

AI-Enhanced Early Childhood English Education in Rural Contexts: A Comparative Study of Pakistan and China

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Abstract

This comparative study critically examines the integration of artificial intelligence (AI) into early English language learning environments within the under-resourced rural contexts of Pakistan and China. Focusing on the affordances and constraints of AI-mediated tools such as automated speech recognition for phonological training and adaptive systems for personalized practice the research interrogates how these technologies are enacted within contrasting policy and sociolinguistic ecologies. Employing a mixed-methods design, it synthesizes data from documentary policy analysis, semi-structured interviews with educators and caregivers, and a review of deployed applications to construct a nuanced cross-national analysis. Findings delineate two predominant implementation paradigms: a state-coordinated, platform-centric model prevalent in China, which aligns AI supplementation with national curricular objectives, and a decentralized, NGO-facilitated model emerging in Pakistan, characterized by innovative low-resource adaptations. The analysis reveals that beyond infrastructure, critical mediating factors include the tools' linguistic sensitivity to local dialects, their culturally embedded design, and their role in either augmenting or inadvertently displacing teacher pedagogical authority. The study contributes to Computer-Assisted Language Learning (CALL) literature by proposing a socio-technical framework for ethical AI integration in linguistically diverse, low-resource settings. It concludes with targeted recommendations for participatory, equity-driven design, underscoring the necessity of developing multilingual corpora, fostering teacher-AI collaboration, and instituting robust data governance for young learners to ensure these technologies support rather than undermine equitable language acquisition.

Keywords: artificial intelligence, early childhood education, rural education, comparative analysis, Pakistan and China

1. Introduction

Early childhood, spanning ages three to eight, represents a critical period for language acquisition due to unparalleled neural plasticity, which makes the brain highly receptive to linguistic input (Mathur et al., 2021; Shah et al., 2021). During this phase, young children possess the ability to discriminate a vast range of phonetic sounds, a foundational skill that narrows with exposure to specific languages. Neuroscientific research confirms that language stimulation is integral to healthy brain development, promoting cognitive functions such as memory, judgment, and analysis (Qayyum et al., 2024). Consequently, English proficiency, as a global linguistic gateway, is increasingly prioritized in the national education policies of countries like Pakistan and China. However, its integration is complex, shaped by aspirations for social mobility, the realities of local linguistic landscapes, and significant regional disparities in educational resources.

Recent advances in artificial intelligence (AI), particularly in automated speech recognition (ASR), natural language processing (NLP), and adaptive learning algorithms, offer a paradigm shift for early language education (Lyu & Andi, 2025). AI-driven tools can provide personalized, scaffolded learning experiences with immediate feedback on pronunciation, tailored vocabulary sequencing, and engaging multimodal practice (Fadieieva, 2023). Empirical evidence, including meta-analyses, indicates a medium-to-large positive impact of AI on language learning outcomes, especially for foundational skills like vocabulary (Son et al., 2025). For young learners who benefit from high-frequency, low-stakes practice, AI can supplement limited teacher time and offer individualized pacing. Furthermore, AI analytics can empower educators by identifying class-wide learning patterns and suggesting targeted interventions, positioning AI as a collaborative tool rather than a replacement for human instruction.

The potential of AI is severely tested by the realities of rural contexts, which are often characterized by limited internet connectivity, a shortage of qualified English teachers, and resource-constrained schools. In China's rural regions, for instance, the proportion of dedicated primary school English teachers remains below 60%, while similar challenges persist in Pakistan. These constraints necessitate innovative "frugal" AI designs, such as offline-first applications and lightweight on-device models (Farooq, 2019). Simultaneously, these areas present a compelling opportunity for high-impact interventions, where scalable digital tools can

be transformative. The success of such initiatives often hinges on community-centered deployment models that leverage local teacher champions and partnerships with non-governmental organizations (NGOs).

While both Pakistan and China grapple with significant rural-urban educational divides, their approaches to integrating educational technology diverge markedly. China's strategy is characterized by large-scale, state-led investment and policy mandates, such as the "Education Informatization 2.0" plan, driving the rapid rollout of digital infrastructure and platform-based AI solutions (Ministry of Education, P. R. China, 2020). This top-down model facilitates broad experimentation but raises concerns about standardization and algorithmic bias. In contrast, Pakistan's ecosystem is more fragmented, with implementation led by provincial authorities, NGOs, and donor-funded projects (Zeewaqaar, 2024). This decentralization fosters context-specific innovations but faces substantial challenges in scaling and sustainability (Bano et al., 2022). The integration of AI in this domain also sits at the confluence of critical pedagogical and ethical issues, including data privacy for minors, cultural appropriateness of content, and the underperformance of ASR systems with children's voices and regional accents.

Despite a growing number of pilot projects, significant research gaps persist. There is a need for longitudinal evidence on sustained learning outcomes, robust comparative studies contrasting the influence of policy and socio-cultural factors, development of optimized AI models for low-connectivity environments, and research on teacher-AI collaboration dynamics (Qayyum et al., 2024). This paper directly addresses these gaps by synthesizing recent empirical studies and policy documents from Pakistan and China (Zawacki-Richter et al., 2019). It aims to provide a structured comparative analysis across infrastructure, policy, pedagogy, and community acceptance, culminating in an evidence-based framework for the ethical and effective scaling of AI-enhanced early English learning in rural settings (Ngo et al., 2024; Tian & Wang, 2025).

The theoretical underpinnings of this study are rooted in several interconnected fields: early childhood language acquisition, technology-enhanced learning, and the socio-cultural context of education. Vygotsky's (1978) sociocultural theory, which emphasizes the role of social interaction and technologically-mediated tools in cognitive development, provides a foundational framework. An AI tutor can be conceptualized as a "more knowledgeable other" (MKO) that scaffolds learning within a child's Zone of Proximal Development (ZPD), offering tailored support that traditional, one-size-fits-all instruction often cannot provide (Yan & Yang, 2021).

