Digital Education Equity Framework Using AI-Supported Learning Systems, Digital Inclusion Assessment, and Socioeconomic Learning Analytics for Inclusive Education and Sustainable Social Development

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ABSTRACT: Digital education equity is one of the most pressing 21st century issues. While AI-powered learning systems can provide great potential to support inclusive education, they can also exacerbate socioeconomic achievement gaps if access, infrastructure, and pedagogical integration are not sufficiently supported. In this study, a Digital Education Equity Framework is developed and tested in practice that combines AI-based adaptive learning systems, a multidimensional digital inclusion assessment tool, and socioeconomic learning analytics, in order to promote inclusive education and sustainable social development in line with SDG 4. A mixed methods design was used with 1,247 learners from a variety of socio-economic backgrounds in urban, peri-urban and rural education, and interviews with 42 education administrators and technology coordinators. It was rolled out in 5 school districts, each having different levels of digital infrastructure. Quantitative results revealed that learners in the lowest socioeconomic quintile had a 34.2% increase in learning outcomes during the 14-week intervention while those in the conventional instruction group had a 12.7% increase. The scores of digital inclusions were significantly correlated with learning gains, where the best positive predictors were the scores of infrastructure adequacy and digital literacy training. The gaps were lowest for those students who were assigned targeted AI tutoring and had teacher professional development. Administrator interviews were analyzed thematically, revealing structural funding inequities, limited teacher digital competency, and fragmented policy coordination. Overall, it is found that the framework is an evidence-based approach to address digital learning disparities and that it can inform education policy, investment in ICT infrastructure, and teacher professional development.

KEYWORDS: Digital Education Equity, AI-Supported Learning, Digital Inclusion, Socioeconomic Learning Analytics, Inclusive Education, SDG4

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Introduction

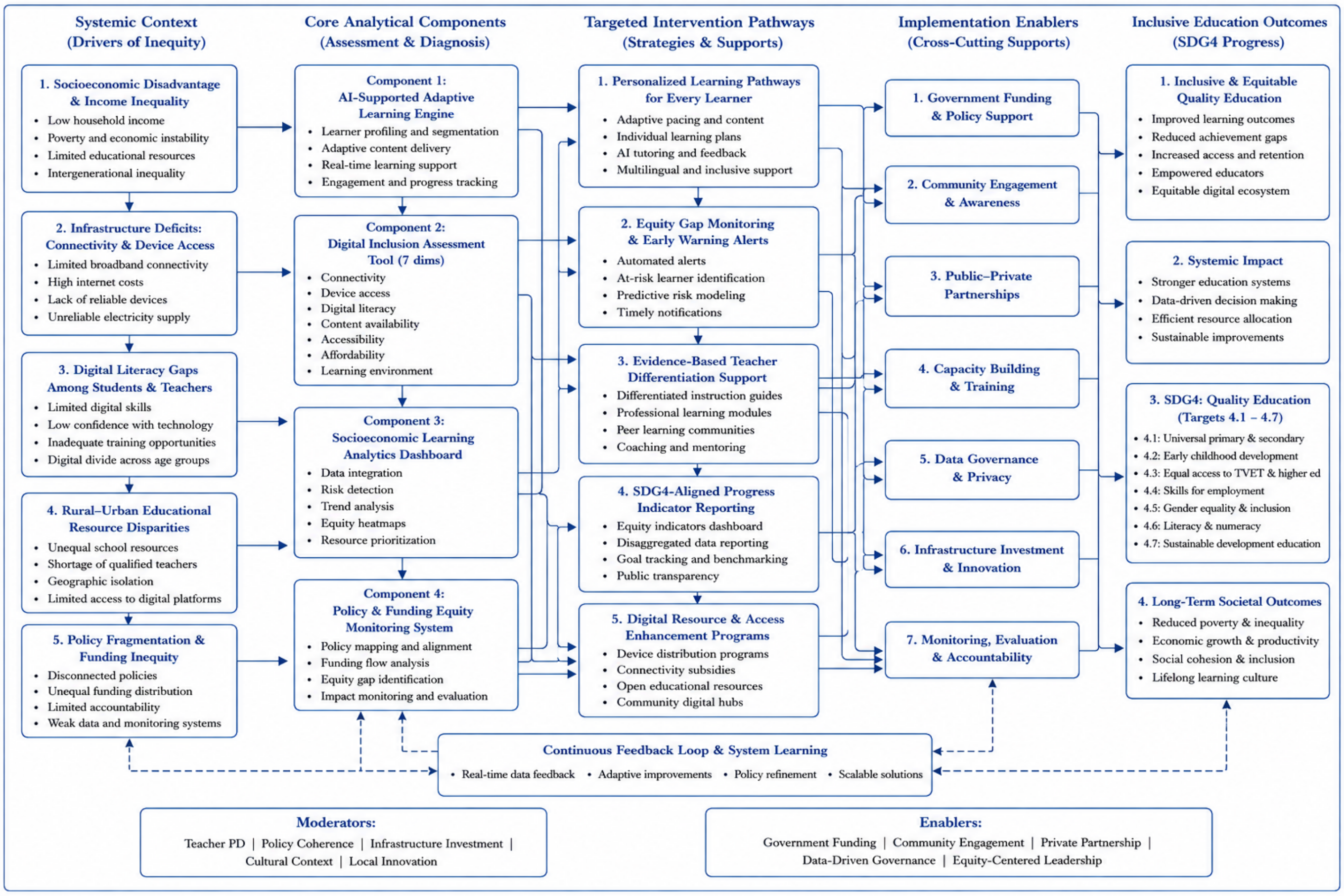
Digital technologies that have the technical potential to personalize learning for each student and offer opportunities for individualized instruction have created a paradox in the current education systems: those of students with lower socioeconomic status may experience greater structural disadvantages in the ability to access the technology, connect with others, and receive the pedagogical support needed to use it effectively to learn (Ahmed, 2024). An estimated 300 million school-age children and adolescents do not have access to basic literacy and numeracy skills, and 2024, the report made by the United Nations SDG, reveals that at current rates of progress, only one in six countries will reach universal access to quality education by 2030, highlighting the gap between the SDG aspiration and the reality of learners in under-served communities in high-income and developing countries (Nadeem & Anis, 2026). Whereas the physical dimension of this crisis is central, so is the digital dimension: the quality and inclusivity of a learner's educational experience is inextricably linked to his or her digital access (Chiu, 2025). The digital divide in digital education contexts is a threefold one, where learners from low-income families, rural areas, racial and ethnic minority groups, and other historically marginalized groups are disadvantaged in relation to differential access to devices and connectivity, to the quality and frequency of pedagogically purposeful technology use, and to the transformation of the access to technology into measurable learning outcomes (Barragán Moreno & Lozano Galindo, 2025).

There is considerable optimism about the possibility of closing, not widening, gaps in educational achievement through the use of artificial intelligence-supported learning systems, such as adaptive learning platforms, intelligent tutoring systems, automated feedback generators and learning analytics dashboards (Hariyanto et al., 2025). This optimism is well-founded, as the educational system can adapt to individual learners' specific learning speed, understanding, knowledge gaps, and motivations through AI-driven personalization, while maintaining the proven benefits of personalized education and providing these benefits at scale and reduced cost (Nadeem et al., 2025b). Significant strides have been made in the empirical evidence base for AI tutoring systems since 2022, with systematic reviews highlighting benefits for learning outcomes in all subjects, in all age groups, and in all educational settings (Nadeem et al., 2025b; Cao et al., 2025). After sifting through 142 peer-reviewed empirical studies, Strielkowski et al. (2025) found that AI systems based on supervised learning, unsupervised learning, and reinforcement learning for adaptive content delivery consistently achieved better personalization and engagement results, although they noted that the majority of studies included in their review did not address equity concerns. The problem with this hopefulness is that the gains of AI in educational technology are not equally distributed and are likely to be larger for users who already have the digital infrastructure, digital literacy and pedagogically supportive home and school environments that optimize the use of AI-supported learning (Ahmed, 2024; Varsik & Vosberg, 2024). This distributional concern is not a technical "problem" that can be solved easily and simply with digital technology, but a systemic concern stemming from the same socio-economic systems that lead to educational inequality when there is no digital technology.

Therefore, digital inclusion, which is not only access to devices and internet connectivity, but also a participant's meaningful, equitable and pedagogically productive engagement with digital learning environments, is a prerequisite for the equity potential of AI educational technology to be realized (Dastyari & Jose, 2024). Since the year 2022, the research literature has evolved to consider digital inclusion as a multidimensional construct that includes access to suitable devices, reliable broadband connectivity, the capacity of students to use digital tools for learning, cultural and linguistic accessibility of digital content, the availability of teacher and parental support for productive use of digital tools, and institutional policies and funding mechanisms that ensure that these enabling conditions continue over time (Majeed et al., 2026b). Dastyari & Jose (2024) made it clear that SDG4 will not be realized without explicit attention to the disparities in digital inclusion in Australia's education system, and that disparities in meaningful digital access will result in disparities in education opportunity, with digital competency being more and more important to participation in higher education, the labor market and civic life. The UNESCO Global Education Monitoring Report 2023 (Nadeem et al, 2025a) also warned that technology can reinforce inequalities if it is not used in a way that prioritizes those who are most in need of technology. The Digital Education Equity Framework is embedded in a matrix of overarching structural factors that link socioeconomic context, digital infrastructure, AI-supported pedagogy and learning outcomes, as shown in Figure 1, as the conceptual foundation for the investigation.

