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Beyond Perceived Usefulness: How Structural Conditions Limit AI Adoption in Pakistani Classrooms

Mehtab Hussain*[1], Sobia Pervaiz[2]

[1,2] Allama Iqbal Open University, Islamabad, Pakistan,
Email: *meh6336@gmail.com, sobiapervaiz333@gmail.com

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Abstract
This qualitative study examines the gap between Artificial Intelligence (AI) awareness and actual classroom practice among teachers in Pakistan. Despite growing global interest in AI-driven education, teachers across Pakistani schools, colleges, and universities continue to face substantial obstacles that prevent meaningful adoption. Drawing on the Technology Acceptance Model as an organising theoretical lens, the study explores how perceived usefulness, perceived ease of use, and institutional context shape whether teachers move from knowing about AI to actually using it. Thirteen teachers from primary, secondary, college, university, and special education settings across public and private institutions participated in semi-structured interviews. Purposive sampling ensured diversity across school types, subject areas, and levels of experience. Data were analysed using the six-phase reflexive thematic analysis framework of Braun and Clarke (2006), supported by NVivo software. Six themes emerged: surface awareness with shallow understanding; structural barriers overriding individual intent; conditional rather than absent readiness; recognition of AI's potential, bounded by systemic constraints; absence of meaningful professional development; and substantive ethical and privacy concerns. The study's central contribution is an evidence-based account of how structural and institutional conditions in Pakistan specifically absent policy, inadequate infrastructure, and no targeted teacher training transform AI from a perceived opportunity into a practical impossibility for most teachers. The findings extend TAM by showing that in low-resource developing country contexts, perceived usefulness is often neutralised by systemic barriers that precede the individual adoption decision entirely. Recommendations are directed at policymakers, teacher educators, and institutional leaders.

Keywords: Artificial Intelligence, Technology Acceptance Model, teachers' perspectives, qualitative research

Introduction
Artificial Intelligence is reshaping how researchers, policymakers, and educators think about teaching and learning. Its applications in education now span intelligent tutoring systems, automated assessment, personalised learning platforms, and natural language processing tools capable of adapting to individual learner needs in real time (Holmes et al., 2019). In theory, these tools hold particular promise for large, resource-constrained systems like Pakistan's, where teacher-student ratios are high, classroom differentiation is difficult, and access to specialist support is limited. In practice, however, the gap between that promise and what actually happens in Pakistani classrooms is wide. Pakistan's formal education system enrolled approximately 56 million students across around 350,000 educational institutions in 2022-23, according to data from the Pakistan Institute of Education (PIE, 2023). Public expenditure on education has remained at

or below 2 percent of GDP for most of the past decade, well below regional and global averages (World Bank, 2023). Technological infrastructure in public schools is uneven: only about 70 percent of schools had access to electricity in 2021-22, and the gap between urban and rural provision is pronounced (PIE, 2022). The National Education Policy 2017-2025 made general references to technology in education but offered no specific guidance on AI integration, no implementation framework, and no dedicated funding for teacher preparation in digital or AI literacy (Ministry of Federal Education and Professional Training [MOFEPT], 2017). This policy silence is significant. It means that teachers who are curious about AI must navigate the landscape without institutional maps or support structures.
The academic literature on AI in education reflects a similar asymmetry. Despite an explosion of research on AI tools and their effects on student outcomes, teacher perspectives remain underrepresented, particularly in non-Western contexts (Zawacki-Richter et al., 2019). What research does exist in comparable developing country settings consistently finds the same cluster of barriers: poor infrastructure, absent training, and the absence of institutional policy and leadership (Almuhanna, 2024). Yet the specific ways in which these barriers interact with teachers' professional identities and vary across educational levels and sectors are not well understood. This study addresses those gaps directly. It investigates how 13 Pakistani teachers across five educational levels and two institutional sectors understand AI, perceive its relevance to their work, and make sense of the obstacles they face. The Technology Acceptance Model (TAM) provides the organising theoretical framework, allowing systematic examination of whether and why teachers perceive AI as useful and usable, and what prevents those perceptions from translating into classroom action. By centring teacher experience and voice, the study aims to produce evidence that is actionable for those who design professional development, write education policy, and lead schools. The study's original contribution is threefold. First, it provides among the first multi-sector comparative qualitative accounts of AI awareness and adoption barriers among Pakistani teachers, spanning primary, secondary, college, university, and special education settings within a single study. Second, it applies TAM in a low-resource developing country context where the framework's assumptions about individual choice are complicated by systemic constraints, generating theoretical insight about the limits of individual-level adoption models. Third, it foregrounds the perspectives of special education teachers, a group consistently marginalised in the educational technology literature despite working in settings where AI-assisted tools have particular relevance for students with learning disabilities.

Background and Literature Review

The formalisation of machine intelligence as an academic discipline dates to the mid-twentieth century, with early educational applications following shortly after. By the 1970s and 1980s, researchers had built expert systems and early intelligent tutoring systems capable of responding to individual learner inputs (Russell & Norvig, 2010). Today's landscape is considerably broader. AI in education now encompasses adaptive learning platforms, natural language processing-driven writing feedback, automated essay scoring, recommendation systems, and conversational agents (Holmes et al., 2019). Chu et al. (2022), in a systematic review of the 50 most-cited studies on AI in higher education, found that personalised learning and predictive analytics dominate the research agenda, reflecting a strong orientation toward measurable and scalable outcomes. The appeal of these tools for systems under resource pressure is genuine. Intelligent tutoring systems can deliver individualised feedback at scale without requiring one-to-one student-teacher contact. Automated assessment tools reduce administrative burden and generate richer data on learning. For a system like Pakistan's, where public school class sizes can exceed 40 students and specialist support is rarely available, these are not trivial capabilities. The question, however, is not what AI can do in principle but what conditions need to be in place for teachers to actually use it.