Research in Computer-Assisted Language Learning (CALL) has long demonstrated the benefits of technology in language education, including increased motivation, learner autonomy, and access to authentic materials. The advent of AI has propelled CALL into a new era, often termed Intelligent CALL (ICALL). AI-powered systems can analyze learner performance in real-time, diagnose errors, and adapt content dynamically. Features like speech recognition provide immediate phonetic feedback, a crucial element in early language learning. Furthermore, the integration of gamification using game design elements in non-game contexts has been shown to significantly boost engagement and persistence among young learners. AI algorithms can optimize gamified experiences by adjusting difficulty levels to maintain a state of “flow,” where the challenge matches the learner's skill level (Racial disparities in automated speech recognition, 2020).

Despite the promise of AI, its implementation in real-world educational settings, particularly in resource-constrained environments, is fraught with challenges. The digital divide is not merely about access to devices and the internet; it encompasses digital literacy, pedagogical integration, and cultural acceptance. In the context of rural Pakistan, studies have highlighted that while mobile phone penetration is high, the use of these devices for educational purposes is nascent. Barriers include the cost of data, lack of relevant local-language content, and insufficient teacher training. Conversely, China's state-led push for "informatization" of education has resulted in widespread hardware deployment in rural schools. However, research indicates a gap between technology provision and its effective pedagogical use, with teachers often reverting to traditional methods or using technology merely for presentation. This "second-level digital divide" concerns the quality of technology use, which is heavily influenced by teacher beliefs and institutional support (Ngo et al., 2024).

Comparative studies on EdTech adoption offer valuable insights into the influence of national context. For instance, research comparing technology integration in East Asian and Western countries has revealed differences stemming from cultural values, educational philosophies, and policy priorities. This study extends this comparative lens to Pakistan and China, two nations with distinct cultural, political, and economic systems, yet a shared ambition to leverage technology for educational advancement. By examining the interplay between a standardized AI intervention and these diverse local contexts, this research aims to move beyond a techno-deterministic view and illuminate the complex socio-technical factors that mediate the success of educational innovations.

1.1. Research Questions

Building on the gaps identified above, this study is guided by the following research questions:

- RQ1: How do the macro-level policy and infrastructure ecosystems of rural Pakistan and rural China differentially shape the conditions for AI integration in early childhood English education?
- RQ2: To what extent do AI-mediated tools improve vocabulary acquisition and pronunciation outcomes for young English learners in these two rural contexts, and what factors mediate the magnitude of these effects?
- RQ3: What ethical and pedagogical challenges emerge from AI integration in early childhood education involving child learners, and how do these challenges manifest differently across the two national contexts?

1.2. Theoretical Framework: The SAMR Model

To provide a structured analytical lens for evaluating the quality of AI integration described in this study, this research adopts the SAMR Model (Puentedura, 2006), which categorizes technology use along a continuum of four levels: Substitution, Augmentation, Modification, and Redefinition. This framework moves the analysis beyond a binary question of whether technology is used to a more nuanced question of how it is used and to what transformative effect.

Applying the SAMR Model to the AI tools documented in this study reveals a spectrum of integration quality across both countries. At the Substitution level, basic offline vocabulary apps used in rural Pakistan function primarily as digital replacements for paper-based flashcards or workbook exercises, with no functional change to the pedagogical task. At the Augmentation level, apps that incorporate immediate automated feedback on pronunciation provide a functional improvement over traditional methods, offering corrections that a single teacher managing a large class cannot feasibly provide in real time. Moving to the Modification level, China's cloud-based adaptive platforms significantly redesign the learning task itself—using learner error-pattern data to dynamically sequence vocabulary and adjust phonics exercises, a capability impossible without the technology. Finally, Redefinition—the highest SAMR level—is approached in more advanced implementations where AI dashboards enable teachers to shift from whole-class instruction to data-guided coaching, fundamentally redefining the teacher's role and creating personalized learning pathways that were previously inconceivable. The analysis in this paper uses these SAMR categories to explain not merely what AI tools are

deployed, but whether they are enhancing or genuinely transforming early English education in these rural contexts.

2. Methodology

2.1. Research Design

This investigation is grounded in a pragmatist paradigm, employing a convergent mixed-methods design (QUAN + QUAL) to generate actionable knowledge for a complex real-world problem. The design is explicitly comparative, structured to illuminate how macro-level systemic factors in Pakistan and China produce divergent micro-level realities in classroom implementation. The study's conceptual framework is informed by Socio-Technical Systems Theory, which posits that technological efficacy is an emergent property of the dynamic interaction between technical tools and their social, pedagogical, and institutional contexts.

2.2. Participants and Sampling

A multi-stage, purposive sampling strategy was deployed to capture depth and facilitate comparison. Four rural districts were selected as primary research sites two in Punjab, Pakistan, and two in Yunnan, China chosen for their engagement with digital learning initiatives amidst representative rural constraints. The study included a teacher cohort of 120 in-service early-grade English teachers (60 per country), a student cohort of 240 children (aged 6-8) assigned to AI intervention or control groups, and an expert cohort of 20 key stakeholders (education officers, NGO directors, trainers, and developers) for semi-structured interviews.

For the purposes of this study, “rural” was operationally defined using three criteria applied consistently across both national contexts: (1) the school is located in an administrative unit classified as rural or semi-rural by the respective national census authority; (2) the school serves a community with a population of fewer than 10,000 residents; and (3) fewer than 50% of households in the surrounding community have fixed broadband internet access. This definition was chosen to ensure that both physical remoteness and digital under-resourcing were captured simultaneously, as either condition alone is insufficient to characterize the constraints facing low-resource early childhood education.

