaptive learning

Tier	Configuration	Personalisation available	Typical learners	Expected effect and main risk
A	Technology only (instead of a teacher)	Pace and some content only	Out-of-school, remote or home users; under-staffed classes	Real foundational gains possible; engagement decay, crutch use, weak higher-order learning
B	Technology plus teacher	Pace and content from software; pedagogy from teacher	Advantaged schools; well-supported programmes such as the Kenyan trials	Largest and most durable gains; risk of widening gaps if access is concentrated among the advantaged
C	Neither	None	Poorest and most remote households and schools	No benefit; the gap to Tiers A and B widens as adoption spreads

The equity effect of a programme is thus the product of how learners from different groups are distributed across the tiers and how large the effect is within each. A programme that moves poor children from Tier C to Tier A can narrow a gap even if Tier A is weaker than Tier B, whereas one whose benefits accrue mainly in Tier B will widen gaps if advantaged learners dominate that tier, even when every group gains.

Propositions. Seven propositions follow.

P1 (personalisation gradient). In audits of adaptive-system decisions, the proportion that alters pace will exceed the proportion that alters content, which in turn will exceed the proportion that alters the form of instruction. The reviews of what systems adapt, and the reliance on pre-tests and learning-style detection, point this way (du Plooy et al., 2024; Essa et al., 2023; Wang et al., 2024).

P2 (need–supply mismatch). The gain from moving a learner from Tier A to Tier B will be larger for learners with low prior attainment or a home language that differs from the language of instruction. Such learners need pedagogical adaptation most, for the reasons given above (Alkateb-Chami, 2024; Lurvink & Pitchford, 2023).

P3 (complementarity and durability). The same system will produce larger and more durable effects when teachers assign and monitor work than under self-directed use, and the difference will grow with duration. Teacher assignment was associated with later dropout and more sustained activity in large-scale log data (Bardach et al., 2026), and the post-midline decline in a Kenyan trial shows that durability cannot be assumed even under classroom integration (Major et al., 2026).

P4 (discretionary use). Where use is discretionary, intensity of use will be positively associated with socioeconomic advantage and the system will widen gaps; where dosage is scheduled within school time, both the association and the widening will be weaker. The contrast between Australian school-level adoption and structured Kenyan and Sierra Leonean programmes supports this moderator (Hannan & Eynon, 2025; Major et al., 2026; Zhao et al., 2026).

P5 (floor-raising). Adaptive systems will narrow gaps when rollout prioritises Tier C learners, content is aligned with the curriculum and available in the language of instruction, and delivery uses channels the poorest households already have. The Kenyan SMS and Tamil Nadu broadcast findings point this way (Jafar et al., 2023; Jordan et al., 2025).

P6 (two-tier substitution). Where adaptive software is introduced to reduce spending on teachers in under-resourced schools while advantaged schools

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retain human-led teaching, gaps in higher-order, oral, collaborative and socio-emotional outcomes will widen even if foundational test scores among poorer learners rise. The proposition is this paper's inference from the asymmetry in Table 1, informed by accounts of how investors promote technology-led visions of education (Komljenovic et al., 2026) and of what AI cannot capture in education (Selwyn, 2024); neither source tests it.

P7 (unsupervised generative tutoring). Unguarded generative assistants used without teacher oversight will raise practice performance while lowering unaided performance, and the harm will be greater in Tier A than in Tier B. The evidence is the crutch effect found when access to an unguarded model was withdrawn (Bastani et al., 2025), set against the gains from a tutor built on research-based pedagogy (Kestin et al., 2025), which together imply that design moderates the effect; that teacher oversight does too is this paper's inference.

4.2 DISCUSSION

The research questions can now be answered. For RQ1, personalisation comprises pace, content and pedagogy, which the evidence suggests current systems supply in descending order (Table 1; P1). Under RQ2, benefits follow how groups of learners are spread across the tiers and the effect within each (Table 2). The answer to RQ3 lies in P2–P7: gaps should narrow when use is scheduled, teacher-supported, aligned with curriculum and language and aimed first at Tier C, and widen when it is discretionary, unsupervised or a substitute for teachers. RQ4 is answered by teacher-complementary deployment (Section 5) and the research priorities closing this section.

The model reconciles apparently contradictory findings. The Australian evidence of amplified advantage (Hannan & Eynon, 2025) and the Kenyan evidence of even gains (Major et al., 2026) are not competing estimates of one effect but descriptions of different configurations. In the first, adoption and intensity were left to schools, so tier placement followed existing advantage; in the second, a structured programme placed every participating classroom close to Tier B, with teachers able to override the sequence. The Ghanaian and seven-country pandemic evidence (Dang et al., 2025; Do et al., 2026) shows what happens when learning moves into Tier A by default.

The decomposition also qualifies meta-analytic optimism. If, as Létourneau et al. (2025) found, intelligent tutors gain less over non-intelligent tutoring systems than over ordinary teaching, much of the measured effect may reside in structured practice, feedback and pacing rather than in sophisticated adaptation. Practice with feedback is valuable, as the strong effects of game-based software in crisis settings confirm (Diazgranados & Thuo, 2026), but claims of "personalisation" should be read as claims mainly about pace and content. The pedagogical layer that Bloom's tutors supplied remains largely with teachers; Kestin et al. (2025) show that a generative tutor can be engineered to carry more of it, but in a trial with university students and an expert-designed system, far from a crowded lower-primary classroom in rural Malawi or northern Nigeria.