The Technology Acceptance Model, originally proposed by Davis (1989), offers a well-established framework for understanding technology adoption decisions. Its two central constructs are perceived usefulness, defined as the degree to which a person believes a technology will improve their performance (Davis, 1989), and perceived ease of use, defined as the degree to which the technology is seen as free of effort (Davis, 1989). Together, these perceptions shape attitudes toward use, which in turn determine behavioural intention and actual adoption. TAM has been applied extensively in educational technology research. Viberg et al. (2024) demonstrated in a cross-national survey of 508 K-12 teachers across six countries that those with higher AI self-efficacy perceived more benefits and reported greater trust in AI tools, a finding that maps directly onto TAM's emphasis on perception as a precursor to use. The model has also been extended to account for institutional context, subjective norms, and facilitating conditions, acknowledging that individual perceptions do not form in a vacuum but are shaped by the environment in which the teacher operates (Granić & Marangunic, 2019). Applying TAM to this study's Pakistani context raises an important theoretical tension. TAM assumes a relatively unconstrained decision environment: individuals who perceive a technology as useful and easy to use are positioned to act on those perceptions. In low-resource settings, however, that assumption may not hold. A teacher may genuinely believe AI could improve her students' learning and may find a tool relatively easy to use, yet still be unable to use it because her school has no reliable internet, no compatible devices, or no institutional authorisation. This study explores that tension directly, using TAM as an analytical lens while remaining alert to where structural conditions override individual perceptions entirely. Zawacki-Richter et al.'s (2019) systematic review of 146 studies on AI in higher education found that educators' perspectives were strikingly absent from the research literature. The dominant orientation was toward what AI could do for students, not toward how teachers experience, navigate, or resist its introduction. Luckin (2018) argued that this is not merely an academic oversight: sustainable AI integration in education is only possible when teachers are positioned as informed agents in the process rather than as passive recipients of change. Where teacher perspectives have been studied, the pattern is broadly consistent. Teachers with higher AI knowledge and stronger self-efficacy are more likely to perceive AI tools as beneficial and to trust them enough to use them (Viberg et al., 2024). Conversely, limited professional development, poor infrastructure, and absent institutional guidance are associated with lower adoption rates regardless of individual interest or motivation (Zawacki-Richter et al., 2019; Hwang et al., 2020). Gunawan et al. (2021) found in an Indonesian context that targeted competency-enhancement programs combining technical training with pedagogical framing produced meaningful changes in AI-related practice, whereas generic awareness sessions did not. Van Brummelen and Lin (2021) demonstrated that co-designing AI curricula with teachers, rather than designing programs for them, significantly increased engagement and confidence.

Research from comparable developing country settings consistently identifies a similar set of barriers to AI adoption in education: unreliable or absent digital infrastructure, limited teacher training, high student-teacher ratios, and weak or absent institutional policy (Al-Qerem et al., 2023). Pinkwart (2016) raised the broader issue of cultural fit, noting that AI systems designed for one context may not translate meaningfully to others, and that privacy, local language, and social norms need to be built into AI design from the start. Pakistan's situation is shaped by several structural features of its educational system. Public spending on education as a share of GDP has remained consistently below 2 percent in recent years, well below comparator countries in the South Asian region (World Bank, 2023). The digital divide between urban and rural schools is pronounced: rural public schools are significantly less likely than urban private institutions to have reliable electricity, internet access, or functioning computers (PIE, 2022). At the policy level, the 2017-2025 National Education Policy mentioned technology in general terms but did not articulate a specific AI literacy agenda, and subsequent iterations have not filled that gap (MOFEPT, 2017).

Teacher preparation programmes at Pakistani universities are similarly silent on AI, meaning most practising teachers have had no formal exposure during initial training.

Existing research on educational technology in Pakistan has focused primarily on e-learning access, mobile learning, and digital literacy in English language instruction (Baig & Jamil, 2020). Teacher-centred qualitative research specifically examining AI awareness and classroom integration remains largely absent, making this study's contribution both timely and distinctive. AI-powered assistive technologies, including text-to-speech systems, predictive text tools, communication aids, and adaptive learning platforms, have demonstrated meaningful potential for students with learning disabilities, communication disorders, and physical impairments (Zdravkova et al., 2022). Marino et al. (2023) argued that special education is one of the fields most likely to benefit from AI integration precisely because the individualisation AI enables aligns directly with what good special education practice demands. Yet teachers of students with disabilities face the same training gaps and infrastructure deficits as their mainstream colleagues, often compounded by a scarcity of tools designed for local languages and cultural contexts. This study includes two special education teachers in its sample, allowing examination of how the AI awareness and adoption landscape differs in that context.

Figure 1. Conceptual Framework

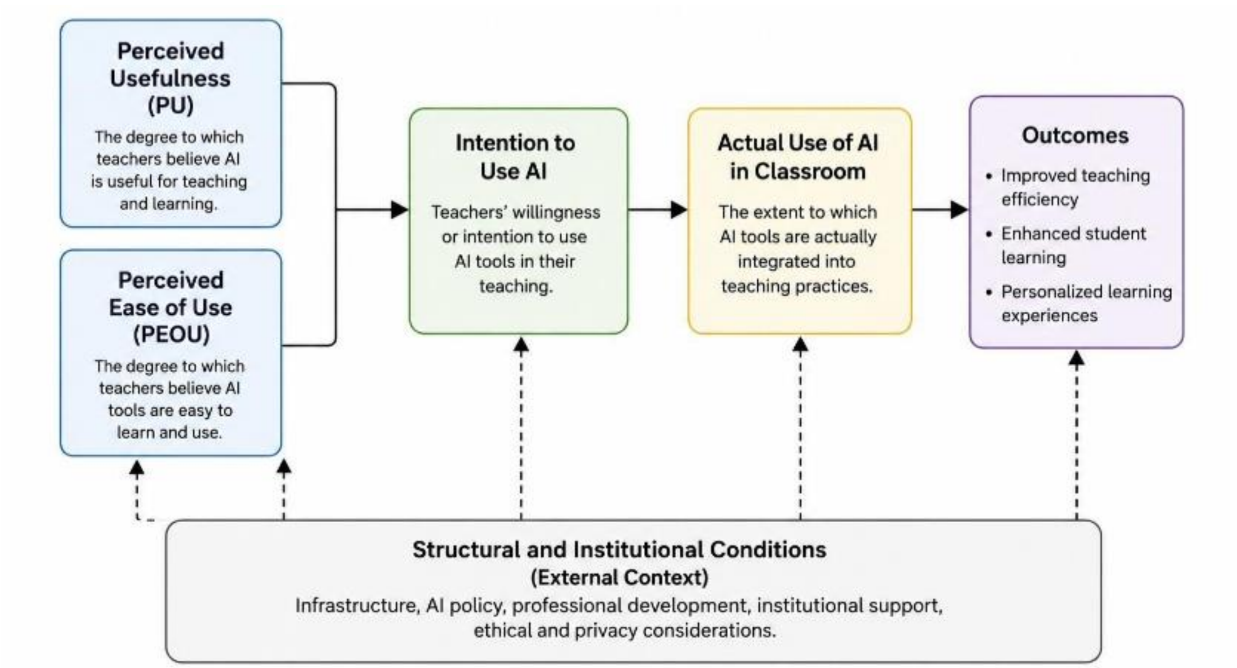

Figure 1 presents the conceptual framework guiding this study. It extends the Technology Acceptance Model (TAM) by illustrating how structural and institutional conditions, including infrastructure, policy, professional development, and ethical considerations, influence the relationship between teachers' perceptions of AI and its actual classroom adoption.