The two Punjab districts selected in Pakistan (Attock and Khushab) are predominantly agricultural communities where the primary economic activities are wheat and cotton farming, seasonal labor migration, and small-scale trade. Per capita income in these districts falls below

the national rural average, and the majority of families in the study schools had monthly household incomes equivalent to less than USD 150. School infrastructure reflects this economic fragility: buildings are frequently multi-purpose community structures, teacher-to-student ratios average 1:45, and fewer than one in ten schools in these districts has an operational computer laboratory. The Yunnan districts selected in China (Luquan and Xundian) are similarly agricultural, with Yi and Hui ethnic minority communities whose home languages are distinct from Mandarin Chinese. While China's poverty alleviation campaigns have substantially improved road access and electricity reliability in these areas over the past decade, per capita rural incomes remain approximately 40% below the national urban average. English is taught as a required subject from Grade 3 in Chinese rural schools but is largely absent from home environments, creating a high-stakes yet low-exposure learning context. These socio-economic profiles are essential for interpreting the infrastructure barrier data and the differential engagement outcomes.

2.3. Data Collection and Instruments

Data collection occurred over a 16-week period using validated instruments. Policy and document analysis involved applying a structured codebook to 15 key policy documents and 30 project reports (2019-2024). A 35-item teacher perception survey (Cronbach's $\alpha = .87$) measured perceived usefulness, ease of use, access, and self-efficacy. Student learning was assessed using an adapted Vocabulary Knowledge Scale (VKS) and pronunciation tasks scored by blinded linguists (Inter-rater Reliability, ICC = .92). Semi-structured interviews with stakeholders explored themes of adoption, integration, ethics, and sustainability, with transcripts validated through back-translation.

The 35-item Teacher Perception Survey was structured across four subscales. The Perceived Usefulness subscale (10 items; e.g., "Using AI tools helps my students improve their English vocabulary") measured teachers' beliefs about the educational value of AI. The Ease-of-Use subscale (8 items; e.g., "I find it easy to operate the AI applications used in my classroom") assessed technological comfort. The Access and Infrastructure subscale (9 items; e.g., "I have reliable internet connectivity in my school") captured contextual enablers and barriers. The Self-Efficacy subscale (8 items; e.g., "I am confident in my ability to integrate AI tools into my English lessons") evaluated pedagogical confidence. All items were rated on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The full survey instrument is provided in Appendix A.

Semi-structured interviews were conducted with 20 key stakeholders (10 per country), including district education officers, NGO program directors, teacher trainers, and application developers. Each interview lasted between 45 and 75 minutes and was conducted in the participant's preferred language (Urdu, Punjabi, or Mandarin) with the assistance of trained bilingual research assistants. Interviews were audio-recorded with participant consent and transcribed verbatim, then translated into English and subjected to back-translation verification by a second independent bilingual reviewer to ensure accuracy. The semi-structured interview protocol covered four thematic areas: (1) adoption drivers and barriers, (2) pedagogical integration practices, (3) ethical concerns regarding data and child safety, and (4) long-term sustainability and scalability. The full interview protocol is provided in Appendix B.

2.4. Intervention Protocol

A 10-week AI intervention was implemented, where students used tablet-based apps for 25-minute sessions three times per week. The apps focused on adaptive vocabulary games and speech-recognition pronunciation practice. Critically, the technology was context-appropriate: Chinese apps leveraged cloud-based AI for real-time feedback, whereas Pakistani apps were offline-first, using compressed on-device models. Control groups continued with standard instruction. Implementation fidelity was monitored and averaged 89%.

2.5. Data Analysis

Quantitative survey data were analyzed using descriptive statistics and chi-square tests. Student learning gains were analyzed via a 2x2 Analysis of Covariance (ANCOVA), with pre-test scores as a covariate, to examine the effects of Country and Condition (AI vs. Control). Qualitative interview data underwent reflexive thematic analysis using NVivo software. Finally, quantitative and qualitative findings were integrated using a joint display technique to construct a coherent explanatory narrative.

2.6. Ethical Considerations

Given that this study involves early childhood participants (aged 6–8), who constitute a vulnerable population under international research ethics guidelines, stringent ethical protocols were observed throughout the research process. Full ethical clearance was obtained from the Institutional Review Board (IRB) of Nanjing University of Science and Information Technology (NUIST) prior to the commencement of data collection. In Pakistan, the study

protocol was additionally reviewed and approved by the relevant district-level Education Authority and the ethics committees of the partnering NGOs.

Written informed consent was obtained from the parents or legal guardians of all child participants before the study began. School principals and classroom teachers also provided written institutional consent. All children were informed of their participation in age-appropriate language, and their assent was secured. Participation was entirely voluntary, and families were explicitly informed of their right to withdraw at any time without consequence. To protect the privacy and confidentiality of all participants, no personally identifiable information was collected or stored. All data were anonymized at the point of collection, assigned unique participant codes, and stored on password-protected, encrypted servers accessible only to the core research team. The collection and processing of children's data complied with applicable data protection regulations, including China's Personal Information Protection Law (PIPL) and Pakistan's Prevention of Electronic Crimes Act (PECA) guidelines concerning minors.

3. Results

3.1. Teacher Demographics, Access, and Infrastructure

The initial analysis reveals a stark contrast in the foundational resources available to teachers in the two countries. The key infrastructure and demographic indicators are summarized in Table 1.

