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### English Teachers' Readiness, Perceptions and Use of AI Tools in Resource-Constrained Public High Schools of Sindh, Pakistan

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#### ABSTRACT

Generative artificial intelligence (AI) tools reach teachers through free smartphone applications, yet evidence on whether English teachers in under-resourced government schools of Pakistan are ready to use them remains thin. Drawing on the Technology Acceptance Model (TAM), AI-TPACK and self-efficacy, this study examined High School English teachers' perceptions, readiness and frequency of AI use, and the contextual conditions that shape them in Sindh. An exploratory cross-sectional survey was completed by 64 English teachers from 13 districts, recruited through convenience and snowball sampling. The instrument measured perceptions, four readiness components (AI literacy, AI pedagogical competence, self-efficacy and ethical awareness); institutional support; and resource challenges ( $\alpha = .77-.95$ ). Data were analysed using correlations, multiple regression, group comparisons, and thematic coding of open-ended responses. Teachers reported high readiness ( $M = 3.88$ ), rated lowest institutional support ( $M = 2.99$ ); only 20.3% had received AI training, and 85.9% relied on personal smartphones. Perceptions, benefits, institutional support and challenges together explained 62% of the variance in overall readiness. However, AI pedagogical competence was predicted by AI literacy ( $\beta = .41$ ) and self-efficacy ( $\beta = .36$ ), not by favourable perceptions ( $\Delta R^2 = .27$ ,  $R^2 = .64$ ). Frequency of AI use was linked to perceptions ( $r = .48-.49$ ) but not to competence or self-efficacy. Urban teachers use AI more often than rural teachers ( $d = 0.53$ ;  $p = .054$ ), though readiness did not differ. Acceptance drives use, whereas literacy and confidence drive the ability to teach with AI.



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## 1. Introduction

Generative artificial intelligence (AI) has shifted from the limits of education into teachers' everyday work and classroom practices. Free available too such as ChatGPT, Google Gemini, DeepSeek and Meta AI can draft lesson plans, generate reading passages and exercises, and give feedback on student writing (Edmett et al., 2024), in line with the long-standing view that AI in education should augment rather than replace teachers (Holmes et al., 2019). Teachers' judgements and capacities have become a central concern in research on AI in education precisely because teachers determine whether these tools reach the classroom (Eedelouei, 2026; Zhou et al., 2026). This pedagogical shift is also visible in the English language teaching (ELT). According to global survey conducted by the British Council found that 57 % of teachers use AI for creating materials, 53% for help students' English practices, and 43 % for lesson planning (Edmett et al., 2024). National studies also articulate comparable patterns in Poland (Sobkowiak, 2026) and Portugal (Brandão, 2026). In these contexts, English teachers express generally positive yet cautious attitudes; while they appreciate the efficiency and personalised feedback that such tools offer, they remain concerned about the accuracy, academic integrity, student over-reliance and their own lack of training (Alzeebaree, 2026; Gurel Cennetkusu, 2026). Teachers' positive attitudes do not translate automatically into effective practices. Research describe this situation as an "attitude–experience gap" in which teachers are willing to use AI, but limited in classroom application (Gurel Cennetkusu, 2026; Laoha et al., 2025), as well as a pattern of "aware incompetence" in which teacher ethical awareness runs ahead of their pedagogical readiness (Hang, 2025). Teacher readiness has accordingly been reconceptualised as a multidimensional construct comprising AI literacy, pedagogical competence, self-efficacy and ethical awareness, all embedded in institutional support (Isaee et al., 2026; Wulan & Santosa, 2026). These tensions are sharper in resource-constrained environments, where

teachers often face electricity shortages, poor internet connectivity, high data costs, and a lack of continuous professional development, which limit teachers' abilities to effectively utilize AI even when they view it positively (Castro et al., 2025; Wu et al., 2026). In addition, AI may widen inequities if its benefits increase where capacity already exists (Sridhar et al., 2026). In Pakistan, the English subject is compulsory and serves as the gateway to higher education and formal employment, but the public schools in the rural areas face persistent shortages of electricity, equipment and trained staff (Mahmood, 2026). Teacher training programmes in Sindh show a gap between policy intent and implementation, with clear urban–rural disparities (Bhatti et al., 2026). Pakistani research on AI in education is growing but remains uneven because it is mostly concentrated in higher education and urban settings and offers very limited field evidence from public schools (Nazir et al., 2026), and in ELT has mostly documented perceptions rather than the capacities that strengthen practice (Hussain et al., 2026).

