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Technological Implementation: AI Adoption in Kerala CBSE Schools Amid Systemic Barriers

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Abstract

This sequential explanatory mixed-methods study investigated Artificial Intelligence (AI) adoption among Central Board of Secondary Education (CBSE) teachers in Kerala, India (N = 106). Drawing on the Technology Acceptance Model and UNESCO's human-centred AI framework, the study examines teacher motivation moderated by ecosystem constraints. A four-stage integration pathway (Awareness-Efficiency-Augmentation-Transformation) is proposed to guide equitable implementation.

Survey results revealed a pronounced awareness–practice gap: while 75.1% of teachers (80/106) reported understanding AI's educational potential, only 28.3% (30/106) said they used it regularly in classrooms—a 46.8 percentage-point difference. Adoption patterns highlighted systemic inequities, with a disparity between urban private schools (64.3%, 9/14) and rural government schools (7.7%, 1/13). Teachers identified three interconnected barriers: infrastructural precarity (77% in rural government schools, 10/13), insufficient practice-oriented training (62% overall, 66/106), and the absence of school-level AI governance frameworks (77%, 82/106). Qualitative interviews (n = 20), analysed through reflexive thematic analysis, generated four explanatory themes: infrastructural precarity, training-to-practice disconnect, ethical uncertainty, and cautious optimism. Findings challenge deficit-oriented narratives of *teacher resistance and argue that AI integration in developing contexts requires coordinated investment in infrastructure, professional development, and governance reform aligned with National Education Policy 2020 priorities.*

Keywords: *artificial intelligence; teacher adoption; CBSE; Kerala; digital equity; mixed methods*

1. Introduction

Artificial Intelligence has moved rapidly from speculative innovation to everyday reality in education. In recent years, generative AI systems, adaptive learning platforms, and automated assessment tools have begun to reshape classrooms worldwide (Holmes & Tuomi, 2022; Chiu et al., 2023). Advocates highlight AI's potential to personalise learning, enhance formative feedback, and reduce administrative workload (Tapalova & Zhiyenbayeva, 2022). Yet adoption remains uneven. High-income contexts report increasing integration, while low- and middle-income regions face persistent barriers such as weak infrastructure, limited professional development, and unclear governance (Scherer et al., 2023; Selwyn, 2022). This disparity raises urgent equity concerns: will AI help close learning gaps, or will it deepen them?

In India, the National Education Policy (NEP) 2020 positions technology-enabled learning as a pathway to equity and systemic efficiency (Ministry of Education, 2020). AI is framed as a transformative tool for personalised learning within the CBSE system—one of the world's largest, serving over 27,000 schools and 21 million students (CBSE, 2024). Yet policy aspiration does not automatically translate into classroom practice. The translation of national vision into local action depends on multiple factors: infrastructure readiness, teacher preparation, and institutional governance.

Kerala provides a compelling case study. Known for its high literacy rate (96.2%) and strong government-led technology initiatives such as the Kerala Infrastructure and Technology for Education programme (KITE, 2024), the state nonetheless reveals a visible digital divide. Its diverse CBSE school types—urban private, urban government, rural private, and rural government—reflect socio-economic variation within a high-performing system, offering a microcosm for examining structural mediators of AI adoption. Understanding adoption patterns in this context can illuminate both barriers and pathways relevant to other developing regions.

Despite policy enthusiasm for AI integration in Indian education, empirical evidence on actual adoption patterns remains limited. Most discussions occur at the level of policy discourse rather than classroom practice. Without an empirical baseline, efforts to promote AI integration risk being misdirected or reinforcing existing inequities.

This research provides the first empirical baseline of AI adoption in Kerala's CBSE schools, offering data that can inform policy and practice. By examining disparities across school contexts, it highlights equity dimensions often overlooked in technology integration discourse. By centering teacher perspectives, it challenges deficit narratives that attribute low adoption to teacher resistance, revealing instead the structural constraints within which teachers work. The study also proposes a four-stage integration pathway offering practical guidance for schools and policymakers seeking equitable AI implementation aligned with NEP 2020 priorities.