The data in Table 2, confirmed by a chi-square test ($\chi^2(3, N = 120) = 32.4, p < .001$), quantifies the stark access gap between the two countries. Seventy-five percent of Chinese teachers report high or moderate access, facilitating regular integration. In contrast, 70% of Pakistani teachers report low or no access, rendering AI a theoretical rather than practical resource for the majority. This statistically significant disparity is directly linked to the infrastructural realities documented in Table 1.

Table 1. Comparison of school infrastructure and teacher training percentage

Demographic / Infrastructure	Pakistan (n=60)	China (n=60)
Average years teaching experience	8.2 years	10.5 years
Formal training in digital tools	15%	85%
School with dedicated computer lab	20%	95%
School with high speed (>10 Mbps) Internet	10%	90%

This disparity in the enabling environment sets the stage for divergent experiences with AI integration. The distribution of teacher access levels across both cohorts is summarized in Table 2.

Table 2. Distribution of teacher access levels to AI tools

Acces/ Usage Level	Pakistan	China
High Access (daily/ weekly use)	6 (10%)	24 (40%)
Moderate access (monthly Use)	12 (20%)	21 (35%)
Low access (rarely, <monthly)	27 (45%)	12 (20%)
No access	15 (25%)	3 (5%)

3.2. Teacher Perceptions, Preparedness, and Identified Barriers

Teacher perceptions of AI's benefits, their self-efficacy in using technology, and the barriers they face further illustrate the divergent ecosystems. While optimism about AI's potential is present in both contexts, the confidence and concerns of educators differ significantly. Table 3 presents a comparison of perceived benefits, Table 4 reports self-efficacy scores, and Table 5 details reported barriers.

As demonstrated in Table 3, teachers in both countries recognize AI's potential, particularly for student motivation. However, Chinese teachers' perceptions are consistently and significantly more positive across all domains, especially for pronunciation support and personalization functions that require more sophisticated, reliable technology. The higher standard deviations in the Pakistani cohort suggest less consensus, likely reflecting highly variable personal experiences with unstable tools. Table 4 presents the self-efficacy scores across four dimensions.

Table 3. Comparison of teacher perceived benefits of AI tools

Perceived Benefit	Pakistan Mean	Pakistan SD	China Mean	China SD
Improves Student Vocabulary	68.0	12.3	80.0	9.1
Improves Student Pronunciation	55.0	15.6	73.0	10.8
Increases Student Motivation	80.0	8.5	90.0	6.2
Allows for Lesson Personalization	50.0	14.2	70.0	11.4

As shown in Table 4, the data reveals a critical human capacity gap. Pakistani teachers report low self-efficacy, particularly in integration confidence and perceived training adequacy. This

indicates that even if access barriers were removed, a significant professional development deficit would hinder effective adoption. Chinese teachers, supported by mandated training, exhibit markedly higher confidence across all dimensions.

Table 4. Comparison of Teacher Self-Efficacy with Technology (Scale 1-5)

Self-Efficacy Dimension	Pakistan Mean	Pakistan SD	China Mean	China SD
Comfort Using Basic EdTech	2.8	0.6	4.2	0.5
Confidence Integrating AI into Lessons	2.1	0.7	3.9	0.6
Ability to Troubleshoot Tech Issues	2.5	0.8	3.5	0.5
Perceived Adequacy of Training Received	1.9	0.6	3.8	0.4

As displayed in Table 5, the barrier profiles between the two countries are fundamentally different. Pakistani challenges are foundational and structural, concentrated in infrastructure, cost, and training. Chinese concerns shift toward pedagogical integration and ethical governance, particularly around time constraints, screen time, and data privacy. Notably, the high concern about data privacy in China (65%) contrasts with lower concern in Pakistan (35%), likely reflecting greater exposure to and awareness of data collection practices within China's platform-centric ecosystem.

Table 5. Comparison of Reported Barriers to AI Implementation

Barrier	Pakistan (n=60)	China (n=60)
Unreliable Internet / Electricity	92%	15%
Lack of Teacher Training	88%	40%
High Cost of Devices/Subscriptions	85%	30%
AI Tools Not in Local Language/Accent	80%	35%
Lack of Time to Integrate into Curriculum	70%	55%
Concern Over Student Screen Time	45%	50%
Data Privacy and Security Concerns	35%	65%

3.3. Student Learning Outcomes and Engagement

The core efficacy of the AI intervention was measured through student learning gains and engagement levels. The results demonstrate that while AI tools were effective in both countries, the magnitude of the effect was mediated by the surrounding ecosystem. Comparative learning

outcomes for AI and control groups are presented in Table 6, while student engagement metrics are summarized in Table 7.

Table 6 provides the core efficacy evidence. AI groups in both countries significantly outperformed their respective control groups across both vocabulary and pronunciation measures (all $p < .001$), validating AI as an effective supplemental intervention. However, the larger effect sizes in China (Vocabulary: $d = 0.92$; Pronunciation: $d = 0.95$) compared to Pakistan (Vocabulary: $d = 0.68$; Pronunciation: $d = 0.72$) demonstrate an ecosystem multiplier effect: the combination of better infrastructure, higher teacher readiness, and more sophisticated tools amplifies the inherent pedagogical potential of the technology.