Objectives of the Study

This study was designed to achieve the following objectives:

- To explore the level and nature of AI awareness among Pakistani teachers across primary, secondary, college, university, and special education levels.
- To understand how teachers perceive the usefulness and practical relevance of AI tools for their specific classroom contexts.
- To document the extent and nature of current AI tool use among teachers in Pakistan.

- To identify the challenges and barriers that prevent AI integration, analysed through the lens of TAM.
- To examine how institutional, infrastructural, and professional development factors facilitate or impede adoption.
- To gather teachers' own recommendations for making AI integration more achievable and contextually appropriate.

Research Questions

The study was guided by the following research questions:

- What do Pakistani teachers know about AI, and how do they understand its relevance to education?
- How do teachers perceive the usefulness and practical applicability of AI tools in their classrooms, and what shapes those perceptions?
- What AI tools, if any, are teachers currently using in their instructional activities?
- What barriers do teachers encounter when attempting to adopt AI, and how do these barriers interact with perceived usefulness and ease of use?
- How do institutional, infrastructural, and professional development factors shape teachers' AI integration decisions?
- What recommendations do teachers offer for improving AI adoption in Pakistani educational settings?

Methodology

Research Design

A qualitative research design was selected because the central aim of this study was not to test hypotheses or measure outcomes but to understand how teachers interpret, experience, and make sense of AI in the context of their daily professional lives. Qualitative inquiry is appropriate when the goal is to capture meaning, complexity, and context as they are understood by participants themselves rather than to produce statistically generalisable results (Creswell & Poth, 2018). This orientation is particularly fitting here, where the social and institutional conditions of Pakistani education are inseparable from understanding the phenomenon under investigation. Data were collected through semi-structured interviews, a format that provides enough structure to ensure comparability across participants while remaining flexible enough to follow unexpected but relevant threads. Each interview was guided by open-ended questions covering AI awareness, perceived relevance, current practice, perceived barriers, institutional context, professional development, and ethical concerns. Thirteen participants were selected using purposive sampling, with the explicit goal of capturing a diverse and informationally rich cross-section of Pakistani educators. The sample spanned public and private institutions, primary through university level, and general and special education settings. This diversity was a deliberate methodological choice: AI awareness and adoption barriers are not uniform across Pakistan's educational landscape, and a sample confined to a single sector or level would have produced a partial and potentially misleading account. Data were analysed using the reflexive thematic analysis framework of Braun and Clarke (2006, 2019), a method chosen for its theoretical flexibility and compatibility with an interpretivist stance. The analytical process is described in detail in Section 9.

Research Paradigm

This study is grounded in the interpretivist research paradigm, which holds that social reality is constructed through individual and collective experience and that meaning cannot be understood apart from the context in which it is produced (Creswell & Poth, 2018). Interpretivism is appropriate for research that aims to understand how people make sense of complex phenomena rather than to measure or predict them. In practice, the interpretivist stance shaped every aspect of this study. Teachers were not treated as passive data sources but as knowledgeable professionals whose interpretations of AI were shaped by their institutional environments, professional histories, and cultural contexts. The goal was not statistical generalisation but contextually rich accounts: descriptions detailed enough that readers can assess how the findings might speak to other settings (McChesney & Aldridge, 2019). The researchers' positionality requires acknowledgment. As an educator with experience in Pakistani special education institutions, the researchers brought directly relevant prior knowledge to both the interviews and the analysis. This was a resource as well as a potential source of interpretive bias. To manage it, a reflective journal was maintained throughout data collection and analysis. Emerging interpretations were deliberately tested against participants' own language rather than assumed, and negative cases, those participants whose responses did not fit the dominant pattern, received particular analytical attention rather than being set aside.

Population

The study population comprised educators working across Pakistan's formal educational system, including primary, secondary, college, university, and special education sectors in the Rawalpindi and Islamabad region. Both public and private institutions were included. Participants varied in their subject specialisations, years of teaching experience, and educational qualifications.

Sampling Strategy

Purposive sampling was used to select participants who were actively engaged in teaching and had at least some awareness of or curiosity about AI or digital technology in education. This approach, standard in interpretivist qualitative research, prioritises informational richness over statistical representativeness (Braun & Clarke, 2006). Participants were recruited through professional networks and direct contact with school and university administrators.

Sample

The final sample comprised 13 educators: 7 male and 6 female, with teaching experience ranging from 8 to 25 years and qualifications ranging from Bachelor's to doctoral level. Five educational levels (primary, secondary, college, university, and special education) and two institutional sectors (public and private) were represented. Table 1 provides a full participant profile.