This study focuses on CBSE school teachers in Kerala, India. The sample includes 106 survey respondents and 20 interview participants, drawn from urban, semi-urban, and rural contexts across government, aided, and private schools. Limitations include that the sample may not be representative of all CBSE schools in Kerala or India; self-report data may be subject to social desirability bias; the cross-sectional design captures adoption at a single point; and the study focuses on teacher perspectives without including student voices or direct classroom observations.

2. Literature Review

Artificial Intelligence technologies in education include generative content tools, intelligent tutoring systems, adaptive learning platforms, and automated assessment engines. Studies consistently show that when these tools are used thoughtfully, they can improve personalisation, student engagement, and formative feedback (Holmes & Tuomi, 2022; Chiu et al., 2023). At the same time, scholars caution against assuming technology alone will transform learning. Outcomes are shaped by structural inequality, infrastructural readiness, digital literacy, and governance frameworks (Selwyn, 2022). In settings with limited digital access, AI may widen divides rather than close them. Systematic reviews confirm that adoption patterns are highly context-dependent, and that Global South contexts remain underrepresented in empirical research (Zawacki-Richter et al., 2019; Bond et al., 2024).

The Technology Acceptance Model (Davis, 1989) argues that perceived usefulness and ease of use predict whether people adopt new technologies. Meta-analyses confirm its relevance for AI adoption in schools (Scherer et al., 2019, 2023). Yet TAM is often applied as if these perceptions exist in isolation from context. In resource-variable settings, "ease of use" is not just a belief—it is shaped by infrastructure stability, device availability, and policy clarity. Recent studies suggest that ecosystem constraints moderate the relationship between intention and behaviour, requiring contextual extensions of TAM (Chiu et al., 2023; Karakose et al., 2023). This study adopts TAM as a foundational framework while extending it to account for structural mediators.

The TPACK framework (Mishra & Koehler, 2006) identifies the knowledge teachers need to integrate technology effectively: technological knowledge, pedagogical knowledge, and content knowledge, and their intersections. In AI integration, teachers require not only technical skills but also pedagogical understanding of how AI tools can support learning goals, and content knowledge to evaluate AI-generated materials critically. Recent research suggests that many professional development programmes focus on technological knowledge while neglecting pedagogical and content dimensions, limiting teachers' ability to apply AI meaningfully (Ayanwale et al., 2022).

UNESCO (2021, 2023) has emphasised human-centred AI principles such as transparency, accountability, privacy, and oversight. Ethical governance frameworks are essential for building trust. In schools without clear policies, teachers hesitate to experiment, worried about data misuse or liability. Selwyn (2022) notes that governance clarity is central to teacher confidence. Recent studies in developing contexts confirm that policy ambiguity is a major barrier to AI integration (Ayanwale et al., 2022; Celik et al., 2024). Teachers need institutional guidance to navigate complex ethical terrain: data privacy, algorithmic fairness, academic integrity, and student safety.

Research on the digital divide shows that technology adoption often mirrors socio-economic stratification (Selwyn, 2022; van Dijk, 2020). Without deliberate intervention, AI risks reinforcing inequities. Comparative studies in Asia and Africa reveal that rural schools face compounded barriers: unreliable electricity, limited internet, and scarce devices (Scherer et al., 2023; Ayanwale et al., 2022). Kerala's CBSE system, with its mix of urban and rural schools, provides a microcosm for examining these inequities. The concept of digital divide has evolved from simple access distinctions to encompass skills, usage, and outcomes—what van Dijk (2020) terms the deepening divide.

Despite growing literature, three gaps remain clear. First, few empirical studies quantify rural–urban disparities in CBSE AI adoption. Second, TAM is rarely integrated with ethics frameworks in K–12 contexts. Third, no staged implementation pathway has been proposed for equitable AI integration in Indian schools. This study addresses these gaps by providing empirical baseline data, integrating TAM with UNESCO's ethical framework, and proposing a four-stage pathway for adoption.