Table 6. Comparison of Learning Gains for AI vs. Control Groups

Country	Group	Pre-Vocab	Post-Vocab	Gain	Pre-Pron	Post-Pron	Gain
Pakistan	AI (n=60)	42.1	58.9	+16.8	36.5	51.4	+14.9
	Control (n=60)	41.5	50.0	+8.5	42.0	48.2	+6.2
China	AI (n=60)	47.3	68.2	+20.9	40.1	60.3	+20.2
	Control (n=60)	46.8	56.9	+10.1	49.2	58.8	+9.6

Table 7. Comparison of Student Engagement Metrics

Engagement Metric	Pakistan AI Group	China AI Group
Average Session Duration (min)	17.2	21.5
% of Sessions Completed	78%	94%
On-Task Behavior (Teacher Report, 1-5)	3.6	4.4
Self-Reported Enjoyment (Student Survey, 1-5)	4.1	4.7

As shown in Table 7, engagement metrics correlate closely with learning outcomes. Higher session completion rates, longer average session durations, and superior on-task behavior in the Chinese cohort point to more reliable and immersive tool usage. It is notable that despite lower completion rates (78%), Pakistani students reported high enjoyment scores (4.1 out of 5.0), suggesting strong intrinsic motivation that is currently constrained by contextual and infrastructural factors rather than by a lack of pedagogical appeal.

3.4. Technology Design, Policy, and Implementation Models

The final set of results examines the underlying technological, policy, and strategic differences that drive the observed outcomes. Table 8 compares the design characteristics of AI tools deployed in each country, Table 9 contrasts the national policy frameworks, and Table 10 synthesizes the key qualitative themes emerging from stakeholder interviews.

Table 8. Comparison of AI Tool Design Characteristics: Pakistan and China

Tool Characteristic	Typical Pakistani Context	Typical Chinese Context
Primary Deployment Model	Offline-first mobile app	Cloud-based platform
Connectivity Requirement	Minimal (for updates)	Constant (for core features)
Language/Accent Adaptation	Limited to none	Moderate (e.g., Mandarin-influenced English)
Primary Content Focus	Vocabulary & Basic Phonics	Vocabulary, Phonics, Listening Comprehension
Teacher Dashboard Analytics	Basic (completion %)	Advanced (error pattern analysis)

Table 8 highlights divergent design philosophies. Pakistani tools are defined by “frugal innovation,” minimizing dependency on unstable infrastructure. Chinese tools leverage robust infrastructure to offer advanced, data-rich functionality. The lack of local accent adaptation in Pakistan, combined with teacher reports in Table 5, points to a major design-for-context gap that likely limits pronunciation tool efficacy.

Table 9. Policy between Pakistan and China about AI-in-Ed

Policy/Support Dimension	Pakistan	China
National AI-in-Ed Strategy	Nascent / Fragmented	Comprehensive & centralized
State Funding for EdTech Hardware	Low (NGO-driven)	High (State-allocated)
Mandated Teacher Digital Training	No	Yes
Data Privacy Guidelines for Schools	Absent	Present (but evolving)
Scale of Implementation	Pilot Projects	Provincial/National Rollout

Table 9 exposes the root cause of the ecosystem divergence: policy and governance. China’s centralized, state-funded strategy creates a coherent implementation pipeline. Pakistan’s fragmented, donor-dependent approach leads to isolated pilots. The absence of data privacy guidelines in Pakistan is a critical oversight, while their presence in China aligns with the higher stakeholder concern noted in Table 5.

Table 10. Key Qualitative Themes by Country: Stakeholder Interview Findings

Theme	Key Insight from Pakistan	Key Insight from China
Funding & Scale	"Project sustainability ends with donor cycle."	"Scale is state-mandated, but innovation can be rigid."
Teacher Role	"Teacher is a crucial mediator and tech supporter."	"Teacher is shifting from instructor to data-guided coach."
Cultural Fit	"Content must reflect local stories and values."	"Tools must better recognize diverse dialects within China."
Future Priority	"Build foundational infrastructure and teacher capacity."	"Move from standardized to adaptive, personalized learning."

The qualitative insights in Table 10 synthesize the key thematic tensions. Pakistan's model is innovative but unsustainable, reliant on external funding and heroic teacher mediation. China's model is scalable but rigid, with a top-down approach that can stifle local adaptation and has not fully solved the cultural and linguistic fit issue internally. Both contexts point toward a future need for contextual personalization, albeit from different starting points.

4. Discussion

The findings of this comparative study illuminate the profound impact of the national socio-technical ecosystem on the potential of AI in early childhood education. The most salient finding is the ecosystem multiplier effect. The larger learning gains observed in China are not attributable to the AI intervention alone but are the product of a reinforcing chain of state policy, reliable infrastructure, advanced platforms, and trained educators. In Pakistan, weaknesses at each stage of this chain attenuate the potential impact of the technology, empirically validating that a tool's efficacy is co-determined by its environment. This study crystallizes two distinct models: Pakistan's Frugal, Teacher-Mediated Innovation, which excels in contextual ingenuity but struggles with sustainability, and China's State-Orchestrated, Platform-Centric Scaling, which delivers uniformity at scale but risks pedagogical rigidity and algorithmic bias.

Beyond these national differences, the results reveal layered challenges. Universal ethical and pedagogical concerns, such as data privacy and the need for meaningful teacher-AI collaboration, are emerging in both contexts. Superimposed on these are context-specific structural barriers. In Pakistan, these are first-order infrastructural and capacity gaps (e.g., electricity, training, cost), whereas in China, they are second-order design and governance gaps related to cultural localization and flexibility. These findings argue against a one-size-fits-all solution, pointing instead toward a hybrid framework that synthesizes the strengths of each model. For contexts like Pakistan, the priority must be to build coordinated scaffolding for

innovation through state-supported “innovation pipelines” that establish minimum infrastructure standards and institutionalize teacher digital literacy. For contexts like China, the imperative is to inject flexibility and teacher agency into platforms, decentralizing design choices and investing in AI models trained on diverse local dialects.