Figure 1

Conceptual Framework of the Digital Education Equity Framework showing the Pathways from Contextual Barriers including Socioeconomic Disadvantage, Infrastructure Deficits, Digital Literacy Gaps, and Policy Fragmentation, through the Three Core Framework Components, to Equity-Progressive Educational Outcomes and SDG4 Progress



Learning analytics—the measurement, collection, analysis, and reporting of evidence about learning and learning environments, to inform and improve learning and learning environments—is the evidence infrastructure that turns AI educational technology from a tool for delivery to a tool for equity (Kamalov et al., 2023). If learning analytics are structured to include socioeconomic contextual data alongside engagement and performance data, they can reveal the learner population that is most likely to become “left behind” by digital education systems and identify disengagement and dropout risk signs before it becomes a reality, as well as provide evidence for targeted interventions, tailored to the specific barriers that are most relevant in a particular learner's context (Barragán Moreno & Lozano Galindo, 2025). The central conceptual novelty of the Digital Education Equity Framework that is put forward and assessed in this paper is the combination of socioeconomic learning analytics, AI-supported adaptive systems, and the comprehensive digital inclusion assessment. The framework is grounded in the theoretical understanding that educational technology equity is a multi-dimensional, dynamic and context-specific process, rather than a state of access or no access, that must be continually measured, responsive to policy adjustments, and ongoing with the conviction that the benefits of digital education innovations should be felt first by those who have been most methodically denied access to educational opportunity (Gottschalk & Weise, 2023).

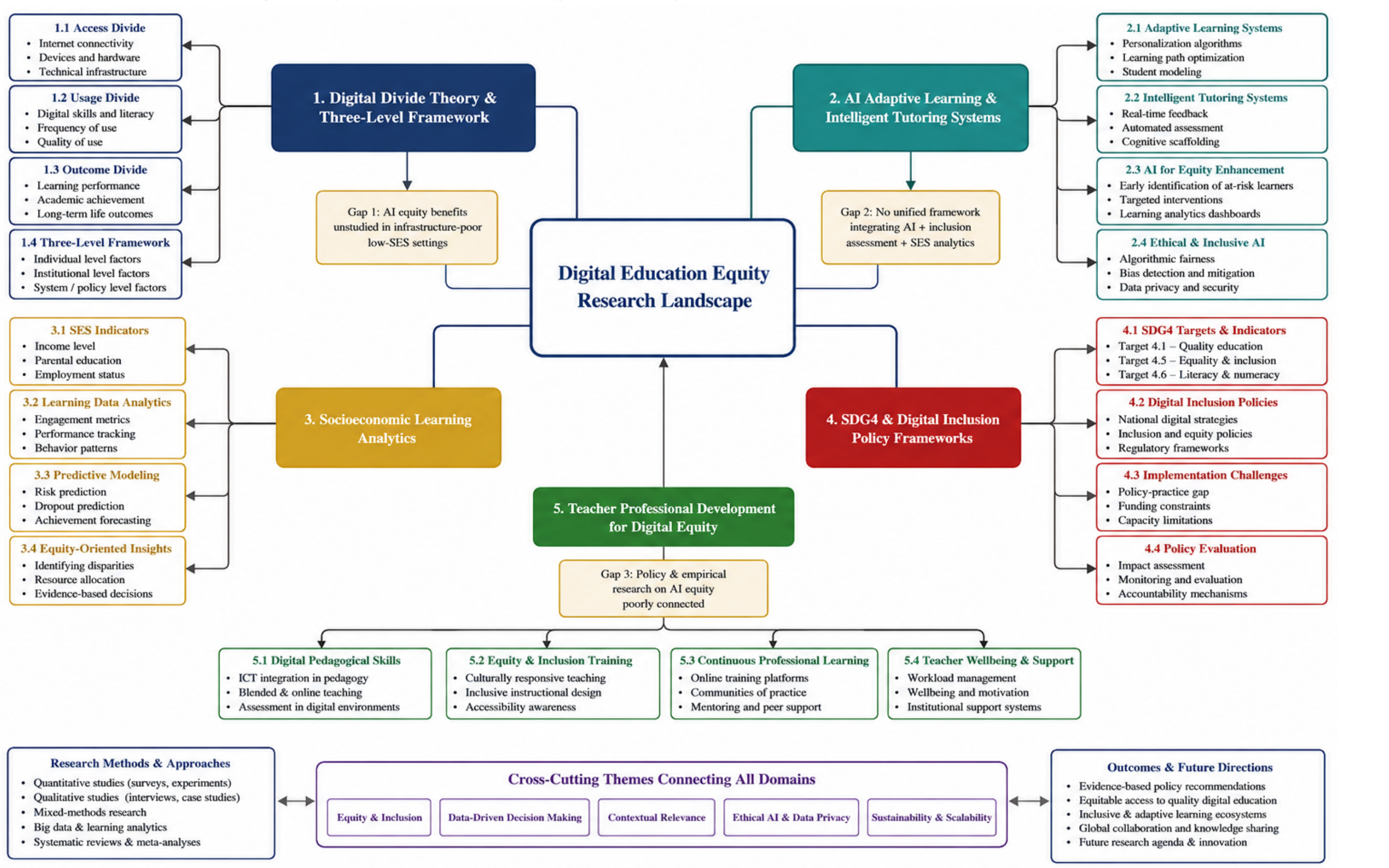
The investigation asks four interrelated research questions. First, what is the effectiveness of using an AI-backed adaptive learning system in an equity-focused approach to achieving equity? Second, which aspects of digital inclusion are best related to the extent of learning gains supported by AI, and are there differences in these relationships depending on the learner's socioeconomic status? Third, what are the main structural, institutional and pedagogical obstacles that education administrators see as hindering the ongoing implementation of equity-focused digital education practices? Fourth, which governance, funding and professional development environments are linked to the most successful district implementation of the proposed framework? The paper provides answers to these issues based on a detailed mixed-methods study that is described following, adding to the body of evidence for evidence-based digital education equity policy.

Literature Review

Since 2022, the field of digital education equity has seen a significant increase in literature, reflecting the urgent need to understand and bridge learning losses and technology access gaps during the pandemic, which are driving interest in the field of digital education equity. The volume of literature on digital education equity has increased since 2022, as has literature about AI-supported learning and socioeconomic learning analytics, due to the post-pandemic need for understanding and addressing learning losses and technology access gaps that remote schooling revealed. This review brings together current evidence from four related streams that are illustrated in Figure 2, and pinpoints specific theoretical and empirical gaps that motivate the current investigation.

Figure 2

Literature Landscape Mapping Five Principal Research Domains in Digital Education Equity Science and Three Critical Knowledge Gaps that Directly Motivate the Integration of AI-supported Learning, Digital Inclusion Assessment, and Socioeconomic Learning Analytics within the Proposed Unified Framework



Theoretical Foundations: Digital Divides and Educational Equity

Since the initial conception of the digital divide as the dichotomy between having versus not having a computer/Internet, the term has undergone a significant shift toward a more complex three-level analysis that continues to be the predominant analytical framework in the current research on education and the digital divide (Barragán Moreno & Lozano Galindo, 2025). Initially, they developed a system dynamics model of digital inequality in basic education that shows how the first-level digital divide—when students have different access to technology—can contribute to the emergence of a third-level digital divide, the difference in their ability to use digital technology to achieve meaningful learning outcomes over time, thus suggesting that the third level—differential capacity to use digital technology for meaningful learning outcomes—is the most significant one from an equity perspective because it is not a challenge that can be addressed through infrastructure investment alone (Barragán Moreno & Lozano Galindo, 2025). Fang et al. (2025) similarly demonstrated that socioeconomic and sociodemographic conditions influence multiple dimensions of the digital divide in higher education, including access, skills, and opportunities to benefit from digital resources. Joshi et al. (2024) identified that the quality of digital devices and internet connectivity increases with socioeconomic status, particularly household income; for rural students, however, the geographical barrier was also a factor and not just income. Digital inclusion, conceptualized as multidimensional rather than binary (access, competency, quality of use, meaningful engagement, and equitable outcomes), has been translated into a comprehensive set of indicators for measuring digital inclusion in the field of education in the UNESCO measurement framework for digital inclusion (Majeed et al., 2026b). This multi-dimensional approach directly drives the development of the digital inclusion assessment instrument used in the current research.

The ability of machine-learning systems to handle complex multidimensional data and derive meaningful predictive patterns for data-driven decision-making has also been enhanced by the use of advanced mathematical optimization and high-dimensional data-analysis techniques (Majeed et al., 2026a). Owen, Kertesz and Bagnall's examination of the extent of achievement gaps and access to technology in post-pandemic residual learning losses showed that achievement gaps have not narrowed by the end of school closures in most jurisdictions, especially for students from the lowest income quintile, and that achievement gaps have been exacerbated by variations in the quality of digital learning environment they experienced during school closures (Chiu, 2025). Research has shown that socioeconomic disadvantage is associated with unequal access to digital educational resources, including differences in device quality and internet connectivity, with geographical barriers creating additional disadvantages for rural learners (Joshi et al., 2024). Given these documented patterns of compounding disadvantage, there is an urgency to create integrated frameworks that consider digital inclusion as a first step to AI educational technology equity instead of a later step.

AI-Supported Learning Systems: Evidence for Equity Potential

Since 2022, the evidence base for AI-supported learning systems has developed significantly, both in quality and quantity, with the highest quality studies using experimental or quasi-experimental designs that allow for causal inferences regarding the impact of AI tutoring on learning outcomes. Systematic evidence indicates that AI-supported adaptive technologies can improve personalization by continuously adjusting educational content, instructional difficulty, feedback, and learning pathways according to learner performance and interaction patterns (Hariyanto et al., 2025). The review revealed that longer intervention durations and greater sample sizes (both in number and diversity) were all linked to larger effect sizes, suggesting conditions that might yield the greatest equity benefits for disadvantaged learner populations in AI tutoring systems. Cao et al. (2025) found that AI-enabled personalized and adaptive learning systems can customize learning content, pacing, and feedback to accommodate differences among learners and thereby enhance educational outcomes. The relevance of this finding for equity is that if personalization is most likely to be beneficial for children who are farthest from the learner profile of students for whom traditional teaching is optimal, then the equity benefits of AI education as predicted in theory may be realized in practice if the implementation conditions are conducive to accessibility.