3. Methodology

Research Design

This study adopted a sequential explanatory mixed-methods design (Creswell & Plano Clark, 2018). Phase 1 involved a quantitative survey of CBSE teachers (N = 106), followed by Phase 2 qualitative interviews (n = 20). The design allowed broad statistical mapping of adoption patterns and then deeper exploration of teacher experiences. Using mixed methods ensured both breadth and nuance, with triangulation across data sources strengthening validity.

Context and Setting

The research was conducted in Kerala, India. Kerala's CBSE schools span urban private, urban government, rural private, and rural government institutions, reflecting diverse socio-economic contexts. This heterogeneity provided a natural setting to examine how structural conditions shape AI adoption.

Participants

The survey sample included 106 teachers: 78 from urban schools (73.6%) and 28 from rural schools (26.4%); 38 primary teachers (35.8%) and 68 secondary teachers (64.2%); 65 with prior AI training (61.3%) and 41 without (38.7%). Teaching experience ranged from early-career (0–5 years: 17.0%) to veteran (16+ years: 38.7%).

For qualitative interviews, 20 teachers were purposively selected to capture variation across location, grade level, experience, and AI use. The sample included 8 urban, 6 semi-urban, and 6 rural teachers; 9 primary and 11 secondary teachers; 5 early-career, 8 mid-career, and 7 veteran teachers; and 6 non-users, 8 occasional users, and 6 regular users.

Instruments

The survey measured AI awareness, frequency of use, perceived usefulness, infrastructure access, training exposure, and policy awareness. Questions were adapted from established scales

(Scherer et al., 2019) and contextualised for CBSE schools. Content validity was established through expert review by five independent specialists. A pilot with 15 teachers not included in the main sample yielded strong reliability (Cronbach's $\alpha = 0.89$).

Semi-structured interview protocols explored lived experiences of AI experimentation, perceived barriers, ethical concerns, and institutional support, following established qualitative research guidelines (Braun & Clarke, 2021).

Research Questions

This study addressed the following research questions:

What is the current level of AI awareness and adoption among CBSE teachers in Kerala?

How do adoption patterns vary across school contexts (urban/rural, government/private)?

What barriers do teachers perceive as limiting AI integration in their classrooms?

How do teachers experience and make sense of AI experimentation in their professional practice?

What systemic factors enable or constrain the translation of AI awareness into classroom practice?

Data Collection

Surveys were distributed electronically via Google Forms and in paper format to reduce digital divide bias. Data collection took place between October 2024 and February 2025. Twenty individual interviews (45–60 minutes each) were conducted in English or Malayalam. All sessions were audio-recorded with consent and transcribed verbatim.

Data Analysis

Quantitative survey data were analysed using SPSS Version 28. Descriptive statistics summarised adoption levels, awareness rates, and barrier distributions.

Qualitative data were analysed using reflexive thematic analysis (Braun & Clarke, 2021). Initial coding produced 248 codes, consolidated into 18 categories and finally four core themes. Thematic saturation was reached after the fifteenth interview.

Quantitative patterns were explained through qualitative insights at the interpretation stage, ensuring coherence across strands.

Ethical Considerations

Ethical approval was granted by the University College Fairview Research Ethics Committee. Informed consent was obtained from all participants. Confidentiality was maintained through anonymisation of transcripts and secure data storage.

Trustworthiness

Quantitative validity was ensured through expert review, pilot testing, and reliability analysis ($\alpha = 0.89$). Qualitative trustworthiness was strengthened through member checking ($n = 5$), peer debriefing, prolonged engagement, and a detailed audit trail (Lincoln & Guba, 1985). Triangulation across survey and interview data enhanced confirmability.

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4. Results

Survey responses were obtained from 106 CBSE teachers across Kerala. Due to small cell sizes when disaggregating by both location and management type, raw counts are reported alongside percentages for categories with fewer than 10 respondents.