4.1. Comparative Synthesis: Why Does the State-Led Model Outperform Decentralized Innovation?

The central comparative question raised by this study is not merely that China’s AI integration produces larger learning gains than Pakistan’s, but why this gap exists and what structural forces sustain it. This synthesis moves beyond descriptive comparison to offer a theoretically grounded explanation rooted in the political economy of educational reform, the architecture of institutional support, and the socio-economic contexts of the two rural settings studied.

At the most fundamental level, the divergence reflects differences in state capacity and political will. China’s rural Yunnan districts, while economically underdeveloped relative to coastal provinces, nonetheless benefit from a coherent vertical policy pipeline: the national Education Informatization 2.0 mandate (Ministry of Education, P. R. China, 2020) flows downward through provincial education bureaus into district-level implementation plans, ensuring that hardware procurement, teacher training, and curriculum alignment occur in coordinated sequence. The rural Punjab districts in Pakistan, by contrast, operate within a fragmented governance landscape in which federal, provincial, and district authorities share overlapping and sometimes conflicting educational mandates. In the absence of a single coordinating authority, AI integration depends on the initiative of individual NGOs and the continuity of donor funding cycles — neither of which can guarantee the systemic consistency that effective technology adoption requires.

A second explanatory axis concerns the socio-economic baseline of the rural communities studied. While both settings are classified as low-resource, the Yunnan districts included in this study have benefited from China’s decade-long poverty alleviation infrastructure campaigns, which have materially improved rural electricity supply, road networks, and mobile broadband coverage. This baseline infrastructure, invisible in the AI-in-education literature but foundational to any digital intervention, allows cloud-based AI tools to function reliably. The Punjab districts in Pakistan lack this baseline: as Table 1 documents, only 10% of schools have high-speed internet access and schools frequently experience power outages, which directly

explains the 92% barrier rate for unreliable internet and electricity reported in Table 5. This is not a failure of the AI tools themselves, but a failure of the pre-conditions for their use — a distinction that has significant implications for policymakers who seek to replicate China's success in lower-baseline contexts.

Third, the human capital dimension is critical. China's mandated digital teacher training produces a measurably higher self-efficacy baseline (Table 4), which the SAMR analysis suggests is the mechanism through which better infrastructure translates into higher-level pedagogical integration. Teachers with greater digital confidence are more likely to use AI tools at the Modification and Redefinition levels rather than treating them as mere Substitution aids. In Pakistan, even the motivated teachers who champion AI tools in their schools — the “teacher champions” described in the qualitative findings — operate without this institutional support, making the quality of integration entirely contingent on personal initiative. This finding aligns with Zawacki-Richter et al. (2019), who argued that without intentional educator empowerment built into institutional design, AI risks being adopted superficially rather than transformatively.

Importantly, this synthesis does not position China's model as categorically superior. The qualitative data in Table 10 reveal that China's top-down coherence suppresses local innovation and produces a standardization that is poorly matched to the dialect diversity within rural China itself. Pakistan's grassroots model, for all its fragility, generates contextually sensitive adaptations — such as offline-first apps that function without connectivity — that China's centralized platforms have not developed. The theoretical contribution of this study is therefore to argue that neither the state-led nor the decentralized model is inherently optimal; rather, effectiveness is a product of the fit between governance architecture and the socio-technical infrastructure of the deployment context. The Hybrid Ecosystem Framework proposed here operationalizes this insight, providing a synthesis pathway that embeds the contextual sensitivity of decentralized innovation within the institutional scaffolding of a coordinated state strategy.

4.2. Ecosystem Effects and the SAMR Continuum

The ecosystem multiplier effect identified in this study finds strong resonance in prior CALL literature. Son et al. (2025) established that AI-mediated language tools produce their strongest gains when embedded within supportive institutional contexts, a finding directly mirrored in the larger effect sizes observed in China (Vocab: $d = 0.92$) versus Pakistan (Vocab: $d = 0.68$).

Critically, applying the SAMR framework (Puentedura, 2006) reveals that the Chinese deployment ecosystem enables tools to operate predominantly at the Modification and Redefinition levels, where AI reshapes the pedagogical task itself through adaptive sequencing and real-time dashboards. In contrast, most Pakistani deployments remain at the Substitution and Augmentation levels, where AI replaces or incrementally improves existing tasks without fundamentally transforming instruction. This SAMR-based analysis extends Ngo et al. (2024), whose meta-analysis found ASR tools most effective for pronunciation when integrated systematically rather than used as standalone supplements, by demonstrating that the level of integration is itself a product of national infrastructure and policy capacity.

4.3. Vygotskian Scaffolding and the Role of the Teacher

Vygotsky's (1978) sociocultural theory, and specifically the concept of the Zone of Proximal Development (ZPD), provides a compelling lens through which to interpret the divergent teacher roles observed in this study. In China's platform-centric model, the AI system itself increasingly functions as a Knowledgeable Other (MKO), delivering calibrated phonological and lexical scaffolding at the individual learner level. This shifts the teacher's role from primary instructor to data-guided coach, a transition documented in Table 10's qualitative insights. In Pakistan's teacher-mediated model, however, the human teacher remains the indispensable MKO, with the AI serving as a supplementary prop rather than a primary pedagogical agent. While this preserves essential human-relational dimensions of early learning, it also means that the quality of AI integration is entirely contingent on individual teacher capacity and motivation. These findings align with Zawacki-Richter et al. (2019), who cautioned that AI in education risks rendering the educator invisible if institutional design does not intentionally preserve teacher agency.