Table 1. Participant demographics

Code	Age	Education	Institution	Level	Subject	Gender	Exp. (yrs)
P1	42	Master's	Private	Primary	Gen. Education	Male	15
P2	39	Master's	Public	Secondary	Science	Female	12
P3	45	M.Ed.	Private	Secondary	English	Male	20
P4	36	M.Phil.	Public	Primary	Mathematics	Male	10
P5	33	Master's	Private	Secondary	Comp. Science	Female	8
P6	41	M.Ed.	Public	Primary	Urdu	Male	18
P7	47	M.Phil.	Public	College	Biology	Male	22
P8	40	Master's	Private	College	Psychology	Female	16
P9	50	PhD	Public	University	Education	Male	25

Code	Age	Education	Institution	Level	Subject	Gender	Exp. (yrs)
P10	44	PhD	Private	University	Education	Female	20
P11	38	M.Ed.	Public	Special Ed.	Special Ed.	Female	14
P12	35	Master's	Private	Special Ed.	Special Ed.	Female	10
P13	37	BS Phys. Ed.	Public	Secondary	Physical Ed.	Male	12

Instrumentation

The primary data collection instrument was a semi-structured interview guide developed specifically for this study. Questions were organised around seven thematic areas: AI awareness and understanding, perceived relevance to education, current practice, perceived barriers, institutional and infrastructural factors, professional development needs, and ethical concerns. Open-ended phrasing was used throughout to invite elaboration and minimise the risk of leading participants toward expected answers. The instrument was reviewed by two colleagues with expertise in educational technology research, who recommended minor revisions to improve clarity and accessibility for participants with limited technical vocabulary. A pilot interview was then conducted with a teacher outside the main sample; this confirmed that the questions were comprehensible and that the interview could comfortably be completed in 45 to 60 minutes. All interviews were conducted in settings chosen by participants, typically offices, staffrooms, or classrooms, to minimise formality and institutional pressure. Interviews were conducted in English or Urdu according to participant preference. Urdu responses were transcribed in Urdu and then translated into English for analysis; translations were reviewed by a bilingual colleague. Each interview was audio-recorded with written consent and supplemented by handwritten field notes capturing non-verbal cues and contextual observations.

Data Analysis Process

Analysis followed the six-phase reflexive thematic analysis framework described by Braun and Clarke (2006): familiarisation with the data, generating initial codes, constructing themes, reviewing themes, defining and naming themes, and writing up the analysis. The framework was selected for its theoretical flexibility, its compatibility with interpretivist inquiry, and its well-documented procedural transparency (Braun & Clarke, 2019). The researchers began by reading all 13 transcripts multiple times, making marginal annotations on initial impressions, surprising moments, and recurring ideas. In the coding phase, data segments were tagged with descriptive codes that stayed close to participants' own language rather than imposing theoretical categories prematurely. For example, responses about limited hardware generated codes such as 'no devices in classroom' and 'phone as only option,' which were later grouped into a broader theme. All 13 transcripts were coded inductively before any grouping was attempted. Candidate themes were developed by grouping related codes and reviewed against the full dataset to assess internal coherence, mutual distinctiveness, and collective coverage of the data. Several candidates were merged, split, or renamed during this process. An initial theme labelled 'attitudes toward AI' was eventually separated into two distinct themes, one addressing perceived potential and one addressing ethical concerns, because the data showed these as meaningfully different in content and implication. NVivo qualitative analysis software was used to manage the data, organise codes, and visualise code co-occurrence patterns. The software facilitated the management of a large volume of text but did not drive the interpretive process; all analytical decisions were made by the researchers. Trustworthiness was addressed through several strategies. Member checking was conducted by sharing a summary of emerging themes with five participants approximately three weeks after their interviews. All five confirmed that the themes reflected their experience; P7 added a clarification that his concern about AI was less about job security and more about the erosion of the mentorship dimension of teaching, which was incorporated into Theme 4. Peer debriefing was conducted with a colleague in educational technology who reviewed the coding framework and challenged two interpretations that were subsequently revised. Negative case analysis is discussed explicitly in the findings, particularly around Theme 3, where P13's resistant position is examined analytically rather than set aside.

Ethical Considerations

All participants received a written information sheet explaining the study's purpose, its voluntary nature, and their unconditional right to withdraw at any point without consequence. Written informed consent was obtained before each interview began. Confidentiality was maintained throughout by assigning each participant a pseudonym code (P1 through P13). All recordings and transcripts were stored on a password-protected device accessible only to the researchers, and participant identities were not disclosed in any research output. Raw data were securely deleted on completion of the study. The researchers were attentive throughout to cultural sensitivities within Pakistan's educational environment, including participants' potential concern that their responses might be shared with school administrators or used for professional evaluation. Participants were explicitly assured that nothing they shared would be passed to institutional authorities. A summary of findings was offered to all participants upon completion; four requested it.

Figure 2. Research Process Flowchart

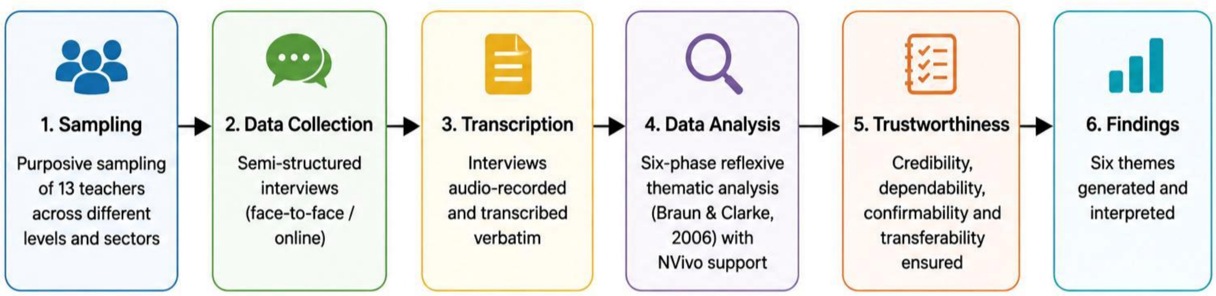

Figure 2 summarises the overall research process followed in this study. It outlines the sequence from purposive sampling and semi-structured interviews to transcription, thematic analysis, and the generation of the final themes, providing a clear overview of the study's methodological procedures.

Findings: Thematic Analysis

Before presenting the six themes, it is important to note a finding that cuts across all of them: of the 13 participants, none reported using AI tools systematically or consistently in their teaching. Several had experimented informally on personal devices, P5 had used an AI writing assistant for lesson planning on one occasion, and P9 had used an AI-generated quiz tool once with a small group. These were isolated experiments rather than integrated practice. The pattern of non-use is itself the central empirical finding, and the six themes that follow explain why it exists. Quotation codes refer to participant pseudonyms from Table 1.