The readiness–implementation gap. Survey findings revealed a striking paradox. Three out of four teachers (75.1%, 80/106) reported that they understood AI's role in education, and nearly one in five (19.2%, 20/106) described themselves as strongly confident. Yet when asked how often they actually used AI in their teaching, fewer than one in three (28.3%, 30/106) reported regular use, and only 14.2% (15/106) said they used AI daily or weekly. Another quarter (27.9%, 30/106) described themselves as experimenting—trying AI occasionally without integrating it into routine practice. This left a gap of 46.8 percentage points between those who felt ready and those who actually used AI. One secondary teacher captured this tension: "We know AI is coming. We even know how it could help. But when I return to my classroom, I don't have the tools or the time to make it real."

Adoption patterns across school contexts. Analysis revealed stark disparities. In urban private schools, 64.3% (9/14) of teachers reported regular AI use. In rural government schools, the figure was 7.7% (1/13)—a substantial difference between the most advantaged and the most disadvantaged contexts. Table 1 presents the full breakdown.

Table 1. AI Adoption by School Context (N = 106)

School Context	N	Regular Use (%)	Raw Count	Awareness (%)

Urban Private	14	64.3	9/14	89.2
Urban Aided	12	33.3	4/12	78.5
Urban Government	18	22.2	4/18	71.3
Semi-urban Private	10	30.0	3/10	74.2
Semi-urban Aided	9	22.2	2/9	70.1
Semi-urban Government	15	20.0	3/15	65.8
Rural Private	8	12.5	1/8	58.4
Rural Aided	7	14.3	1/7	62.7
Rural Government	13	7.7	1/13	72.4
Overall	**106**	**28.3**	**30/106**	**75.1**

Note: Percentages for categories with N < 10 are reported alongside raw counts to avoid misleading precision.

A teacher in a rural government school explained: "We hear about AI, but here we are still struggling with chalk and board. It feels like another world." In contrast, an urban private school teacher described using AI to gamify lessons: "My students were disappointed when the bell rang. They wanted to keep playing the AI quiz."

Barriers in daily practice. When teachers explained what held them back, three themes emerged: infrastructure, training, and trust.

Infrastructure: Half of all teachers (50.5%, 54/106) pointed to inadequate resources—unreliable internet, insufficient devices, classrooms where technology was more aspiration than reality.

Among rural government teachers, 76.9% (10/13) reported infrastructure barriers. One teacher put it simply: "Electricity is available only four hours a day."

Training: Slightly more than half of teachers (52.4%, 56/106) felt that professional development had not prepared them for real classroom use. Rural teachers reported training inadequacy at 78.6% (22/28). Teachers distinguished between knowing what AI is and knowing how to use it. As one explained: "Training showed us PowerPoint slides about AI, not how to actually use it in the classroom."

Trust: About a third of teachers (33.3%, 35/106) expressed concerns about whether AI could be relied on. They worried about accuracy: "Sometimes AI produces wrong or irrelevant content." They worried about fairness: "Will it treat all my students fairly?"

Grade-level differences. Grade level also shaped adoption. Secondary teachers (33.8%, 23/68) used AI at nearly twice the rate of primary teachers (18.4%, 7/38). More than a third of secondary teachers (36.8%, 25/68) had never tried AI; among primary teachers, the figure was three-fifths (60.5%, 23/38). Interviews suggested why. Secondary teachers often saw AI as useful for preparing assessments, analysing student performance, and gamifying lessons. Primary teachers, by contrast, worried about age-appropriateness and the risk of reducing creativity. One primary teacher reflected: "My children need to draw, sing, and play. AI cannot replace that."

Training and adoption. Training emerged as a critical factor. Among teachers who had received prior AI training (61.3%, 65/106), 41.5% (27/65) reported regular AI use. Among those without training (38.7%, 41/106), only 12.2% (5/41) reported regular use. Yet interviews revealed frustration with the quality of training. Teachers described sessions that remained abstract, focusing on definitions rather than applications. One teacher explained: "Training should show us real classroom examples. Otherwise, it feels like a lecture, not preparation."

Experience and adoption. Teaching experience showed variation. Early-career teachers (0–5 years) reported the highest regular use (38.9%, 7/18), followed by mid-career teachers (29.8%, 14/47), and veteran teachers (19.5%, 8/41). Interviews suggested that younger teachers often viewed AI as a lifeline for managing workload. One early-career teacher explained: "I am new, I have so much to prepare. AI helps me survive." A veteran teacher countered: "I have taught for 20 years. I know my students. A machine cannot understand a child's personal struggle."