Against the theories in Section 2.2, the model extends more than it overturns. It agrees with mastery-learning theory that corrective feedback and time may explain much of what software achieves, but departs from any reading of Bloom (1984) in which software alone could reach two sigma, since his tutors' diagnosis and re-explanation belong to the pedagogical layer. It extends the layered account of Scheerder et al. (2017) by asking, at the level of outcomes, whether a teacher stands between the learner and the software. And where Bulathwela et al. (2024) and Selwyn (2024) argue that AI will not democratise education unaided, the model specifies how it may fail to: through discretionary use, the missing pedagogical layer and substitution for teachers.

For African school systems, the first implication concerns language. Alkateb-Chami (2024) links mismatch between home language and language of instruction to learning poverty across 56 countries, with Burundi as a case. A system that adapts pace in a language a child does not understand personalises the wrong thing, and language demand was among the features distinguishing the most effective Tanzanian apps (Huntington et al., 2023). The second concerns channel. Ghanaian universities' pandemic strategies for remote teaching centred on affordable internet access and technology resources (Kumi-Yeboah et

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al., 2023), South African reviewers name hardware, connectivity and funding as the main barriers in rural schools (Saal et al., 2025), and Kenya's SMS platform shows that adaptive logic can run on basic phones (Jordan et al., 2025). The third concerns teachers. Curriculum alignment, classroom management and dashboard design shaped uptake and results in Kenya (Daltry et al., 2025; Sun et al., 2026), and structured pedagogy, combining materials, training and ongoing support, already has a substantial evidence base as a response to low foundational learning in the region (Piper & Dubeck, 2024). Adaptive software is most defensible as a component of such programmes, not an alternative.

The two-tier danger is not that poor children receive software, which in Tier C may be much better than nothing, as the gains of out-of-school Tanzanian children suggest (Huntington et al., 2023). It arises when software is presented as a substitute for teachers and used to justify not hiring, training or supporting them, while advantaged children keep human teaching with technology as a supplement. Foundational scores might converge while gaps widen in what adaptive systems cannot teach: argument, oral language, collaboration and the motivational relationship with an adult who knows the child. This paper suggests that investor narratives casting public policy as failing and venture capital as rescue (Komljenovic et al., 2026) make this more likely, as does the absorptive-capacity problem: where foundational capacity is weak, technology is hardest to absorb (Khan et al., 2024), yet such systems may be the most tempted to substitute it for teachers. The evidence for this risk is inferential, and that is itself a finding: no study reviewed tracks non-foundational outcomes when adaptive systems replace teachers.

No proposition is accepted or rejected here; all are offered for empirical testing. P1 fails if audits of logged decisions find changes of content or pedagogy as frequent as changes of pace. P2 and P3 call for trials varying teacher involvement around the same software, and fail if the Tier B advantage is uniform across prior attainment and home language or shrinks over time. P4 fails if advantage predicts intensity of use no more under discretionary than scheduled deployment, and P5 if prioritised, aligned, low-technology rollouts do not narrow gaps. P6 needs comparisons of schools that do and do not substitute software for teachers on higher-order, oral, collaborative and socio-emotional measures; stable gaps would count against it. P7 is disconfirmed if withdrawing an unguarded assistant harms unaided performance no more without teacher oversight than with it.

Future research has three priorities. On the teacher's role, studies should observe what teachers do in Tier B classrooms, whether adaptive systems deskill or extend their practice, and how workload changes. On motivation, longer trials should track engagement decay, learner choice and teachers' motivational contribution. On outcome distribution, evaluations independent of developers should report quantile and subgroup effects, include higher-order and socio-emotional outcomes, follow learners beyond a school year and collect cost data.

5. CONCLUSION AND RECOMMENDATION

Adaptive learning systems are neither an equaliser nor a stratifier by nature; their distributive effect depends on which component of personalisation they deliver and on who is placed in which tier. Because, on the evidence reviewed, they appear to supply pace far more readily than pedagogy, they are likely to help most where a teacher supplies the rest, and the children who most need responsive teaching receive the least of it from software alone. The gravest risk is a quiet one: a settlement in which software is the education of the poor and teachers the privilege of the rest.

Five deployment principles follow: teacher-complementary design, protected in-school dosage, language and curriculum alignment, low-technology channels and distribution-sensitive monitoring. In African systems, ministries of education should not let spending on adaptive technology displace investment in teacher posts, training and coaching, and should plan it within structured-pedagogy programmes. Use should be scheduled in school time with protected dosage rather than left to household discretion, and rollout should begin with the schools and learners furthest from access. Procurement should require curriculum alignment, content in the language of instruction and, where possible, learners' home languages, and delivery through basic phones, offline devices or other channels the poorest schools

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can sustain. Ministries should also monitor adaptive programmes by subgroup and quantile, not only by average score.

Developers and funders should build adaptive systems as teacher-facing as well as learner-facing tools, with dashboards co-designed with teachers, teacher authority to override sequences and guardrails that stop generative assistants completing learners' work, and should audit fairness by language, disability, rurality and poverty as well as gender. School leaders and teachers should assign and monitor adaptive work rather than leave it to learner choice, treating system data as a prompt for pedagogical judgement, not a substitute for it.

6. CONTRIBUTION TO EXISTING KNOWLEDGE

Theoretically, the paper decomposes personalisation into pace, content and pedagogy and argues, as a testable proposition (P1), that adaptive systems supply these unequally, which would explain why average effects say little about equity. Its three-tier access model joins mastery-learning, digital-divide and critical accounts in one configurational explanation. Practically, it offers deployment principles for low-resource, and especially African, school systems, grounded in the available African evidence, chiefly Kenyan, Sierra Leonean, Tanzanian and Ghanaian. For research, it supplies seven falsifiable propositions and an agenda on the teacher's role, learner motivation and the distribution of outcomes. The contribution is conceptual; its value depends on whether the propositions survive empirical test.

7. REFERENCES

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