Figure 3. Thematic Map

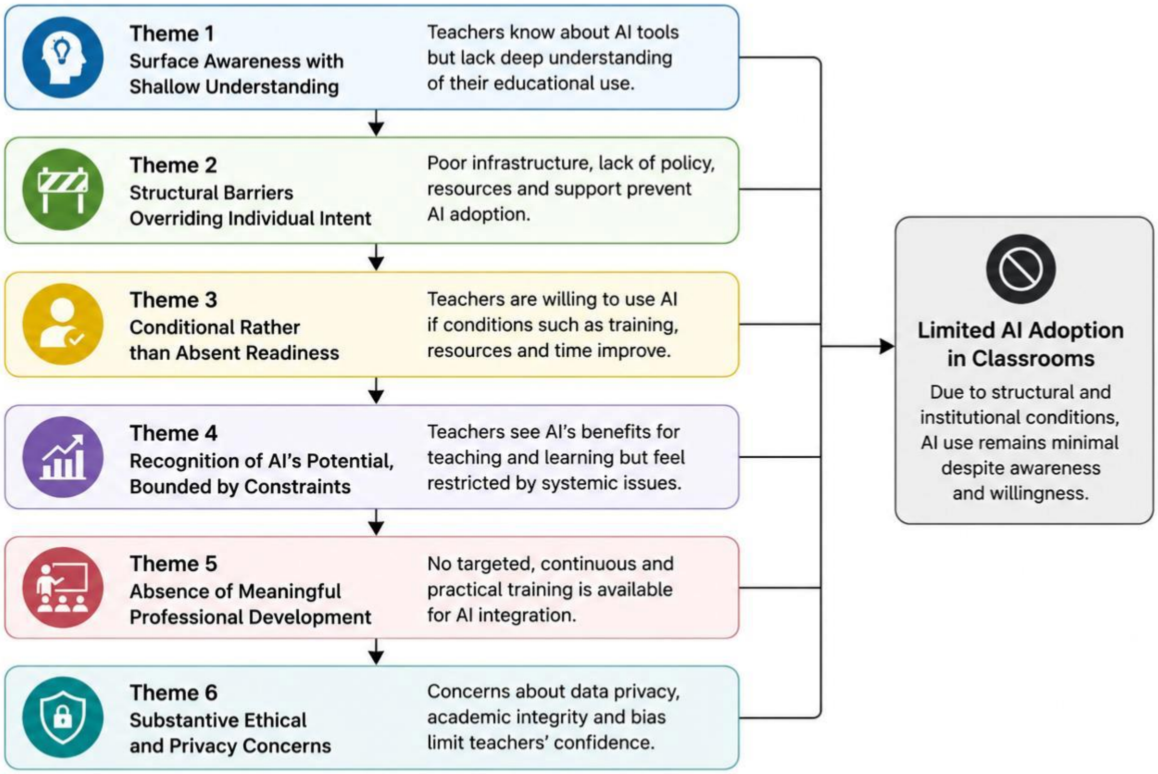

Figure 3 presents the thematic map developed through reflexive thematic analysis. It illustrates the relationships among the six themes and demonstrates how they collectively explain the limited adoption of AI in Pakistani classrooms despite teachers' awareness of its potential.

Theme 1: Surface Awareness, Shallow Understanding

Every participant had heard of AI, and most could name one or two applications, most commonly voice assistants, automated grading tools, or content recommendation systems. But depth of understanding varied considerably, and for the majority it did not extend far beyond general media exposure. Knowing that AI exists and knowing how it might function in a specific classroom lesson are very different things, and most participants sat firmly in the former category. P1, a primary school teacher with 15 years of experience, captured this directly: 'I know AI is there. I see it mentioned in the news, my son talks about it. But when I sit down to plan a lesson for my class, I honestly have no idea how to connect the two. It feels like something happening somewhere else.' P3, a secondary English teacher with two decades of classroom experience, described a similar position: 'I have read about AI in magazines and education newsletters. I understand the concept. But I have never seen it working in a Pakistani school. All my understanding is theoretical.' The form this surface awareness took differed across levels. University-level participants (P9, P10) had stronger conceptual knowledge through academic reading and conference attendance, even if their practical experience remained limited. Primary school teachers (P1, P4, P6) described their awareness as largely media-derived. Special education teachers (P11, P12) occupied a distinctive position: both were aware that AI assistive tools existed for students with disabilities and were genuinely interested in them, but neither had encountered them in any professional context. As P11 explained: 'I have heard that there are AI tools that can help children with dyslexia read better. I find that very exciting. But I have never seen one, and I would not know where to start. From a TAM perspective, this pattern is analytically significant. Perceived usefulness, one of TAM's two core predictors of adoption, cannot be meaningfully formed when understanding of what a technology actually does remains too thin to support a genuine judgment. For most teachers in this sample, awareness had not produced a usability perception; it had produced a vague aspiration.

Theme 2: Structural Barriers Override Individual Intent

Every participant identified barriers to AI adoption. Across the sample these clustered into three interconnected categories: technological infrastructure deficits, resource and time constraints, and institutional absence. What is analytically significant is that these barriers were not experienced as personal limitations but as systemic facts, pre-existing conditions that the individual teacher had no power to change. Infrastructure was the most commonly cited obstacle. P8, a college psychology teacher, described a situation familiar to several participants: 'My college has computers, but they are old, they are slow, and half of them do not connect to the internet reliably. Even if I wanted to use an AI tool in class, I would spend the first twenty minutes just getting the technology to work. By that point the students have lost interest and so have I.' P11 described the situation in her special education school as even more constrained: 'We have one computer lab for the whole school. It is shared between all classes. I get to use it maybe once a month if I am lucky.' Time and curriculum pressure emerged as a second structural barrier. P6, a primary Urdu teacher in a public school, was candid about the competing demands on his attention: 'Our curriculum is full. There is a syllabus to cover, there are exams to prepare for. Learning a new technology on top of that is not a small thing. It takes time I genuinely do not have, especially in a government school where there is no one to cover your class while you attend a workshop.'

The third and most consequential barrier was institutional silence. P10, a university professor, articulated this precisely: 'My university has no AI policy. No one has told us we should use AI, no one has told us we should not. There are no guidelines, no support, no approved tools. In that environment, trying something new feels professionally risky. What if a student complains? What if something goes wrong with data? There is nothing to fall back on.' P4 made a similar observation at the primary level: 'In my school, the head teacher is supportive in general, but there is nothing coming from above. No directive, no resource. You are entirely on your own.'

These findings complicate TAM's standard model in an important way. For most participants, the operative question was not 'do I perceive this technology as useful enough to use?' but 'do the material and institutional conditions of my workplace make use possible at all?' That is a structurally prior question that TAM, in its original form, does not directly address.