4.4. The Digital Divide as a Socio-Technical Phenomenon

The barrier profiles documented in Table 5 reveal that the digital divide in these rural contexts is not a simple binary of access versus no access, but rather a layered socio-technical phenomenon. Pakistan's foundational barriers, including unreliable electricity (92%), lack of teacher training (88%), and device cost (85%), constitute what prior scholarship terms a first-level digital divide, concerned with physical access to technology (Ngo et al., 2024). China's barrier profile, however, has largely transcended this first level and now grapples with a second-level divide centered on the quality and cultural appropriateness of technology use. The high concern regarding local accent and dialect recognition (35%) in China, and the even more acute

concern in Pakistan (80%), directly corroborates findings from the landmark study on racial and linguistic disparities in automated speech recognition systems (Racial disparities in automated speech recognition, 2020), which demonstrated systematic underperformance of ASR models on non-dominant language varieties. This technical limitation has profound pedagogical consequences in early childhood contexts, where inaccurate pronunciation feedback can actively mislead developing learners and undermine confidence.

4.5. Policy Architecture and Sustainable Scaling

The policy divergence documented in Table 9 illuminates a fundamental tension between state-coordinated scaling and decentralized, NGO-led innovation. China's Education Informatization 2.0 framework (Ministry of Education, P. R. China, 2020) demonstrates how a coherent national policy architecture can rapidly build the enabling conditions for AI integration, including hardware rollout, mandatory teacher training, and centralized data governance. However, as the qualitative findings in Table 10 indicate, this top-down coherence carries a risk of pedagogical rigidity and suppression of context-sensitive innovation. Pakistan's model, driven by NGOs and donor funding cycles, generates genuinely responsive local solutions, such as offline-first compressed on-device models adapted to low-bandwidth environments, but these innovations remain unsustainable beyond the donor cycle. This tension echoes Fadieieva's (2023) cluster analysis of adaptive learning literature, which found that the most durable implementations combine centralized quality assurance with decentralized content customization. The Hybrid Ecosystem Framework proposed in this study operationalizes precisely this synthesis, offering a theoretically grounded and empirically supported pathway toward equitable AI integration in low-resource early childhood education settings.

5. Conclusion

This comparative analysis of AI integration for early childhood English learning in rural Pakistan and China yields a central, unequivocal finding: the national socio-technical ecosystem is the paramount determinant of implementation success and educational impact. The study reveals two distinct paradigms China's state-orchestrated scaling and Pakistan's decentralized innovation each with unique affordances and constraints. The primary contribution of this research is the development of a Hybrid Ecosystem Framework for equitable scaling. This framework posits that the optimal path forward is not the replication of a single model but the strategic synthesis of each model's core strength: embedding the

contextual sensitivity of Pakistan's grassroots approach within the coordinated support of China's state-led model.

The practical implications are clear. For developing contexts, the focus must be on building “scaffolded innovation pipelines” through cohesive national policies. For more advanced systems, the imperative is to “humanize the platform” by designing for flexibility and empowering teachers. Ultimately, this study argues that the discourse on AI in education must evolve from a technocentric focus on the tool to an ecological focus on the context. The promise of AI to bridge educational divides will only be realized if its integration is guided by a deep understanding of local realities, pedagogical wisdom, and an unwavering commitment to serving the most marginalized learners first.

5.1. Limitations

This study's findings should be interpreted with consideration for several limitations. The quantitative results are derived from a synthesis of pilot-scale data and require validation through large-scale, longitudinal field research to confirm the observed effect sizes. The analysis captures short-term outcomes, leaving questions about the long-term retention of skills and the development of higher-order communicative competence unanswered. Furthermore, the findings from specific rural districts in Pakistan and China may not be generalizable to all sub-regions within these diverse nations or to other countries with different governance structures. Finally, the rapid pace of technological change means that specific tool recommendations should be viewed as principles for context-aware development rather than as permanent technical specifications.

Additional limitations warrant acknowledgment. First, the sample sizes—60 teachers and 120 students per country—while sufficient for exploratory analysis, are modest relative to the populations they represent, and results should not be extrapolated to all rural schools in Pakistan or China without further validation. Second, potential language barriers during semi-structured interviews with Pakistani and Chinese educators, conducted through interpreters and back-translation procedures, may have introduced subtle nuances of meaning that were difficult to fully preserve. Third, self-reported teacher perception data are subject to social desirability bias, as respondents may have over-reported positive attitudes toward technology in the presence of researchers. Fourth, the 10-week intervention window captures only immediate learning gains and cannot speak to the durability of vocabulary and pronunciation improvements over a longer

academic year. Future research should address these gaps through larger longitudinal studies, participatory action research designs that involve teachers as co-investigators, and the development of locally validated assessment instruments that better capture the full range of communicative competence in these diverse linguistic contexts.

5.2. Practical Recommendations for Rural Practitioners

The findings of this study carry direct, actionable implications for teachers working in low-resource rural contexts, particularly in Pakistan. While systemic change requires national policy action, individual practitioners can take concrete steps today to maximize the impact of available AI tools within existing constraints. The following three recommendations are grounded directly in the study's empirical findings:

- **Recommendation 1: Prioritize offline-first vocabulary apps for daily warm-up routines.** This study found that Pakistani students using offline-capable AI apps achieved a vocabulary gain of +16.8 points compared to +8.5 for the control group, even without reliable internet. A rural teacher can begin each lesson with a 5–10 minute session on a shared tablet or smartphone using a pre-downloaded app (such as an offline vocabulary game). This requires no data connection, minimal preparation time, and directly targets the vocabulary deficit identified as the primary barrier to English proficiency. The teacher's role during this period shifts to observer, using the time to note which students struggle and need individual follow-up.
- **Recommendation 2: Use AI pronunciation feedback as a peer-learning scaffold, not a replacement for instruction.** The data showed that despite high enjoyment scores (4.1 out of 5) among Pakistani students, session completion rates were only 78%, partly because students abandoned tasks when pronunciation feedback felt discouraging or culturally mismatched. Teachers can reframe AI pronunciation tools as a “practice partner” used in pairs: one child speaks into the device while a partner observes and encourages. This cooperative structure sustains motivation, reduces the anxiety of direct machine evaluation, and builds communicative confidence even when the AI's accent recognition is imperfect.
- **Recommendation 3: Document and share local implementation adaptations to build a community knowledge base.** One of the most significant findings is that Pakistan's model succeeds through grassroots, teacher-driven adaptation—yet this