Studies from Sindh have examined school heads' AI readiness (Panhwar, Syed, & Abbas, 2026; Qaim-ud-Din et al., 2026), general technology integration (Panhwar, Ghaloo, & Shah, 2026), and college teachers' views of ChatGPT (Bhutto et al., 2026). English teachers in Sindh's public high schools, the people who would use AI with adolescent learners, have not been studied directly. The only large school-level survey of Pakistani language teachers' technology readiness focused on the Urdu language teachers rather than English teachers (Abid et al., 2026). The gap is also international: of the 221 studies of AI in EFL/ESL education reviewed by Javadinejad and Davari (2026), only 7.2% were conducted in secondary schools. This study addresses that gap and makes three contributions. First, it provides school-level evidence from one of Pakistan's most under-resourced provinces. Second, it distinguishes acceptance (how teachers perceive AI) from capability (whether they can teach with it), and tests whether the two have different antecedents. Third, it examines institutional support, resource

challenges and teachers' frequency of use alongside readiness, so that readiness is interpreted in the light of what teachers can realistically do. The study addresses four research questions. RQ1. How ready are English teachers in Sindh's public high schools to use AI tools, how do they perceive these tools, and how often do they use them? RQ2. What resource-related challenges do teachers face, and how adequate is the institutional support they receive? RQ3. Which perceptions and contextual conditions predict (a) teachers' overall readiness and (b) their AI pedagogical competence, and how are these related to frequency of AI use? RQ4. Do readiness and AI use differ by school location and other teacher characteristics?

## 2. Theoretical Framework and Literature Review

### 2.1 Acceptance: The Technology Acceptance Model

The Technology Acceptance Model (TAM) holds that acceptance of a technology depends mainly on its perceived usefulness and perceived ease of use (Davis, 1989). TAM remains the most widely used lens for teachers' acceptance of AI. A meta-analysis of TAM in AI-in-education research confirmed strong relationships among its constructs and found that, in lower-income settings, ease of use more strongly shapes perceived usefulness (Xue et al., 2026). Studies of K-12 teachers in China (Tang & Zhong, 2026), Morocco (Boughanzai et al., 2026), Greece (Karagiorgou et al., 2026) and Khyber Pakhtunkhwa, Pakistan (Qureshi, 2026) all found that usefulness and ease of use predicted intention to use AI. Beyond these two beliefs, teachers weigh specific benefits, such as saving time and generating materials, against concerns about accuracy, bias and student dependence (Alzeebaree, 2026; Sobkowiak, 2026). Among 485 Chinese secondary and university English teachers, the perceived usefulness of AI for lesson planning depended on the quality and job relevance of its output (Sun et al., 2026). In this study, TAM frames the **acceptance** side of teachers' engagement with AI: what they believe AI can do for them.

### 2.2 Capability: AI literacy, AI-TPACK and self-efficacy

Acceptance of AI does not, on its own, prepare teachers to use it well in the classroom. The Technological Pedagogical Content Knowledge framework (TPACK) holds that effective technology integration depends on how technological, pedagogical and content knowledge work together (Mishra & Koehler, 2006). More recent scholarship has extended the TPACK framework to AI. Intelligent-TPACK, for example, adds AI literacy and ethics as core components and recasts the teacher as a validator of machine-generated content (Chiu, 2026; Younas & Noor, 2026). For language teachers specifically, Ren and Li (2026) proposed a TPACK-based model of AI literacy built around six dimensions: conceptual understanding, technical proficiency, pedagogical integration, adaptive expertise, ethical reasoning and self-efficacy. AI literacy, the ability to understand, apply and critically evaluate AI, is increasingly treated as the foundation of readiness (Nabhan & Habók, 2026; Xie et al., 2026). Across 342 English teachers in four countries, AI literacy was the strongest predictor of implementation readiness (Isaee et al., 2026). Self-efficacy, the belief in one's capacity to act successfully (Bandura, 1997), converts knowledge into practice: it was the strongest predictor of attitudes toward generative AI among teachers (Darko et al., 2026) and determined whether Ghanaian ESL teachers used AI in structured or only surface-level ways (Ofori & Debreli, 2026). In Sindh, self-efficacy partly mediated the link between digital competence and technology-integrated teaching (Roshan et al., 2026). Large K-12 studies confirm these links. Among 931 Chinese teachers, AI-TPACK and self-efficacy jointly predicted the quality of AI-supported teaching, with AI-TPACK acting partly through self-efficacy (Du et al., 2026). Self-efficacy was also the strongest predictor of AI-TPACK readiness among 412 pre-service teachers (Xie & Luo, 2026). Secondary EFL teachers in China showed only moderate AI-TPACK, weakest in the pedagogical use of AI (An et al., 2025). Together these constructs frame the capability side of

readiness: whether teachers know enough, and feel able enough, to teach with AI.