Theme 3: Readiness is Conditional, Not Absent

Despite the barriers described above, the picture on teacher readiness was not uniformly negative. Most participants expressed genuine interest in AI and described specific scenarios in which they could imagine using it productively. The more revealing finding is that readiness was conditional: it depended not on whether teachers wanted to engage with AI but on whether the right conditions would ever materialise to make engagement possible. P2, a secondary science teacher with 12 years of experience, put it plainly: 'If someone trained me properly and gave me a working tool that I could actually use in my classroom with my students and my syllabus, I would absolutely try it. The problem is not my willingness. The problem is that no one has ever offered that.' P7, a college biology teacher, expressed a similarly conditional openness: 'I would need hands-on training, not a lecture about what AI is. I would need to sit with the tool and practise with it, ideally with support from someone who knows the subject. Then I think I could do it.'

The clearest exception was P13, a secondary physical education teacher, who was actively rather than conditionally sceptical. His position was not technophobic in any simple sense: he used his smartphone daily and expressed no general resistance to digital tools. His scepticism was pedagogical. 'Physical education is about the body, about movement, about being present with students,' he said. 'I do not see what AI adds to that. My job is to build confidence and physical skill. That requires a human relationship, not an algorithm.' This was a genuine negative case worth engaging with analytically rather than dismissing. It suggests that AI adoption readiness may be partly domain-specific, shaped by teachers' beliefs about what their subject fundamentally is and requires. Comparing responses across sectors, private sector teachers (P1, P3, P5, P8, P12) tended to express slightly higher readiness, likely reflecting better baseline infrastructure and somewhat more institutional flexibility. However, this difference was not absolute: P12, a private school special education teacher, reported resource constraints as severe as her public sector colleague P11, suggesting that sector alone is an insufficient predictor of readiness. This cross-sector variation, and its limits, is an empirical contribution of sampling deliberately across both sectors.

Theme 4: AI's Potential is Recognised but Structurally Blocked

Most participants, particularly those at college and university level, identified specific ways AI could strengthen their practice. The most commonly cited applications were differentiation for diverse learners, administrative automation, and assessment support. Analytically, within the TAM framework, these responses indicate that perceived usefulness is not absent but is prevented from becoming an adoption driver by the structural barriers documented in Theme 2. P9, a university professor with 25 years of experience, was specific about administrative work: 'Marking attendance for 180 students, grading objective test items, generating progress summaries, these are tasks I spend hours on every week. If AI could handle even part of that, I would have more time to actually talk to students about their learning. That seems very valuable to me.' P4 and P6, both primary teachers, focused on differentiation: 'My class has children at very different levels,' P4 explained. 'Some already know what I am teaching, others are struggling with basics from the year before. AI that could adapt the task to each child would make a real difference. Right now I cannot do that, there are 45 students.' Concerns about the limits of AI were also present and pedagogically grounded rather than simply resistant. P8 raised the question of relational learning: 'I worry that if students use AI tools too much, they stop forming a real relationship with learning. They get the answer but they do not struggle, and the struggle is part of learning.' P7, during member checking, clarified that his concern was specifically about the mentorship dimension: 'What students need from me is not just the biology content. They need someone to model how to think, how to question, how to deal with not knowing something. I am not sure AI can do that, and I am not sure students would understand what they were missing if it tried to.' These concerns echo broader arguments in the literature about the importance of preserving relational and metacognitive dimensions of teaching that AI systems cannot replicate (Hwang et al., 2020; Luckin, 2018).

Theme 5: Professional Development is Absent in Both Quantity and Quality

The absence of adequate professional development was the one issue raised explicitly and emphatically by every participant without exception. But the analysis reveals something more specific than a simple training shortage: what participants described wanting was not more of the professional development they had experienced but a fundamentally different kind of learning opportunity. P2 was direct about the current situation: 'My school has organised exactly zero workshops on AI. Nothing. I have had to find whatever I know from YouTube, from articles I come across online. That is not professional development. That is just trying to keep up on my own time.' P12 described a related experience: 'I was sent to a one-day IT workshop two years ago. We were shown how to use email and how to make a PowerPoint. AI was not mentioned. That is the level of training that exists for special education teachers in this city.'

Several participants were specific about what better training would look like. P5, a secondary computer science teacher, was the most articulate: 'I do not need someone to tell me what AI is. I need someone to sit with me and show me how to use a specific tool for a specific lesson in my subject. Show me how to set it up, how to explain it to students, what to do when it goes wrong. That is the kind of training that would actually change something.' P11 raised a dimension specific to her context: 'Whatever training is offered for AI in special education needs to include tools that work in Urdu and in our cultural context. A speech-to-text tool designed for English does not help my students.' This finding is consistent with Van Brummelen and Lin (2021), who found that teachers benefit most from collaborative, subject-specific curriculum design processes rather than generic awareness sessions, and with Gunawan et al. (2021), who demonstrated that competency-enhancement programmes pairing AI tools with pedagogical context produced meaningful changes in practice. The pattern from this study suggests that even the more basic version of this kind of targeted training is largely unavailable in the Pakistani context.

Theme 6: Ethical Concerns are Substantive, Not Residual

Ethical concerns about AI were raised most forcefully by the more experienced university-level participants (P9, P10) but were present in recognisable form across the sample. These were not vague discomforts but specific, substantive concerns about fairness, data governance, and potential harm to students. P9 raised algorithmic bias with precision: 'AI systems are trained on data. If that data comes mostly from students in the United States or the United Kingdom, the AI's idea of what a good answer looks like will reflect those students, not my students. It may assess Pakistani students by standards that were never designed for them. That is not a small problem.' P6 extended the concern to educational equity: 'If an AI system has learned that students from certain backgrounds perform less well, it may give those students less challenging work, expecting less of them. That would make inequalities worse, not better.'

Data privacy was the most widely raised concern. P8 was direct: 'I would want to know exactly what happens to the data these tools collect about my students. Who stores it, where, for how long, and who can see it. In Pakistan, there are no regulations I am aware of that govern this specifically. Without that protection, I am not comfortable using a tool that processes student information.' P12 expressed a similar concern with particular urgency in her special education context: 'My students have learning disabilities. That is sensitive information. I would be very uncomfortable with an AI tool collecting detailed data about their learning difficulties and sending it to servers I know nothing about.' These concerns align with longstanding arguments in the literature about the need for transparency, accountability, and cultural sensitivity in the design of AI educational systems (Pinkwart, 2016). They also identify a concrete regulatory gap: Pakistan currently has no framework specifically governing student data in the context of AI-enabled educational tools.