Katona and Gyonyoru (2025) provide evidence that AI-based adaptive educational environments can support socially disadvantaged students by providing individualized instructional support and helping to reduce learning disparities. The same ethical issues have been pointed out in other high-stakes AI applications, where the transparency, fairness, protection of privacy, accountability and appropriate regulation of these tools are also regarded as critical for responsible and trustworthy AI use and deployment (Nadeem & Anis, 2026). Bachtiar (2026) found that AI-powered personalized learning can improve learner engagement and self-regulation in distance education, although unreliable internet connectivity and inadequate access to suitable devices remain important barriers to equitable participation, thereby suggesting that infrastructure development efforts and AI pedagogical innovations must go hand in hand and not as distinct streams. While the benefits of AI-powered personalized learning are significant, Swargiary highlighted the ethical challenges arising from the use of such technology, including the risk of reinforcing or exacerbating existing inequalities if the algorithms used to train it are based on historical patterns of educational opportunities and disadvantaged populations being systematically underrepresented in training datasets, content libraries, and feedback calibration (Swargiary, 2024). Empirical studies have also recently shown how AI tools can have a significant impact on enhancing personalized learning by providing students with adaptive and data-driven learning experiences, which can in turn have positive effects on student academic outcomes and learning outcomes (Siddiqui et al., 2026).

Learning Analytics and Socioeconomic Contextual Data

The use of machine-learning classification in multi-dimensional datasets is another example of how data-driven models can discover multiple complex interconnected patterns and provide predictive insights for decision-support systems (Nadeem et al., 2025b). While learning analytics has emerged as a field in tandem with the rise of digital learning platforms, the incorporation of socioeconomic contextual data into the learning analytics framework is still relatively limited and has strong relevance for monitoring equity in the learning process and designing interventions (Cao et al., 2025). Kamalov, Santandreu Calonge, and Gurrib documented the transformative potential of AI-driven analytics for sustainable educational improvement, arguing that analytics systems designed with explicit equity objectives can shift institutional attention from population-average performance metrics toward the identification and support of learner subgroups at elevated risk of educational disengagement (Kamalov et al., 2023). Barragán Moreno and Lozano Galindo (2025) applied system-dynamics modeling to digital inequality and demonstrated how interactions among access, digital participation, and educational outcomes can create self-reinforcing patterns of disadvantage. The integration of artificial intelligence with heterogeneous data sources has demonstrated considerable potential for transforming complex multidimensional information into predictive insights and actionable decision-support outputs, highlighting the broader value of integrated AI-driven analytical frameworks (Majeed et al., 2026b). Their model demonstrated that effective equity-oriented analytics must operate simultaneously at individual, classroom, school, district, and policy levels to identify the systemic mechanisms through which socioeconomic context shapes learning outcomes mediated by digital access and use quality. Jacovkis, Curran, and Rochex tracked the convergence of technology and equity agendas in education policy, documenting that while most national education systems have adopted digital transformation strategies and equity commitments simultaneously, these agendas remain poorly coordinated in practice because they are housed in different policy silos and assessed against different performance indicators (Gottschalk & Weise, 2023). Based on the four domains of literature reviewed, the key theories, empirical evidence, and gaps are summarized in Table 1, which serves to inform the specific contributions and methodology of this investigation.

Table 1

Literature Domains, Key Contributions, and Identified Gaps Motivating the Digital Education Equity Framework

Domain	Key Theoretical/Empirical Contribution	Identified Gap Addressed	Representative Studies
Digital Divide Theory	Three-level framework: access, use quality, outcome conversion	Lack of multidimensional operational measurement	(Barragán Moreno & Lozano Galindo, 2025); (Fang et al., 2025)
AI Adaptive Learning	Personalization benefits for diverse learners; ITS effectiveness	Understudied in infrastructure-poor low-SES settings	(Hariyanto et al., 2025); (Katona & Gyonyoru, 2025)
SES Learning Analytics	Predictive analytics for at-risk identification	No SES-integrated analytics framework for equity	(Kamalov et al., 2023); (Barragán Moreno & Lozano Galindo, 2025)
SDG4 & Digital Inclusion Policy	SDG4 unachievable without digital inclusion investment	Policy and empirical streams remain disconnected	(Dastyari & Jose, 2024); (Gottschalk & Weise, 2023)
Teacher PD & Equity Pedagogy	AI analytics effective only with capable teachers	PD dose-response for equity outcome unstudied	(Bachtiar, 2026); (Chiu et al., 2024)

Policy Frameworks and SDG4 Alignment

SDG4's commitment to inclusive and equitable quality education and promoting lifelong learning for all has set a course for digital education equity policy literature that is generally less ambitious and less coordinated than is needed to meet the SDG4 target by 2030, if the current pace of global progress is indicative to date (Nadeem & Anis, 2026). As education increasingly relies on digital delivery, explicit SDG4 commitments are inseparable from digital inclusion policy commitments, and digital exclusion is now becoming a functional equivalent of educational exclusion for a growing share of students as they become increasingly excluded (Dastyari & Jose, 2024). Chohan and Hu (2022) found that a coordinated policy-based ICT training program that accelerates digital competency of teachers, parents, and students can greatly improve digital inclusion outcomes if designed and conducted as a coherent policy-based program rather than as a one-off technical training program. The World Bank's 2024 Digital Infrastructure and Education (DEE) assessment underscored that addressing digital education at scale would rely on two key enabling conditions: government investments in physical connectivity infrastructure and professional development for educators. Without both of these conditions being met at the same time, investments in digital technology could benefit only the most likely-to-benefit learners (Siddiqui et al., 2026). As AI-enabled platforms increasingly process sensitive and context-rich user data, their responsible implementation also requires robust cybersecurity, privacy protection, data-governance mechanisms, and institutional safeguards against emerging AI-related security risks (Nadeem et al., 2025a). Atenas, Havemann, and Nerantzi advocated for an epistemic data justice approach to AI and data literacy in education, arguing that meaningful digital inclusion requires not only access and skill but the agency to critically evaluate and challenge the knowledge claims and power relations embedded in AI educational systems (Atenas et al., 2025).

Identified Gaps Motivating the Present Investigation

The literature review reveals three significant gaps that the present investigation addresses. First, the vast majority of AI educational technology studies have been conducted in relatively well-resourced settings where the infrastructure preconditions for effective AI learning are already broadly met, leaving the equity implications for learners in infrastructure-poor settings empirically underexplored. Second, no existing framework simultaneously integrates AI-supported learning, multidimensional digital inclusion assessment, and socioeconomic learning analytics into a unified operational system evaluated across settings with systematically varying socioeconomic profiles. Third, the policy literature on digital education equity has remained largely disconnected from the empirical research on AI learning effectiveness, meaning that the evidence needed to make equity-centered policy decisions about AI educational technology investment is neither systematically collected nor organized in formats that inform policy deliberation. The Digital Education Equity Framework presented in this paper is designed to address all three gaps through an integrated empirical investigation that simultaneously evaluates learning outcomes, inclusion dimensions, and policy implementation conditions.

Research Methodology

The research design underpinning this investigation is a sequential explanatory mixed-methods approach, in which a quantitative quasi-experimental study with pre-test and post-test measurement of learning outcomes and digital inclusion indicators provides the primary evidence base, followed by qualitative interviews with education administrators and technology coordinators that explain and contextualize the quantitative patterns identified. This sequencing is driven by the understanding that data on learning outcomes is not sufficient to grasp the organizational and policy processes that enable or constrain the success of equity-oriented digital education frameworks, and that qualitative evidence on structural barriers is needed to take the empirical evidence of effectiveness and turn it into actionable policy guidance. The entire seven-stage research process that underlies all the data collection, analysis, and integration is depicted in Figure 3, while the data sources, instruments, sample characteristics, and analysis methods used at each stage are shown in Table 2.