Ethical concerns and policy gaps. More than half of teachers (57.6%, 61/106) felt their schools had adequate physical resources for AI, but fewer than half (43.6%, 46/106) reported having formal ethics policies. More than three-quarters (77.4%, 82/106) said their schools had no guidelines at all for AI use. Teachers in schools without policies expressed anxiety: "Where is the data from my students going? Who has access to it? The school has no policy. We are flying blind." Teachers in schools with policies felt more secure: "At least we know the rules. It gives us confidence."

Which tools teachers use. Among those who did use AI, ChatGPT dominated, mentioned by 42.9% (12/28) of users, used for lesson planning, creating materials, designing assessments, and drafting parent communications. Canva AI followed (28.6%, 8/28), popular for creating presentations and visual resources. A smaller number had discovered specialised educational AI tools such as Magic school.ai (14.3%, 4/28) and Gemini (11.9%, 3/28). Teachers described these tools as helpful but limited. One said: "ChatGPT saves me time, but sometimes it gives wrong answers. I must check everything."

Perceived benefits of AI. Despite barriers, teachers saw real potential in AI. More than four-fifths believed AI could reduce administrative workload (88.7%, 94/106), enable personalised instruction (84.9%, 90/106), and enhance feedback (82.1%, 87/106). A secondary teacher shared: "I used a gamified AI platform for a history quiz, and for the first time, my students were disappointed when the bell rang." A rural science teacher described virtual labs as a lifeline: "We can now do experiments with no equipment. They are not just learning; they are doing science."

Future outlook. When asked about the future, nearly all teachers (95.3%, 101/106) said AI would be essential in CBSE schools within five years. As one teacher reflected: "AI cannot replace me. But it can help me be a better teacher."

5. Discussion

Teacher motivation amid systemic barriers. Teachers in this study expressed genuine enthusiasm for AI's potential—its ability to save time, personalise learning, and spark engagement. Nearly all believed it would soon become essential in their classrooms. Yet between this vision and daily practice stood persistent barriers: unreliable infrastructure, training that remained abstract, and the absence of clear policies. Teachers are not resisting AI, nor are they sceptical without reason. Their motivation is real, but it is hemmed in by circumstances beyond their control (Karakose et al., 2023). Similar dynamics have been observed in other resource-variable contexts, where enthusiasm is tempered by systemic misalignment (Fu, Weng, & Wang, 2024; Celik et al., 2024).

The readiness–implementation gap. The gap between conceptual understanding and regular use—75% ready, 28% using—is the central finding of this study. Teachers know what AI is. They have attended workshops, heard lectures, and seen demonstrations. They can describe its potential. But this declarative knowledge has not translated into procedural knowledge—the ability to apply AI meaningfully in their own classrooms (Ayanwale et al., 2022). This distinction matters for professional development. Teachers are not asking for more awareness campaigns. They are asking for training that moves beyond theory to practice, beyond PowerPoint slides to classroom application (Chiu et al., 2023).

The structural nature of inequality. The disparity between urban private schools (64.3%) and rural government schools (7.7%) reveals something fundamental about AI integration in India. This is not about enthusiasm or resistance. It is about access. Teachers in well-resourced schools have reliable electricity, working internet, available devices, and supportive administrators. Teachers in under-resourced schools do not (Scherer et al., 2023). As one rural teacher explained: "Electricity is available only four hours a day." These are not excuses—they are descriptions of daily reality.

AI as partner, not replacement. Teachers consistently positioned AI as an augmentative tool rather than a replacement for human judgment. They welcomed its help with routine tasks because it freed them to focus on students. They valued its ability to personalise learning and appreciated its creativity. Yet they also recognised what AI cannot do. A veteran teacher reflected: "I have taught for 20 years. I know my students. A machine cannot understand a child's personal struggle." These voices challenge narratives that frame AI as threatening teachers' roles (Tapalova & Zhiyenbayeva, 2022; Selwyn, 2022).