knowledge remains informal and unsustainable because it is not recorded. A rural teacher who discovers that a specific app works better when used before lunch, or that a particular vocabulary set resonates with local agricultural contexts, should document this in a simple shared logbook (physical or digital via WhatsApp). Sharing these micro-adaptations with NGO coordinators and other teachers builds the “contextual knowledge base” that this study identifies as essential for transitioning from unsustainable pilot projects to durable, community-owned programs.

Disclosure Statement

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Appendix A: Teacher Perception Survey Instrument

The following 35-item survey was administered to all teacher participants (n = 120). Items were rated on a five-point Likert scale:

1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree

Subscale 1: Perceived Usefulness (Items 1-10)

Item 1: Using AI tools helps my students improve their English vocabulary.

Item 2: AI-based pronunciation tools improve the quality of my students' spoken English.

Item 3: AI tools make my English lessons more engaging and interactive for young learners.

Item 4: AI tools allow me to personalize lessons to individual student needs.

Item 5: AI tools provide feedback to my students that I am unable to give due to class size.

Item 6: The AI tools used in my classroom are appropriate for the age of my students.

Item 7: Using AI tools helps me identify which students are falling behind in English.

Item 8: AI tools support students' independent learning outside of classroom hours.

Item 9: Overall, I believe AI tools have a positive effect on English learning outcomes.

Item 10: I would recommend AI-enhanced English tools to teachers in other rural schools.

Subscale 2: Ease of Use (Items 11-18)

Item 11: I find it easy to operate the AI applications used in my classroom.

Item 12: I was able to learn how to use the AI tools without extensive training.

Item 13: When a technical problem occurs, I am able to resolve it without external help.

Item 14: The user interface of the AI tools is clear and appropriate for young learners.

Item 15: Setting up the AI application at the start of a lesson does not waste class time.

Item 16: The AI tools function reliably during lessons without frequent crashes or errors.

Item 17: The instructions provided with the AI tools are clear and easy to follow.

Item 18: Overall, I find the AI tools easy to integrate into my daily teaching routine.

Subscale 3: Access and Infrastructure (Items 19-27)

Item 19: I have reliable internet connectivity in my school.

Item 20: My school has a sufficient number of devices for students to use AI tools.

Item 21: My school has a dedicated space or computer lab for digital learning activities.

Item 22: Power supply in my school is reliable enough to support regular AI tool use.

Item 23: The cost of devices and software subscriptions is manageable for my school.

Item 24: Technical support is available to me when I encounter problems with AI tools.

Item 25: I have sufficient time within the curriculum to use AI tools regularly.

Item 26: School administration actively supports and encourages AI tool use.

Item 27: Parents and the community are generally supportive of AI-based learning.

Subscale 4: Self-Efficacy (Items 28-35)

Item 28: I am confident in my ability to integrate AI tools into my English lessons.

Item 29: I feel adequately trained to use AI tools for teaching purposes.

Item 30: I can design lesson plans that effectively incorporate AI-based activities.

Item 31: I am able to explain to parents how AI tools are used in my classroom.

Item 32: I can adapt AI tools to suit the specific cultural and linguistic needs of my students.

Item 33: I feel comfortable discussing the benefits and limitations of AI with my colleagues.

Item 34: I am confident I can continue using AI tools even without ongoing external support.

Item 35: Overall, I believe I have the skills needed to be an effective AI-assisted English teacher.

Appendix B: Semi-Structured Interview Protocol

The following protocol guided interviews with 20 key stakeholders. Questions were translated into Urdu, Punjabi, and Mandarin as appropriate. Interviewers were trained to use follow-up probes such as "Can you give me a specific example?" and "How did that make you feel/respond?" to elicit richer responses.

Section 1: Adoption Drivers and Barriers

Q1: How did your school or organization first decide to adopt AI tools for English language teaching? What was the primary motivation?

Q2: What were the most significant challenges you faced when introducing AI tools? How did you address them?

Q3: What external support (government, NGO, donor) was available during adoption, and was it sufficient?

Q4: How have teachers in your context responded to the introduction of AI tools — with enthusiasm, resistance, or mixed reactions?

Section 2: Pedagogical Integration

Q5: In what ways have AI tools changed how teachers teach English in rural classrooms? Can you describe a specific lesson where AI was used effectively?

Q6: Do teachers use AI as the primary mode of instruction or as a supplementary tool? What factors drive this choice?

Q7: How do AI tools accommodate the local language background of young learners — for example, students whose home language is Punjabi or a regional Chinese dialect?

Q8: In your view, has AI enhanced or diminished the role and authority of the classroom teacher? Please explain.

Section 3: Ethical Concerns and Child Data

Q9: What concerns, if any, do you have about collecting and storing data from young children through these applications?

Q10: Are parents and guardians informed about what data is collected from their children? How is this communicated?

Q11: What safeguards are in place to protect student data, and who is responsible for enforcing them?

Section 4: Sustainability and Future Direction

Q12: What do you see as the biggest threat to the long-term sustainability of AI-enhanced English education in your context?

Q13: If you had complete freedom and resources, what one change would you make to improve AI integration for young English learners in rural areas?

Q14: What advice would you give to policymakers in other developing countries who are considering similar AI-in-education initiatives?