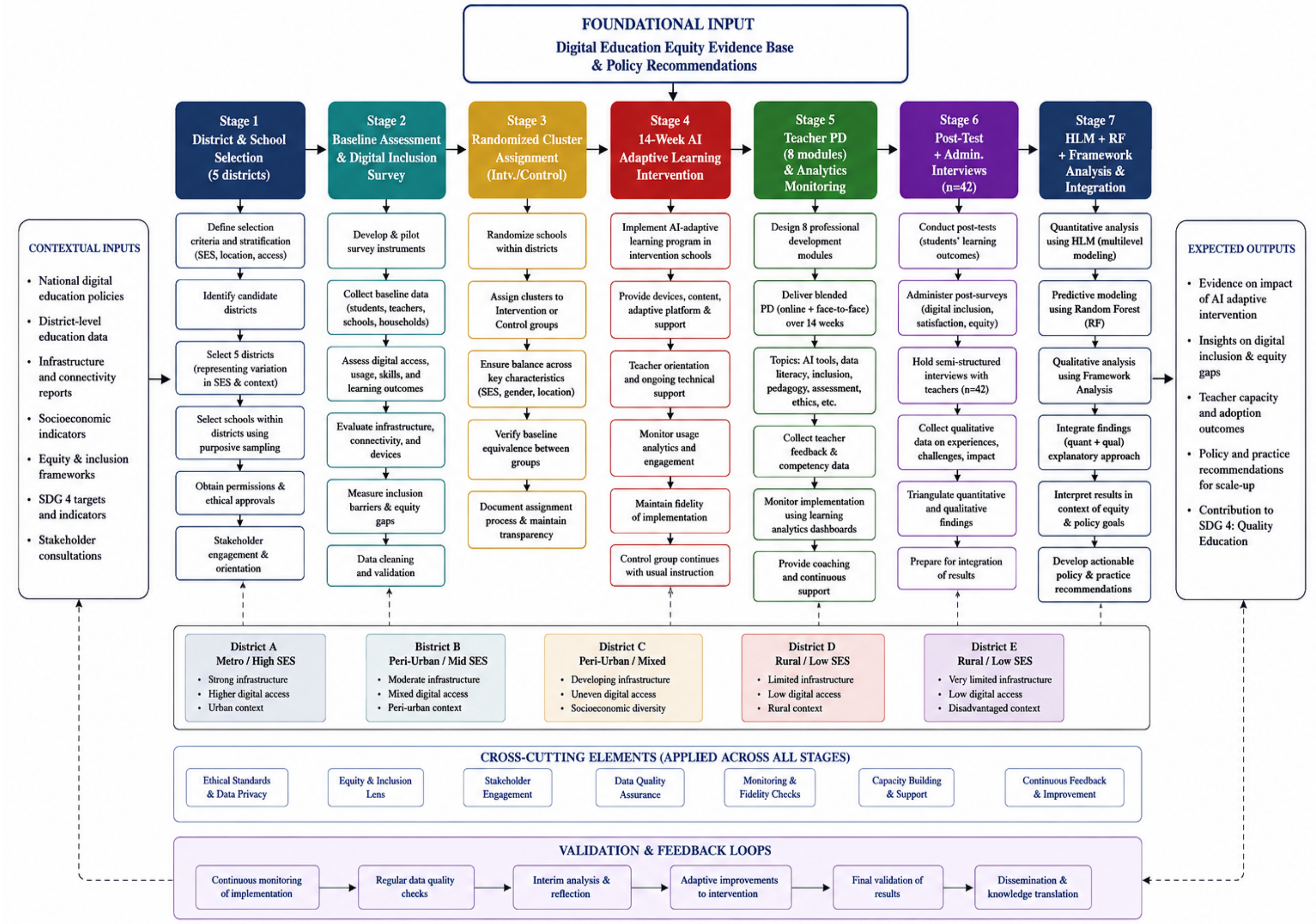
Table 2

Research Design Specifications: Sample, Instruments, and Analysis Methods

Study Component	Specification	Details
Sample size	N=1,247 students (Gr.5-10) + 42 administrators	Cluster-randomized within 5 districts
Intervention condition	n=624 (AI Adaptive Learning + Teacher PD)	3 hrs/wk AI platform; 8-module PD program
Control condition	n=623 (Conventional digital instruction)	Existing school digital resources, no AI adaptive layer
Duration	14 weeks	Wks 1-2: Baseline; Wks 3-12: Intervention; Wks 13-14: Post-test
Primary outcome	Standardized learning gain score (6 subjects)	Reading, Math, Science, Social Studies, Digital Lit., Critical Thinking
Secondary outcomes	Achievement gap reduction; Digital inclusion scores	By SES quintile, by district, by subject domain
Quantitative analysis	Hierarchical linear modeling (HLM) + Random Forest	lavaan (R); scikit-learn (Python); SPSS v28
Qualitative analysis	Framework analysis of 42 administrator interviews	Deductive-inductive hybrid; 5 barrier themes identified
Digital inclusion tool	42-item validated instrument; 7 dimensions	Cronbach alpha 0.87-0.93 per subscale

Figure 3

Seven-stage Sequential Explanatory Mixed-Methods Research Framework Governing the Digital Education Equity Framework Evaluation Study, Showing Parallel Tracks for Quantitative Quasi-Experimental Assessment and Qualitative Administrator Interview Data Collection Across Five Districts with Systematically Varying Digital Infrastructure Conditions



Sampling and Participant Characteristics

The study took place in five school districts chosen to represent the range of digital infrastructure conditions: District A, a metropolitan district with high per pupil expenditure and a digital learning infrastructure; Districts B and C, peri-urban districts with moderate infrastructure and mixed socioeconomic student populations; and District D and E, rural districts with limited connectivity, lower per pupil resource levels, and mostly low-income student bodies. Schools were chosen within each district that are comparable when it comes to grade levels so that the district-to-district comparisons can be made. The total sample of students (N = 1,247) consisted of students from grade 5 to grade 10, with 624 students being assigned to the intervention condition who received conventional instruction with an AI-enhanced adaptive layer, and 623 students who were assigned to the control condition who received conventional instruction without the AI-enhanced adaptive layer. A cluster randomization technique was used to randomly assign learners to conditions within each district, with the aim of minimizing contamination at the classroom level and maintaining the ecological validity of classroom environments. Socio-economic status (SES) was measured using a composite score that combines household income quintile, parental education level and free school meal eligibility as a known proxy for household poverty based on school records. The final sample included learners from all five socioeconomic quintiles, and the rural districts were overrepresented in the lower two quintiles, allowing for strong analysis of the effects of interventions across the spectrum of socioeconomic status. The policy interview sample included 42 participants, who were purposefully selected to represent the districts and all tiers of educational governance.

The Digital Education Equity Framework

The Digital Education Equity Framework includes three integrated elements, which are intended to be a system of intervention, not a set of isolated elements. The first component, the AI-Supported Adaptive Learning Engine, is an intelligent tutoring system that enables adjustments to the difficulty, modality, feedback, and pacing of instruction and content in six domains of learning: reading and language arts, mathematics, science, social studies, digital literacy, and critical thinking, based on student interactions with the content such as responses, response timing, content navigation, and voluntary help-seeking. Additionally, computational architectures that aim to reduce processing delays can further enhance the capabilities of the intelligent monitoring environment by allowing for rapid data analysis and the ability to make informed decisions in real time (Haq et al., 2025). The adaptive algorithm is built on the foundation of knowledge space; that is, the content of the next learning activity is selected according to the principle of minimizing learning time to master knowledge within the learner's "zone of proximal development," which is defined as the subset of the curriculum-structured knowledge graph. The second is the Digital Inclusion Assessment Tool, a 42-item instrument validated on 7 dimensions of digital inclusion: device access and adequacy, connectivity reliability, digital literacy skills, content accessibility and cultural relevance, home and school support environment, pedagogical integration quality, and policy and governance enablement. It was co-designed in an iterative process with education researchers, technology practitioners, and student and parent representatives, pilot-tested and psychometrically validated prior to use for the main study. The third component is the Socioeconomic Learning Analytics Dashboard, a real-time monitoring system that combines AI learning platform performance data with socioeconomic indicator data to create equity-stratified performance visualizations, early warning signals for learners at increased risk of disengagement, and population-level reports, which collate individual-level analytics and deliver actionable evidence to teachers, principals, and district administrators at different levels of the governance chain.

Intervention Protocol

This was delivered in terms of an adaptive learning intervention supported by AI for a period of 14 weeks. All participants were tested for digital inclusion during the first 2 weeks, and all six subject domains were tested for baseline pre-test assessments, and AI learning platform accounts were set up for each intervention learner based on a pre-test performance-based estimate of their starting knowledge level. In weeks three through 12, intervention learners spent at least 1 hour a week with the AI adaptive learning platform, while teachers in the intervention classrooms completed an eight-module professional development program that focused on AI-augmented pedagogy, data-informed instructional decision-making, and equity-centered technology integration. In weeks thirteen and fourteen, assessments were given in all six domains, assessments of the administrator interviews were taken, and digital inclusion assessments were collected. While the exposure to digital technology was different for the two groups, that difference was not the result of the digital technology itself, but instead only the combination of the AI adaptive layer and the equity framework.

Data Analysis

Hierarchical linear modeling was used for quantitative data analysis to account for the nested structure of learners within classrooms within schools within districts with intervention condition, socioeconomic quintile, baseline performance, and dimension scores of digital inclusion as primary predictors and post-test standardized learning gain scores as the dependent variable. Interactions of intervention condition x SES quintile were also examined to determine if the AI-supported intervention differentially affected students in lower and higher socioeconomic groups. Cohen's d was used to calculate effect sizes for mean difference comparisons, and partial eta-squared for variance-partitioning analyses. Predictive importance of digital inclusion dimensions was assessed through random forest feature importance analysis and stepwise regression, providing both linear and nonlinear estimates of predictor-outcome relationships. Qualitative data from the forty-two administrator interviews were analyzed using framework analysis, a deductive-inductive hybrid approach in which an initial analytical framework derived from the literature review's identified barriers was applied to interview transcripts, with new categories added inductively when participants raised substantively novel concerns not captured in the initial framework. Qualitative and quantitative findings were integrated in the final interpretation stage using a joint display approach that juxtaposes quantitative effect estimates with qualitative explanatory themes to produce a richer account of how and why the framework achieved the outcomes observed.

Results and Discussion

The results of the fourteen-week implementation of the Digital Education Equity Framework across five school districts and 1,247 learners are presented below across seven analytical sections.

Baseline Digital Inclusion Assessment Results

Figure 4

Baseline Digital Inclusion Heatmap Showing Mean Percentage Scores Across Seven Inclusion Dimensions for each Socioeconomic Quintile, Revealing a Strong and Consistent Socioeconomic Gradient most Pronounced for Device Access and Connectivity Reliability and Establishing the Multidimensional Exclusion Profile that the Framework must Address