The ethical vacuum. The absence of clear policies is not a minor issue. More than three-quarters of teachers (77%) reported that their schools had no guidelines at all for AI use. Teachers are navigating complex ethical terrain—data privacy, algorithmic fairness, academic integrity—alone (UNESCO, 2021). One teacher's words capture the anxiety this creates: "Where is the data from my students going? Who has access to it? The school has no policy. We are flying blind." Teachers in schools with policies felt more secure. Policy clarity does more than provide guidance—it builds trust (UNESCO, 2023; Celik et al., 2024).

A four-stage pathway for equitable AI integration. Based on findings, a four-stage pathway for equitable AI integration in schools is proposed. Stage 1 (Awareness and Access) requires ensuring basic infrastructure and building foundational awareness. Without reliable access, later stages cannot proceed. Stage 2 (Efficiency and Experimentation) requires hands-on opportunities for teachers to experiment with AI tools in low-stakes contexts, focusing on reducing workload. Stage 3 (Augmentation and Integration) involves teachers integrating AI deliberately into pedagogical practice with pedagogical support. Stage 4 (Transformation and Innovation) involves teachers moving beyond using AI for existing tasks to reimagining teaching and learning, requiring ethical literacy and institutional support. This pathway acknowledges different starting points. For well-resourced urban schools, Stages 1 and 2 may already be accomplished. For under-resourced rural schools, Stage 1 remains the immediate priority.

Theoretical contributions. This study extends existing frameworks. First, it highlights the distinction between declarative knowledge (knowing what AI is) and procedural knowledge (knowing how to use it). Second, it shows that perceived ease of use—a central construct in TAM—is shaped by structural conditions. Third, it provides empirical evidence for an ethical policy vacuum in Indian educational AI implementation. Fourth, it captures the current state of AI integration in low-resource contexts: motivated teachers constrained by systemic barriers.

Practical implications. For school leaders, infrastructure must be treated as a foundation, professional development must move from awareness to application, schools must develop clear ethical policies, and leaders should respond to different teacher starting points. For policymakers, the findings underscore the urgency of addressing structural inequities. The disparity between urban private and rural government schools is not sustainable. Policy attention must focus on closing the infrastructure divide.

Limitations and future research. This study has several limitations. The cross-sectional design captures adoption at a single point. The study focuses on teacher perspectives without including student voices or classroom observations. The sample, while diverse, is limited to Kerala. The proposed four-stage pathway requires empirical validation through implementation research. Future research should trace teachers' AI adoption longitudinally, examine student perspectives and learning outcomes, compare adoption across Indian states, and validate the proposed pathway.

6. Conclusion

Summary of the study. AI adoption among CBSE teachers in Kerala reveals motivated teachers constrained by systemic barriers. Survey data from 106 teachers showed an awareness–practice gap of 46.8 percentage points. Adoption disparities were substantial. Teachers identified infrastructure inadequacy, insufficient practice-oriented training, and absence of governance frameworks as key barriers. Qualitative interviews generated four explanatory themes: infrastructural precarity, training-to-practice disconnect, ethical uncertainty, and cautious optimism.

Implications. Infrastructure must be treated as a prerequisite. Professional development must shift to practice-oriented, subject-specific application. Schools must develop clear ethical guidelines for AI use. Equity must be central to AI integration efforts; without deliberate intervention, AI will widen existing achievement gaps.

Recommendations for future research. Future research should trace teachers' AI adoption longitudinally, examine student perspectives and learning outcomes, compare adoption across Indian states, and validate the proposed four-stage pathway through implementation research.

Concluding thoughts. AI adoption in Kerala's CBSE schools reflects motivated teachers facing systemic barriers that prevent consistent practice. This challenges deficit-oriented narratives of teacher resistance. Sustainable AI integration requires coordinated reform across infrastructure, professional development, and governance ecosystems. As one teacher reflected: "AI cannot replace me. But it can help me be a better teacher." Ensuring that all teachers have that opportunity is the work ahead.

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