Figure 4. Barrier Model

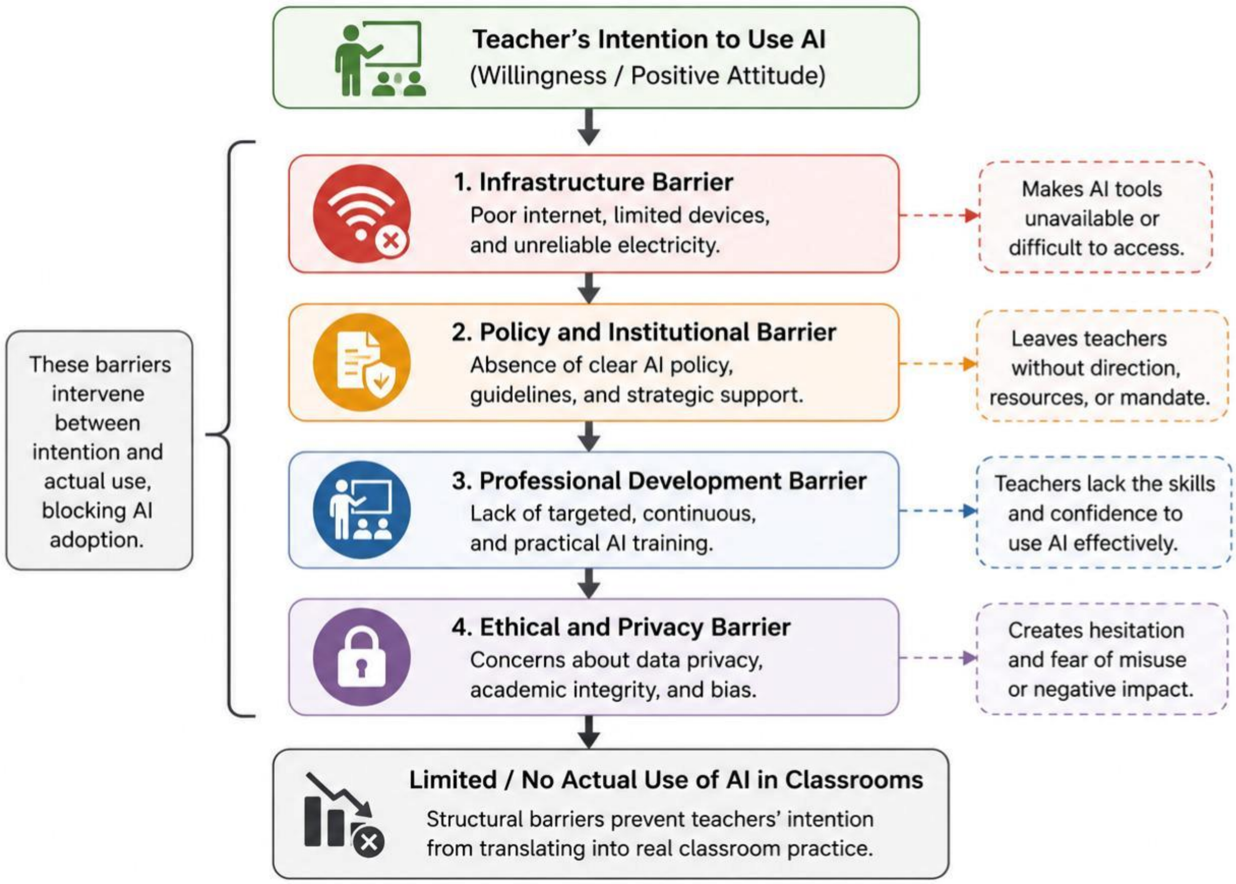

Figure 4 illustrates the structural barriers that intervene between teachers' intention to use AI and its actual classroom implementation. The model highlights how inadequate infrastructure, limited institutional support, insufficient professional development, and ethical concerns collectively restrict meaningful AI adoption in educational settings.

Discussion

The six themes together describe a situation in which AI's educational potential is broadly recognised by Pakistani teachers but consistently blocked from becoming practice by structural conditions that precede any individual adoption decision. Read through a TAM lens, the findings reveal something theoretically significant: the model's standard logic, in which perceived usefulness and ease of use drive adoption, cannot operate in the way it typically does when the material and institutional conditions necessary for adoption are absent. Addressing the research questions in turn: RQ1 showed that teachers' AI knowledge is mostly surface-level and media-derived, with conceptual depth concentrated among university-level participants. RQ2 demonstrated that perceived usefulness exists in principle, particularly for differentiation and administrative automation, but remains disconnected from practice by structural obstacles. RQ3 established unambiguously that systematic AI use in classrooms was absent across all 13 participants; isolated informal experiments were the closest any participant had come. RQ4 identified three categories of barriers, infrastructure deficits, institutional silence, and time pressure, that interact to make the adoption question effectively moot for most teachers regardless of their perceptions. RQ5 showed that institutional factors, specifically absent policy and absent training, were the most consequential determinants of non-adoption. RQ6 yielded consistent recommendations for hands-on training, clear institutional policy, infrastructure investment, and a student data governance framework. The theoretical contribution to TAM is worth stating precisely. In well-resourced settings, the model has repeatedly demonstrated that teachers who perceive AI tools as useful and accessible are more likely to use them (Viberg et al., 2024; Feng, 2020). In this study, several participants clearly perceived AI as useful: P9's comments on administrative automation, P4's on differentiation, and P5's on assessment support all reflect genuine TAM-type perceived usefulness. Yet none were using AI. The obstacle was not a perception deficit but a structural one: absent infrastructure, no institutional policy, and no training. This suggests that in resource-constrained developing country contexts, TAM's explanatory power is bounded by structural conditions external to the model. Perceived usefulness is a necessary but not sufficient condition for adoption when systemic barriers make acting on those perceptions practically impossible. This is an additive finding, not a refutation of TAM: the model holds once the material and institutional preconditions for choice are in place.