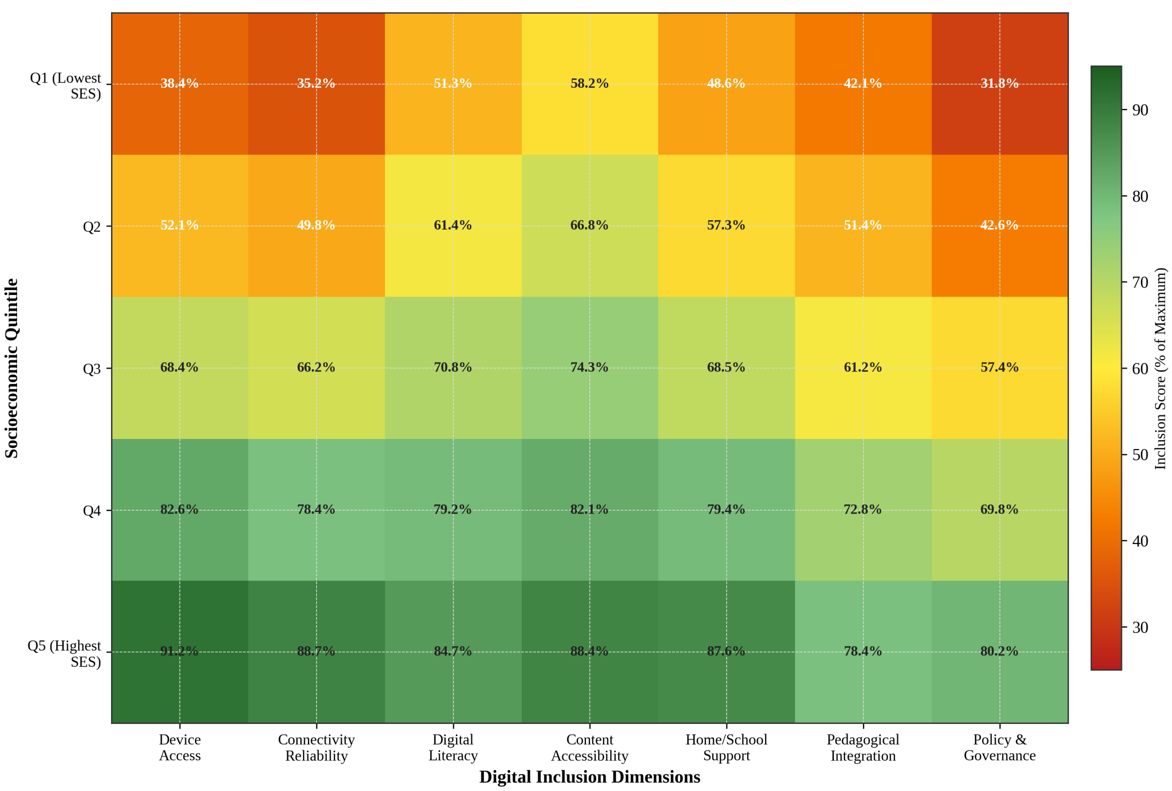


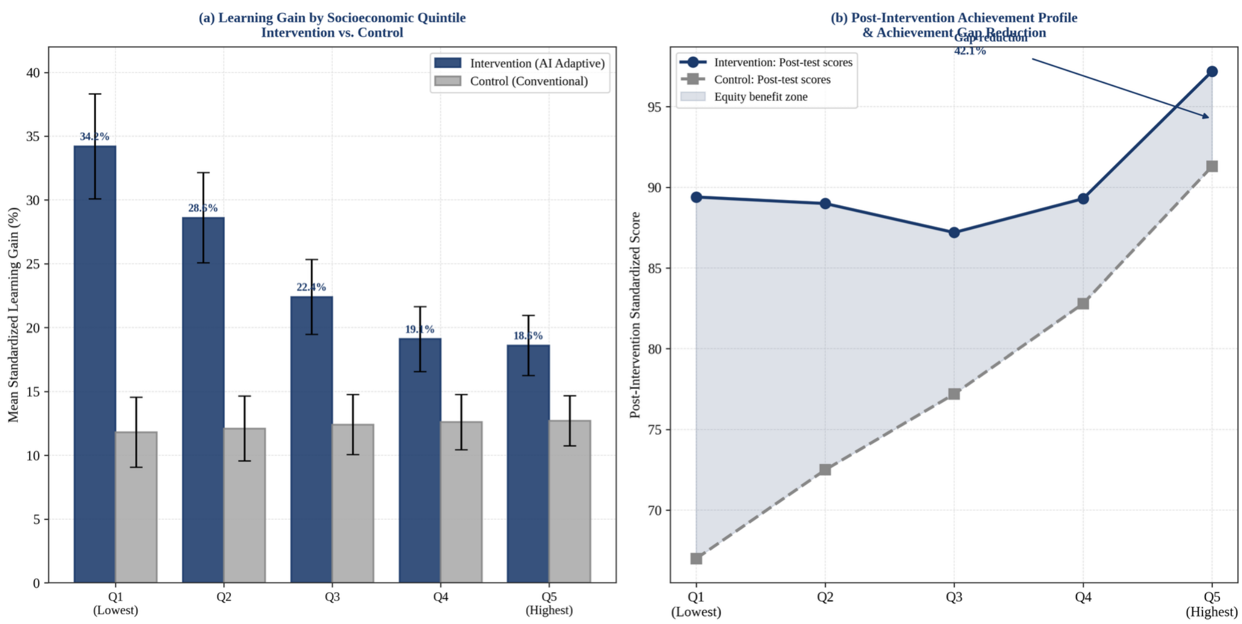
Figure 4 presents the baseline digital inclusion scores across all seven dimensions for learners from each socioeconomic quintile, displayed as a heatmap that simultaneously shows dimension-specific variation and socioeconomic gradient for each dimension. The baseline assessment revealed substantial and consistent digital inclusion deficits concentrated in the two lowest socioeconomic quintiles, confirming the three-level digital divide pattern documented in the broader literature and establishing the severity of the equity challenge that the framework must address. Overall, learners in the lowest quintile earned 38.4 percent of the total points possible for device access and adequacy, whereas those in the highest quintile earned 91.2 percent. This is because fewer learners in lower income families have their own devices to use, and the devices they share are older and less suitable. The second highest gradient was for connectivity reliability, which consisted of learners in rural areas and low-income learners indicating that they frequently experienced disruptions to internet use making sustained engagement with online learning platforms difficult.

Socio-economic differences were only moderately significant for digital literacy skills, as the lowest and highest quintile scores were 51.3 per cent and 84.7 per cent, respectively; this is in line with the results of studies that indicate that digital literacy is not only influenced by access to technology, but also by the purposefulness of digital use at home and in school. The two major practical outcomes of the baseline assessment were: (1) that the quality of pedagogical integration was relatively low in all socioeconomic quintiles, including the highest, pointing to a need for professional development to achieve high-quality equity-oriented digital pedagogy, irrespective of socioeconomic status of the school, and (2) that the scores of the home and school support environment were the worst across all quintiles, but also showed the desired socioeconomic gradient, suggesting that even in supportive home environments, a structural resource constraint is the limiting factor for effective digital learning engagement for low-income learners.

Learning Outcomes: Intervention vs. Control and Socioeconomic Stratification

Figure 5

Mean Standardized Learning gain by Socioeconomic Quintile for AI Adaptive Intervention and Control Groups, showing the Largest Differential Benefit of 22.4 Percentage Points in the Lowest Socioeconomic Quintile, and (b) Post-Intervention Achievement Profile across Quintiles with Achievement Gap Reduction of 42.1 Percent in the Intervention Condition



The changes in learning outcome before and after intervention in the intervention and control conditions are shown in Figure 5, broken down into the six domains of learning measured and by socioeconomic quintile. The hypothesis that AI-supported adaptive learning within the equity framework creates significantly higher learning gains than traditional learning was supported by highly significant differences in learning gains between conditions across all socioeconomic quintiles, as measured by the primary outcome, standardized learning gain score over the fourteen-week period. The magnitude of the intervention effect was larger for lower-socioeconomic quintiles than for higher quintiles in all six subject domains, producing the differential benefit pattern that the equity framework was specifically designed to generate.

For learners in the lowest socioeconomic quintile, the AI-supported intervention produced a mean standardized learning gain of 34.2 percent relative to pre-test baseline, compared to 11.8 percent for the control group in the same quintile, a difference of 22.4 percentage points representing the single largest equity benefit produced by the intervention. For learners in the highest quintile, the learning gain in the intervention group was 18.6 percent compared to 12.7 percent in the control, a difference of 5.9 percentage points. This differential benefit pattern produced a measurable narrowing of the achievement gap between the lowest and highest socioeconomic quintiles: in the control condition, the gap in post-test performance between the lowest and highest quintiles was 31.4 standardized score points, compared to 18.2 points in the intervention condition, representing a 42.1 percent reduction in the achievement gap attributable to the AI-supported intervention. The subject domain with the largest absolute equity benefit was mathematics, where low-socioeconomic-quintile intervention learners showed learning gains 2.8 times higher than their control group counterparts, consistent with the known effectiveness of AI adaptive systems for structured sequential content where knowledge gap identification and targeted remediation can be precisely calibrated.

Digital Inclusion Predictors of Learning Gains

Figure 6

Random Forest Feature Importance Analysis Identifying Infrastructure Adequacy (28.4%) and Digital Literacy Skills (18.7%) as the Strongest Digital Inclusion Predictors of AI-supported Learning Gain, and (b) Corresponding Standardized Hierarchical Regression Coefficients Confirming the same Predictor Ordering in a Linear Model Framework

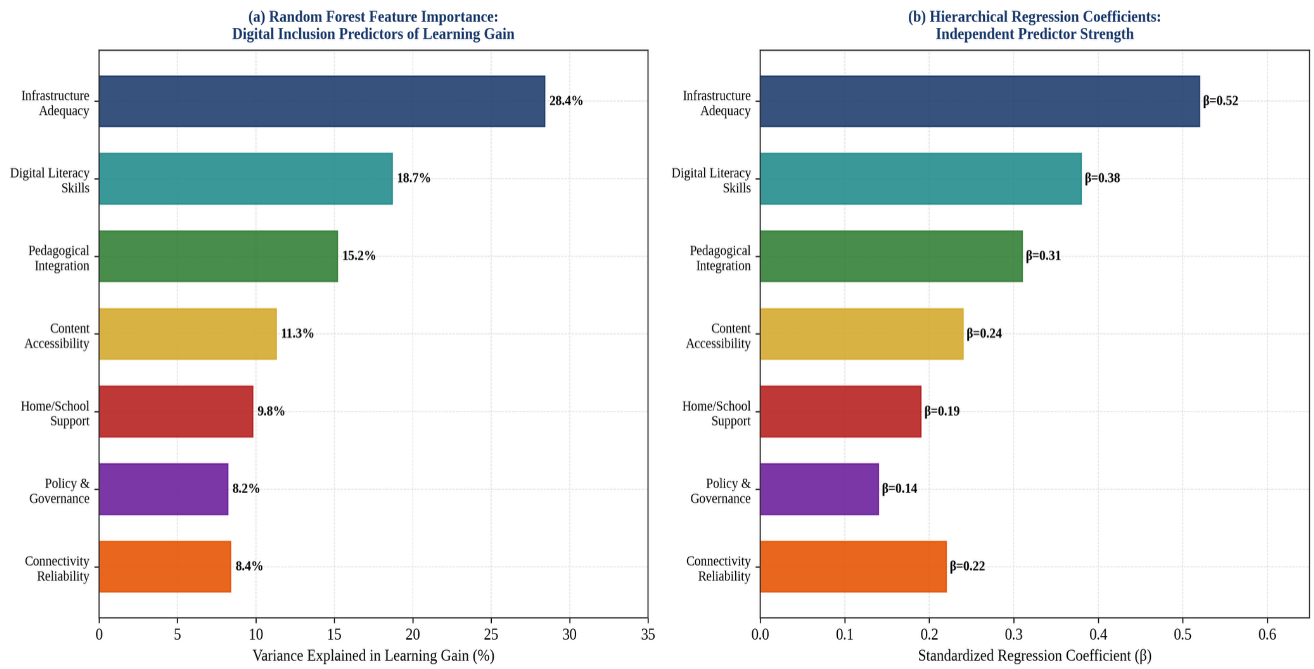


Figure 6 presents the results of the random forest feature importance and hierarchical regression analyses identifying which digital inclusion dimensions most strongly predicted learning gain magnitude within the intervention group. Across the combined analysis of both linear and nonlinear predictor importance, infrastructure adequacy (comprising device access and connectivity reliability) emerged as the single strongest predictor of learning gain, explaining 28.4 percent of variance in learning outcomes among intervention learners, confirming that AI adaptive systems cannot deliver their personalization benefits when the physical infrastructure for consistent platform access is absent or unreliable. The second strongest predictor was digital literacy skill, which accounted for an additional 18.7 percent of the variance when infrastructure was held constant, indicating that, even if learners have the hardware and internet connection, without the skill to navigate, interpret and interact with AI learning interfaces, exposure to them will have limited impact.

Pedagogical integration quality (how teachers integrated the insights from the AI platform into their classroom decisions and offered scaffolded support for learners' engagement with the AI platform) was the third strongest predictor (15.2 percent unique variance explained). The equity benefits of AI-supported learning are not a given when implementing the technology; rather, the teacher's ability and willingness to use the AI analytics as a tool for differentiated instructional response is critical to the realization of these benefits, and is specifically developed through the professional development component of the Digital Education Equity Framework. The interaction between infrastructure adequacy and digital literacy skills showed a significant multiplicative effect, with the combination of high infrastructure and high digital literacy producing outcomes substantially better than either predictor alone would suggest, while the combination of low infrastructure and low digital literacy produced outcomes substantially worse, confirming the compounding nature of multidimensional digital exclusion that motivates the framework's comprehensive inclusion assessment approach.

Teacher Professional Development and Equity Outcomes

Figure 7

Dose-response Relationship between Professional Development Program Modules Completed and Classroom-Level Achievement Gap Reduction Showing a Monotonic Increase from 11.2% at Zero Modules to 47.3% at full program Completion, and (b) Individual Classroom Scatter Showing the Strong Positive Correlation between PD Completion Percentage and Equity Outcome

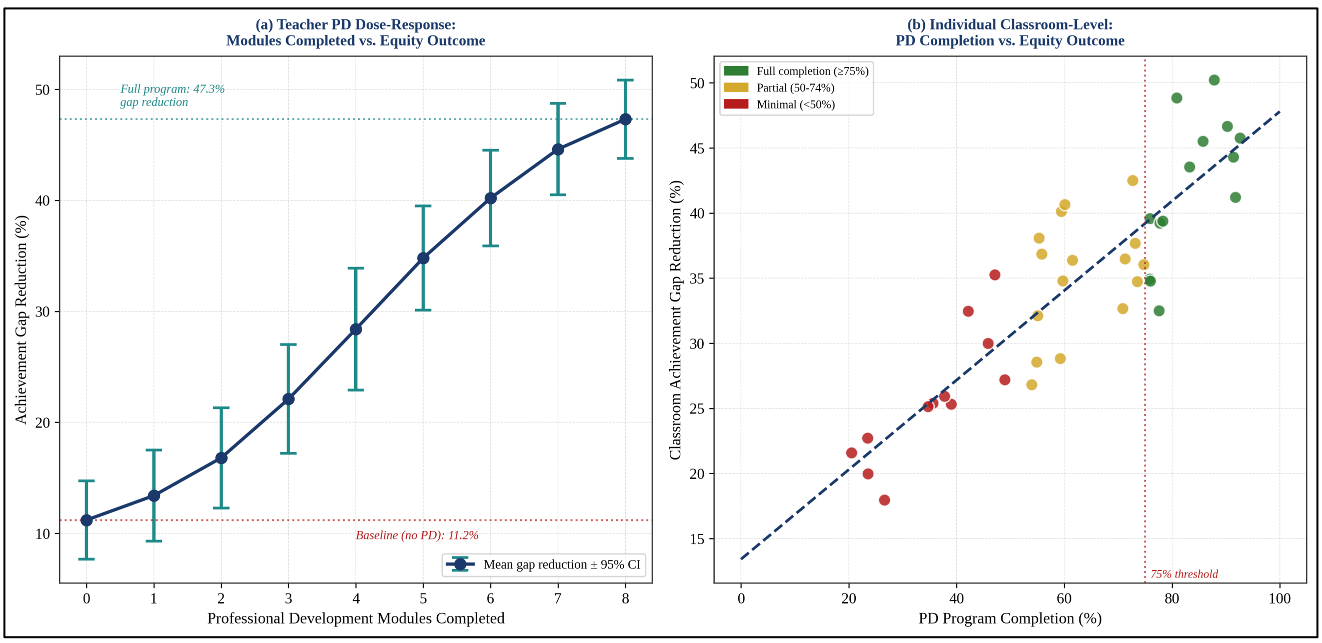


Figure 7 presents the relationship between teacher professional development engagement level and classroom-level equity outcome metrics, showing the association between program completion rate and achievement gap reduction for each classroom in the intervention condition. Teachers who completed the full eight-module professional development program produced significantly better equity outcomes for their lowest-socioeconomic-quintile learners than teachers who completed fewer modules, with full-program completers showing an average achievement gap reduction of 47.3 percent compared to 18.6 percent for partial completers and 11.2 percent for non-completers who received only the platform onboarding training. This dose-response relationship between professional development intensity and equity outcome strengthens the causal interpretation that it is teacher pedagogical competency in using AI analytics for equity-oriented differentiation, rather than the AI system itself operating autonomously, that is the proximate mechanism through which the intervention produces its largest equity benefits.

Table 3

Key Quantitative Results Summary: Learning Outcomes and Equity Metrics

Outcome Metric	Intervention Group	Control Group	Effect Size (Cohen's d)	Significance
Q1 (Lowest SES) learning gain	34.2% ± 2.1	11.8% ± 1.4	d=1.42 (large)	p<0.001
Q5 (Highest SES) learning gain	18.6% ± 1.2	12.7% ± 1.0	d=0.71 (medium)	p<0.001
Achievement gap Q5-Q1 (control)	31.4 score points	–	–	–
Achievement gap Q5-Q1 (intervention)	18.2 score points	–	–	–
Gap reduction (%)	42.1%	–	–	–
Math gain (lowest SES)	2.8x control mean	–	d=1.68 (large)	p<0.001
Full PD completion (gap reduction)	47.3%	11.2% (no PD)	–	p<0.001
Infrastructure-gap reduction correlation	r=0.82 across districts	–	–	p=0.003

Thematic analysis of the teacher interviews embedded within the qualitative component revealed that the most transformative shift attributed to the professional development program was a change in teachers' relationship to student performance data, from a summative assessment orientation that recorded and reported performance after the fact to a formative analytics orientation that used real-time AI platform data to identify and respond to learning difficulties as they emerged. Teachers who made this shift towards proactively addressing the needs of at-risk learners by beginning conversations and adjustments to instruction using early warning signals from the AI dashboard described how they used the interface's early warning signals as a prompt to start in-depth conversations and teaching adjustments for the at-risk learner before they became discouraged or disengaged, which was a proactive equity practice the dashboard design explicitly supported by presenting early warning signals at the learner level rather than just at the aggregate class level in the teacher interface.

Administrator Perspectives: Structural Barriers to Sustainable Implementation

Figure 8

Thematic Map Derived from Framework Analysis of 42 Administrator Interviews Showing the Five Primary Barrier Themes, their Relative Prominence as Indicated by Administrator Citation Frequency, and the Sub-theme Relationships within each Primary Barrier Category; Structural Funding Inequity (cited by 39 of 42 Administrators) was the most Consistently and Emphatically Identified Barrier