This finding extends work from comparable developing country contexts (Kaplan-Rakowski et al., 2023, Ng et al., 2023). What this study adds is a multi-sector, multi-level account showing that barriers are not experienced uniformly. University teachers faced primarily an institutional policy vacuum. Primary school teachers faced a more material combination of device scarcity and unreliable connectivity. Special education teachers faced both, plus a specific absence of culturally and linguistically adapted tools. These are structurally distinct obstacles requiring different policy responses, not a single undifferentiated barrier problem. The professional development findings are particularly actionable. The kind of training participants described, hands-on, subject-specific, contextually adapted, and sustained, is precisely what the literature identifies as effective (Van Brummelen & Lin, 2021; Gunawan et al., 2021). The fact that virtually no participant had encountered anything approaching this standard suggests not just a training gap but a conceptual gap in how professional development for AI integration is being thought about.

The ethical concerns raised deserve serious engagement rather than reassurance. Pakistani teachers who ask where student data goes, or who worry that AI systems calibrated to other populations may unfairly assess their students, are not obstacles to adoption. They are exercising exactly the kind of critical professional judgment that responsible AI integration requires. Pinkwart's (2016) argument that cultural context, privacy, and fairness need to be designed into AI systems from the start rather than managed as afterthoughts is directly relevant here. P13's domain-specific scepticism about AI in physical education points to something the standard adoption literature underexamines: teachers' subject-area identities and their beliefs about what the core work of teaching in their discipline requires. For P13, the relational and embodied dimensions of his teaching were not peripheral but central. Whether AI belongs in that space is a genuine pedagogical question, and studying it as such is more productive than treating it as technophobia.

Conclusion

This study set out to understand why Pakistani teachers, most of whom are aware of AI and many of whom recognise its potential, have been largely unable to integrate it into their classroom practice. The answer that emerges from the data is structural before it is individual. The material conditions of many Pakistani schools, combined with an institutional vacuum at the policy level, make AI adoption effectively inaccessible for most teachers regardless of their attitudes or intentions. Three specific contributions emerge from the work. First, the study provides among the first multi-sector comparative qualitative accounts of AI awareness and adoption barriers among Pakistani teachers, revealing that while the overarching pattern is consistent, the specific form barriers take differs meaningfully across educational levels and institutional sectors. Second, it applies TAM in a context where the model's standard assumptions are systematically challenged by structural conditions, generating the theoretical insight that perceived usefulness cannot drive adoption when systemic preconditions for choice are absent. Third, it gives voice to special education teachers in a conversation from which they are almost entirely absent in the existing literature, documenting both the particular promise of AI-assisted tools in their context and the particular depth of the barriers they face. The study is equally an argument for a different kind of policy attention. Broad national technology strategy statements are of limited value if they do not reach teachers at the classroom level. What teachers in this study needed was not more policy text but practical support: reliable devices, internet access, subject-specific training, institutional guidance, and a regulatory framework that protects student data. These are concrete and achievable goals. The gap between them and the current reality is the gap this study has documented.

Limitations

Several limitations should be considered when interpreting these findings. First, the sample of 13 participants, is not statistically representative of Pakistani teachers as a whole. The findings describe patterns within a specific, purposively selected group and should not be read as a precise account of conditions across Pakistan's entire educational system.

Second, the study was conducted in the Rawalpindi and Islamabad metropolitan region, which is comparatively urban and well-resourced by Pakistani standards. Conditions in rural schools, particularly in Khyber Pakhtunkhwa, Balochistan, and rural Punjab and Sindh, are likely to reflect even greater infrastructure deficits and training gaps. The barriers documented here may understate the severity of the situation nationally.

Third, the study relied exclusively on self-reported data. What participants described about their AI awareness and practice may not perfectly reflect what they know or do, a standard limitation of interview-based research. Classroom observation data would have enriched the account, though the interview-based design was appropriate given the study's exploratory focus.

Fourth, the researchers’ dual identity as an educator within the same institutional system may have shaped both what participants were willing to share and how the data were interpreted. The reflexivity strategies described in Section 6 were designed to manage this, but the potential for interpretive bias cannot be fully eliminated.

Finally, this is a cross-sectional study capturing a single moment in a rapidly changing technological and policy landscape. Teachers' AI awareness and engagement are evolving, and the findings from this period may require updating as AI tools become more prevalent in Pakistani society and as policy begins to respond.

Recommendations

Based on the findings, the following recommendations are offered to education stakeholders:

- Professional development programmes should be redesigned around subject-specific, hands-on AI training rather than generic awareness workshops. Teachers need guided practice with specific tools within their own curricular contexts. Programmes modelled on the co-design approach described by Van Brummelen and Lin (2021) would be particularly valuable.
- Education authorities should develop and communicate clear institutional AI policies that reach teachers at the school level. The current policy vacuum leaves individual teachers without guidance, approved tools, or professional protection. That needs to change before widespread adoption can reasonably be expected.
- Infrastructure investment is a precondition for meaningful AI adoption and should be treated as such in education budgets. Reliable internet access, functioning devices, and ongoing technical support are not luxuries; they are the material conditions without which AI integration is impossible for most teachers.

- A student data governance framework specific to AI-enabled educational tools should be developed and made accessible to teachers. Privacy concerns are legitimate and currently unaddressed by Pakistani regulatory frameworks. Clear, enforceable guidance on data collection, storage, and access would remove a significant barrier and protect students.
- Special education contexts require dedicated attention and dedicated resources. AI assistive technologies for students with learning disabilities are potentially highly valuable, but tools designed for English-speaking Western contexts do not automatically transfer to Pakistani classrooms. Investment in locally adapted tools and specific training for special education teachers is needed.
- Communities of practice and peer learning networks should be facilitated within and between schools. Teachers making progress with AI integration can serve as important resources for colleagues. Structured horizontal knowledge-sharing is more sustainable than relying on formal training alone.
- Future research should include longitudinal designs that track changes in AI awareness and adoption over time, as well as studies with larger and more geographically diverse samples, to build a fuller picture of AI integration dynamics across Pakistan's educational system.

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Data Availability:

The data generated during this study consist of audio recordings and interview transcripts collected from human participants under a confidentiality agreement. These data are not publicly available in order to protect participant privacy and to honour the terms of informed consent under which they were collected.

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