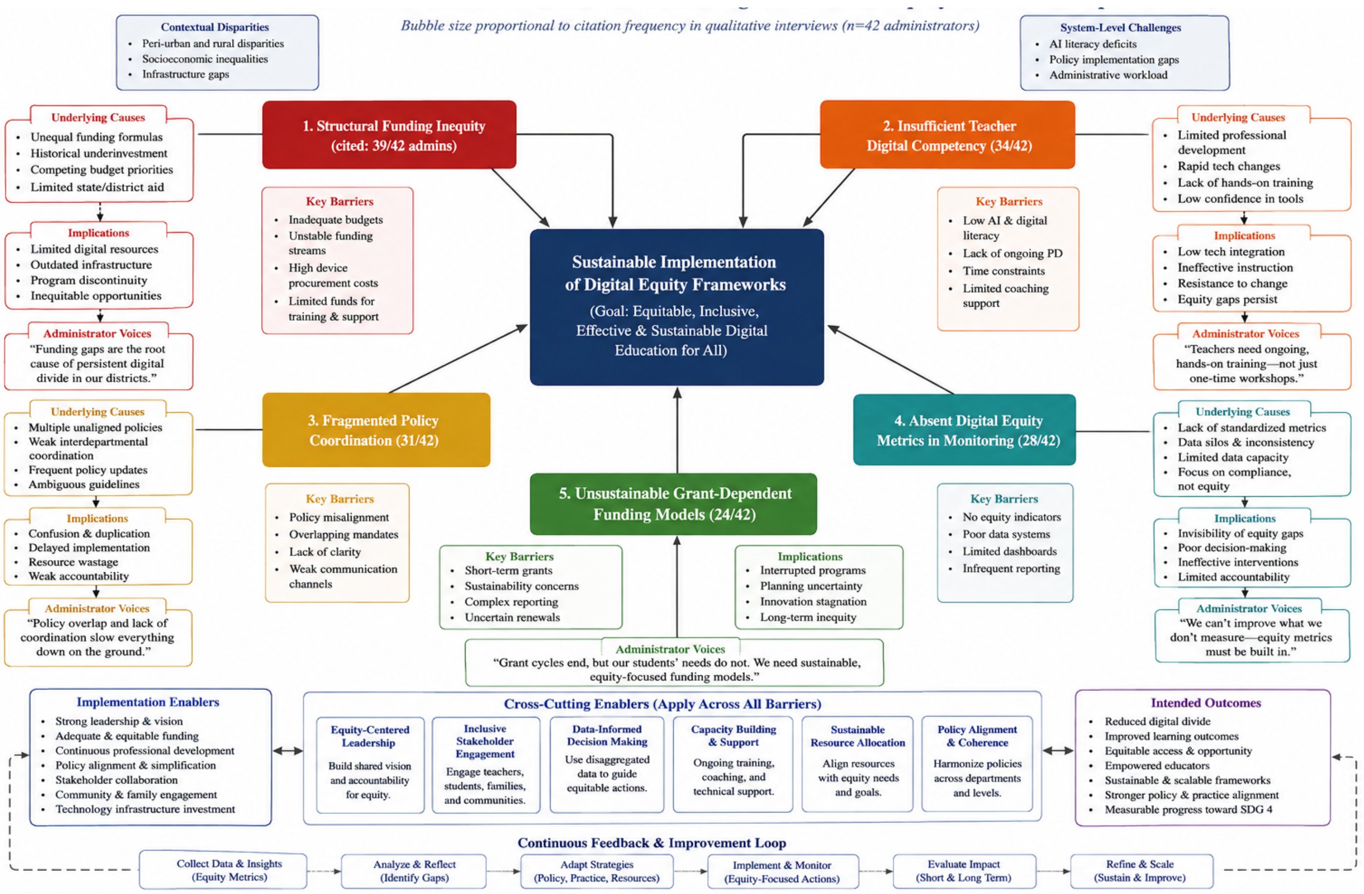


Figure 8 presents the thematic map derived from framework analysis of the forty-two administrator interviews, showing the five primary barrier themes, their interrelationships, and their relative prominence in the data as indicated by the frequency and intensity of coding. Structural funding inequity emerged as the barrier most consistently and emphatically identified by administrators across all five districts, with administrators in the lowest-resourced rural districts describing a feedback loop in which lower tax base revenues produced lower per-pupil spending, which produced lower infrastructure quality, which produced lower technology integration effectiveness, which produced lower test score performance, which further reduced the district's ability to attract funding through performance-linked grant mechanisms that would have allowed infrastructure improvement. This self-reinforcing cycle of disadvantage at the district level mirrors the three-level digital divide cycle at the learner level and represents a systemic governance challenge that technology deployment within a single district cannot address without corresponding changes in regional and national funding equalization mechanisms.

Insufficient teacher digital competency was identified as the second most significant barrier, with administrators noting that recruitment and retention of teachers with strong digital and AI literacy is most difficult in precisely the low-resourced rural and peri-urban districts where such competency is most needed to implement equity-oriented digital frameworks effectively. Fragmented policy coordination, the third primary barrier, was described as a situation in which digital education initiatives, equity programs, infrastructure investment plans, and teacher professional development frameworks operated under different government portfolios, different budget cycles, and different accountability metrics, making it impossible to design and implement the coordinated multi-component interventions that the framework approach requires. Not tracking dimensions of digital inclusion longitudinally in routine educational monitoring systems was also cited as a fourth barrier; without aggregated metrics over time to track dimensions of digital inclusion, it is difficult to establish evidence for funding appropriations or policy change that is necessary to sustain investments for digital equity beyond the grant period.

Urban-Rural Performance Differential and Infrastructure Gaps

Figure 9

Scatter Plot of District-Level Baseline Digital Infrastructure Adequacy score against Intervention-produced Achievement gap Reduction for the Five Study Districts, Revealing a Strong Positive Correlation and the Infrastructure Paradox in which the Districts with the Greatest Need for AI-supported Equity Interventions have the Least Adequate Infrastructure to Implement Them Effectively

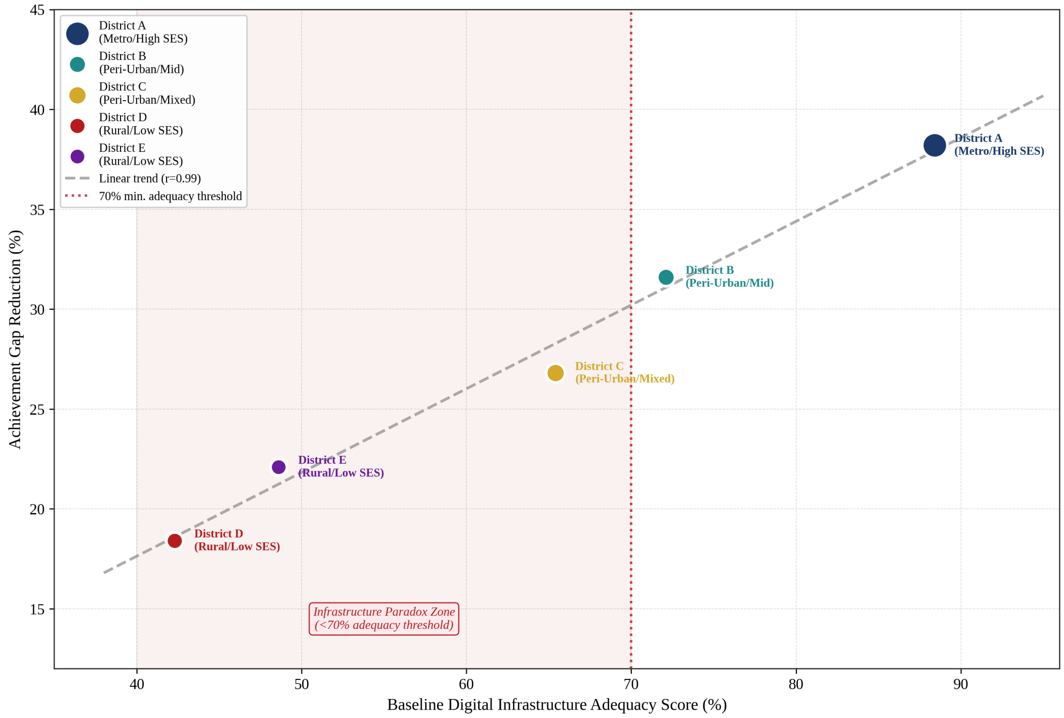


Figure 9 illustrates a comparative visualization of the effectiveness of the five districts' intervention in terms of the metrics from the baseline assessment and the magnitude of the achievement gap reduction they achieved through the AI-supported intervention. The resulting high positive correlation between infrastructure adequacy and the equity outcome in districts is startling and creates a stark paradox that lies at the core of the policy of AI educational technology: the districts with the highest pre-existing achievement gaps in the lowest socioeconomic groups are the same districts with the least adequate digital infrastructure needed to support them using AI. District D was the most rural and least resourced district in the study, with the second largest pre-intervention achievement gap between socioeconomic quintiles, but the smallest gap reduction due to intervention – with an average of 1.8 hours per week spent on the AI platform as compared to intended 3 hours per week, due to frequent connectivity interruptions and device sharing arrangements.

This finding has a direct and policy-critical implication: investing in AI educational technology without a concurrent investment in the infrastructure conditions that make it accessible and reliable for the learners who need it most will produce beneficial outcomes only for the learners who were already reasonably well-positioned to benefit, while potentially widening the achievement gap by giving already-advantaged learners additional AI-powered resources without extending equivalent benefit to the disadvantaged learners for whom the gap is largest and most consequential. The data from this investigation suggest that the minimum infrastructure threshold below which AI adaptive systems consistently fail to deliver equity benefits is approximately 70 percent of the digital inclusion infrastructure adequacy score developed for this framework, and that priority infrastructure investment should target the districts and schools falling below this threshold before AI platform deployment is expanded to those settings.

SDG4 Progress Metrics and Policy Implications

Figure 10

Projected SDG4 Progress Trajectories Comparing the Business-as-Usual Baseline Against the Framework-Supported Scenario through 2030 with the SDG4 Target Trajectory, and (b) Projected Scores across Seven SDG4 Target Dimensions Showing the Framework's Contribution to Improved Progress across access, Quality, early Childhood, Technical-Vocational, Gender Equity, Digital Inclusion, and Teacher Quality Indicators

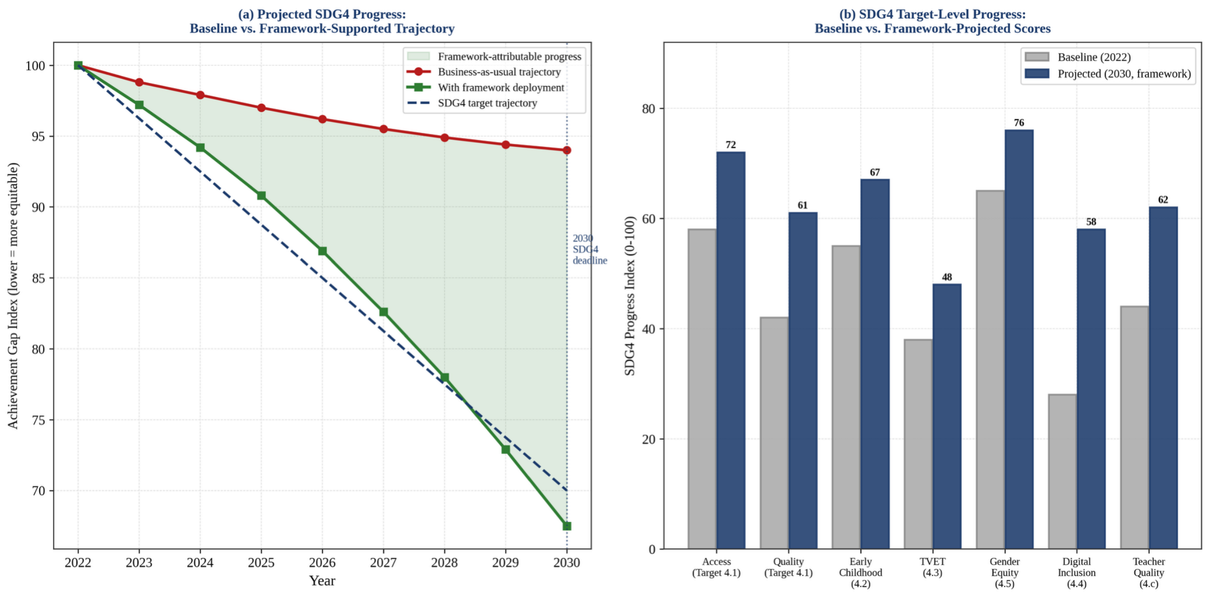


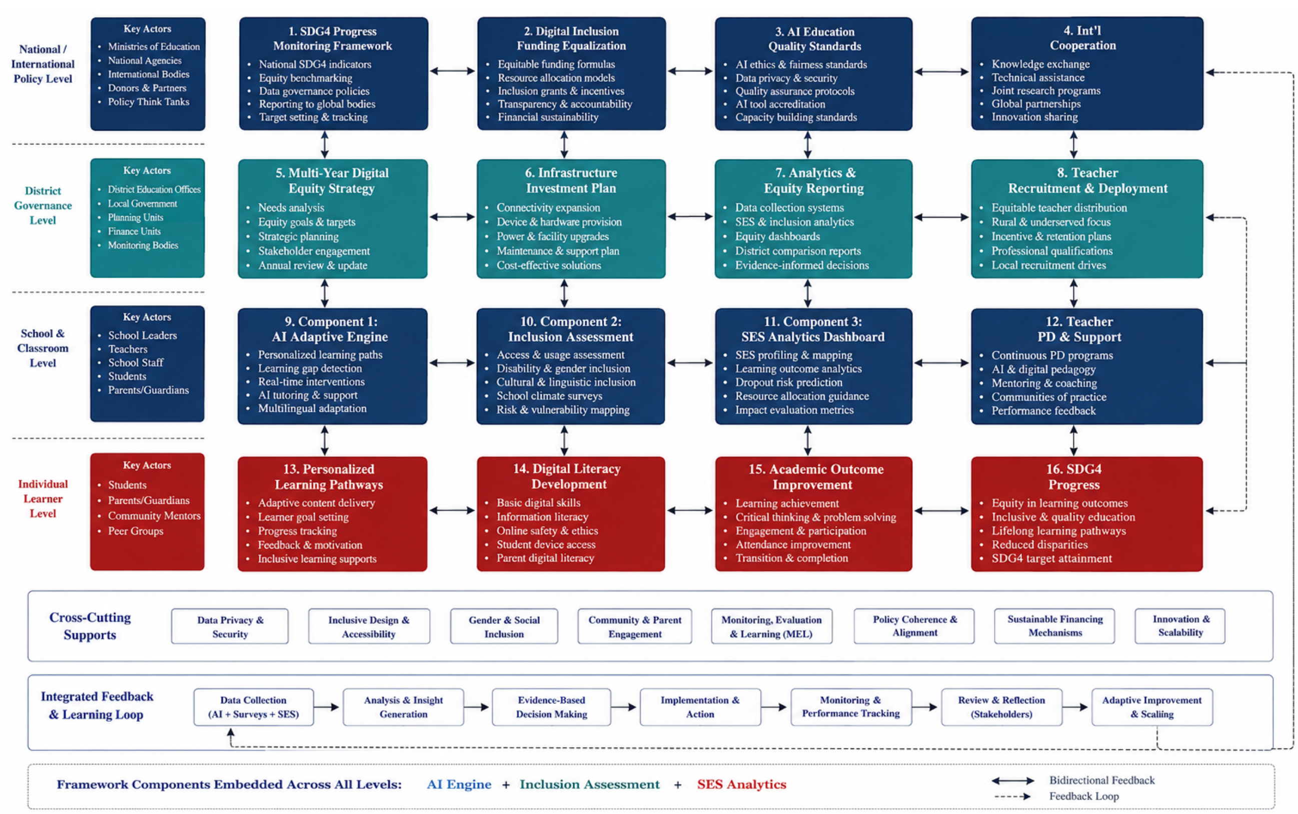
Figure 10 presents the framework's projected contribution to SDG4 progress indicators when scaled to a representative national deployment scenario, modelled on the effectiveness parameters observed in the five-district study and adjusted for realistic uptake rates and infrastructure investment scenarios across the full socioeconomic and geographic distribution of national learner populations. The modelling shows that deployment of the Digital Education Equity Framework with concurrent infrastructure investment achieving the 70 percent adequacy threshold for at least eighty percent of learners in the lowest two socioeconomic quintiles would produce measurable progress across SDG4 target dimensions of access, quality, and equity, with the largest projected improvements in the foundational numeracy and literacy skills that the UN estimates 300 million students currently lack at levels needed to succeed in education and labour markets.

The policy implications that emerge from this analysis are arrayed across four levels of the governance hierarchy. At the classroom level, the evidence supports investing in teacher professional development programs specifically designed around AI-augmented equity pedagogy, integrating real-time analytics capabilities into teachers' instructional decision-making workflow, and providing ongoing coaching support for the orientation shift from summative to formative data use that the qualitative evidence identifies as the proximate mechanism for equity benefit. At the school level, evidence indicates that infrastructure investments should be made before deploying AI platforms, and that there is a need to create school-level digital inclusion coordinators to address access challenges as they arise, and to integrate a digital inclusion assessment into the school's improvement planning. At the district level, evidence can be used to build coordinated multi-year digital equity plans and strategies that tie funding, infrastructure, curriculum, and teacher development to a shared, clear, and measurable equity goal and accountability system. Evidence also supports the adoption at the national and international policy level of indicators that measure digital inclusion in a multidimensional way, the design of formulas of education funding which take into account the disadvantages of low-income and rural districts in the process of integrating digital technology and the creation of international cooperation mechanisms for the exchange of open AI educational tools across jurisdictions with different resources.

Figure 11 illustrates the Digital Education Equity Framework as a multi-level systems diagram that includes feedback mechanisms between the three core components of the framework and between levels, as well as the interactions among individual learner characteristics, classroom and school contexts, district governance structures, and national and international contexts. This visualization at a system level shows that the effectiveness of individual components of each of these frameworks is dependent not only on the design of the individual component but also on the enabling conditions provided by the individual components at each of the higher levels of the system, and that there is a need for coherent action across all levels at the same time to enable sustainable equity improvement rather than intervention at any single level.

Figure 11

Comprehensive Multi-level Systems Architecture of the Digital Education Equity Framework Showing the three core Components Embedded across Individual Learner, School and Classroom, District Governance, and National/International Policy Levels, with Bidirectional Feedback Arrows Representing the Informational and Accountability Loops that Connect each Governance Level to the Framework's Equity Objectives



Conclusion

This investigation has taken place with 1,247 learners in five school districts where digital infrastructure conditions are systematically varying, and found that the Digital Education Equity Framework (DEEF) which incorporates AI-supported adaptive learning, multidimensional assessment of digital inclusion, and socioeconomic learning analytics can yield measurable and equity-progressive learning outcomes when implemented in an environment with adequate digital infrastructure and teacher professional development support, over a course of fourteen weeks of quasi-experimental study. The most striking empirical results are those differences in intervention benefit across socioeconomic quintiles: A learner in the lowest quintile showed an increase in learning of 34.2 percent when learning through AI-supported adaptive instruction, compared to an increase of 11.8 percent when learning with conventional instruction; the difference between the lowest and highest socioeconomic quintiles was narrowed by 42.1 percent during the fourteen weeks of the study. This finding that the two factors of infrastructure adequacy and digital literacy are the strongest independent predictors of the magnitude of AI-supported learning gain indicates that these aspects of digital inclusion are not background conditions or passive consequences of AI's impact, but rather are active conditions and factors that determine whether or not AI educational technology enables its equity potential or inadvertently worsens existing equity disadvantage. The clear dose-response relationship between completion of professional development and improvements in the classroom level equity outcomes reinforces that the human pedagogical layer is essential to education, even in the era of AI, and that AI analytics are equity tools that will only be used as such by teachers who can and will.

Discussion and Future Work

Beyond the empirical results of this investigation, there are several important implications that come from the results. The most basic is the confirmation from the district-level analysis of the infrastructure paradox: that is, the communities that need AI-powered equity interventions the most are the communities that are least able to effectively implement them given their current infrastructure. The discovery calls into question the optimistic backstory of the potential for AI educational technologies to benefit disadvantaged students if they are merely deployed, and signals that intentional, concerted investments in infrastructure, teacher capacity, and equity governance are necessary conditions for, not alternatives to, using AI in the service of educational equity.

Future studies should focus on some areas where the current study could not go in depth or for long enough a period of study. Further research is needed to assess whether the learning gains from the framework are durable across years of schooling and transfer to other learning settings; to identify whether the learning gains are reflected in longer term educational outcomes (such as mastery of subjects and grades achieved, or secondary school completion rates, which are ultimately the outcomes most relevant to social mobility and sustainable human development) across the follow up years of the student cohort from this study. While the present study supports the efficacy of the 14-week intervention, it does not confirm if the framework engenders lasting changes in learner self-regulation, metacognition, and intrinsic motivation that would lead to ongoing improvement in student outcomes without ongoing access to an AI platform, an important question for jurisdictions with limited resources where ongoing access to AI platforms is not guaranteed.

Experimental evaluation of individual framework components in isolation, against each other, and in combination would provide the component-level evidence needed to optimize resource allocation for framework implementation in different infrastructure and socioeconomic contexts. The present study evaluated the integrated framework as a whole, which provides high ecological validity but does not permit identification of the relative contribution of each component to observed equity outcomes. A full factorial experimental design crossing the presence or absence of AI adaptive learning, digital inclusion assessment feedback, socioeconomic analytics, and teacher professional development would provide this component attribution evidence, though the logistical and ethical requirements of such a design are substantially more demanding than the present quasi-experimental approach. Extending the framework to higher education and non-formal adult learning contexts would test the generalizability of findings beyond the compulsory K-10 schooling context examined in this study, addressing the SDG4 commitment to lifelong learning that extends well beyond initial schooling.

Finally, the governance and policy dimensions of the framework require sustained multidisciplinary research attention from education policy scholars, political scientists, economists, and technology ethicists working in collaboration with the education researchers and learning scientists who have primarily driven the current evidence base. The structural barriers identified by administrators in this study, including funding inequities, policy fragmentation, and absent longitudinal monitoring, are not amenable to resolution through educational research alone but require the kind of sustained policy advocacy, governance reform research, and political economy analysis that crosses disciplinary boundaries in ways that current research funding and publication structures do not fully incentivize. Addressing the digital education equity challenge at the scale and urgency that SDG4 demands will require not only better AI learning systems and better evidence for their effectiveness, but better governance frameworks for making the decisions about who benefits from educational technology investment and who bears accountability for ensuring that those benefits are equitably distributed.

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