### **2.3 Context: institutional support and first-order barriers**

Even capable teachers act within institutions. Ertmer (1999) distinguished first-order barriers (resources, time, training and support) from second-order barriers (beliefs and practices). In low-resource settings, first-order barriers dominate. Among K-12 EFL teachers in under-resourced regions of China, insufficient training, weak hardware and tool overload were the main obstacles (Wu et al., 2026). Rural elementary teachers welcomed AI but lacked devices and stable internet (Castro et al., 2025), and rural Indonesian English teachers held favourable attitudes but limited practical readiness (Waruwu, 2026). Institutional support consistently receives the lowest ratings in readiness studies (Isaee et al., 2026), yet it predicts teachers' perceived usefulness and competence, and prior training strengthens these paths (Al-khresheh et al., 2026). AI-related professional development affects both beliefs and classroom use (Liu et al., 2026). Among 586 Indonesian high school English teachers, institutional support and motivation, rather than pedagogical practice, drove technology integration (Haryanto et al., 2026), and among Filipino EFL teachers, technology skills were almost inseparable from perceived external support ( $r = .91$ ; Tiblani & Julhamid, 2026).

### **2.4 The Pakistani and Sindh context**

The research evidence from Pakistan reveals a consistent trend that teachers have positive attitudes towards artificial intelligence but are not comfortable with its implementation and are not getting much support. Bhutto et al. (2026) found that college teachers in Hyderabad considered ChatGPT very useful but were not comfortable using it in the classroom. Access also depends on context. Rural primary teachers reported significantly less internet access than their urban counterparts (17% vs 78%) and course completion pressure was more of a barrier than hardware (Ali et al., 2026). Most government high school teachers in Taluka Sehwan, Sindh, were still

at the entry or adoption phase of technology integration (Panhwar, Ghaloo, & Shah, 2026), and school heads in Larkana reported unreliable infrastructure, low funding and inadequate teacher training as barriers to AI (Qaim-ud-Din et al., 2026). Research on English language teachers provides additional details. ESL teachers in Karachi appreciated the use of ChatGPT for producing materials that helped them make up for poor textbooks, but the use of ChatGPT was contingent on prompting skill (Sultan, 2026). Among 212 university English teachers in Punjab, organisational support and policy clarity predicted digital teaching competence, while teachers sought informal support, such as peer WhatsApp groups, in the absence of formal support (Raza et al., 2026). A survey of 483 Urdu teachers highlights a similar gap: attitudes of teachers towards artificial intelligence were high but readiness only moderate, and pedagogical preparedness was the strongest predictor of technology-supported practice (Abid et al., 2026). Critical studies also caution that AI tools encode native-speaker norms, which may marginalize Pakistani English (Abbasi et al., 2026; Khan & Ali, 2026).

### **2.5 Theoretical Framework**

The study integrates three theoretical lenses into a single acceptance–capability–context model (Table 1). The first lens, acceptance, draws on the Technology Acceptance Model (Davis, 1989) to explain why teachers use AI tools. The second, capability, combines TPACK (Mishra & Koehler, 2006) and its AI-focused extension, Intelligent-TPACK (Chiu, 2026), with self-efficacy theory (Bandura, 1997) to explain whether teachers can teach with these tools into their students. The third lens of this study is Ertmer's (1999) distinction between first and second order barriers to situate both acceptance and capability within the institutional and material conditions of Sindh's public schools. In this theoretical framework, each lens compensates for the limitations of others. Like Technological acceptance model accounts for the adaptation of technology but limits about the teachers' pedagogical capabilities. TPACK describes teachers' capability teachers, but it treats in isolation from the resources. The barriers lens of

this theoretical framework explains why teachers' positive attitudes, favourable beliefs, and adequate knowledge may still fail to produce the classrooms in the resource constrained environment schools.

TPACK describes capability but treats the teacher in isolation from resources. The barriers lens explains why favourable beliefs and adequate knowledge may still fail to produce classroom use in resource-constrained schools.

**Table 1:** *Theories Underpinning the Study and the Constructs They Inform*

| Theory                                                                       | Core proposition                                                                                                        | Constructs in this study                                                      | Hypotheses |
|------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------|------------|
| <b>Technology Acceptance Model (Davis, 1989)</b>                             | Acceptance depends on perceived usefulness and ease of use                                                              | Perceived usefulness, ease of use, benefits and concerns; frequency of AI use | H1, H2, H6 |
| <b>AI-TPACK / Intelligent-TPACK (Mishra &amp; Koehler, 2006; Chiu, 2026)</b> | Teaching with AI requires integrated technological, pedagogical and content knowledge, including AI literacy and ethics | AI literacy, AI pedagogical competence, ethical awareness                     | H5         |
| <b>Self-efficacy theory (Bandura, 1997)</b>                                  | Belief in one's capability turns knowledge into action                                                                  | Self-efficacy for AI use                                                      | H5         |
| <b>Barriers to technology integration (Ertmer, 1999)</b>                     | External (first-order) barriers constrain teachers even when beliefs are favourable                                     | Institutional support, resource challenges, school location                   | H3, H4, H7 |

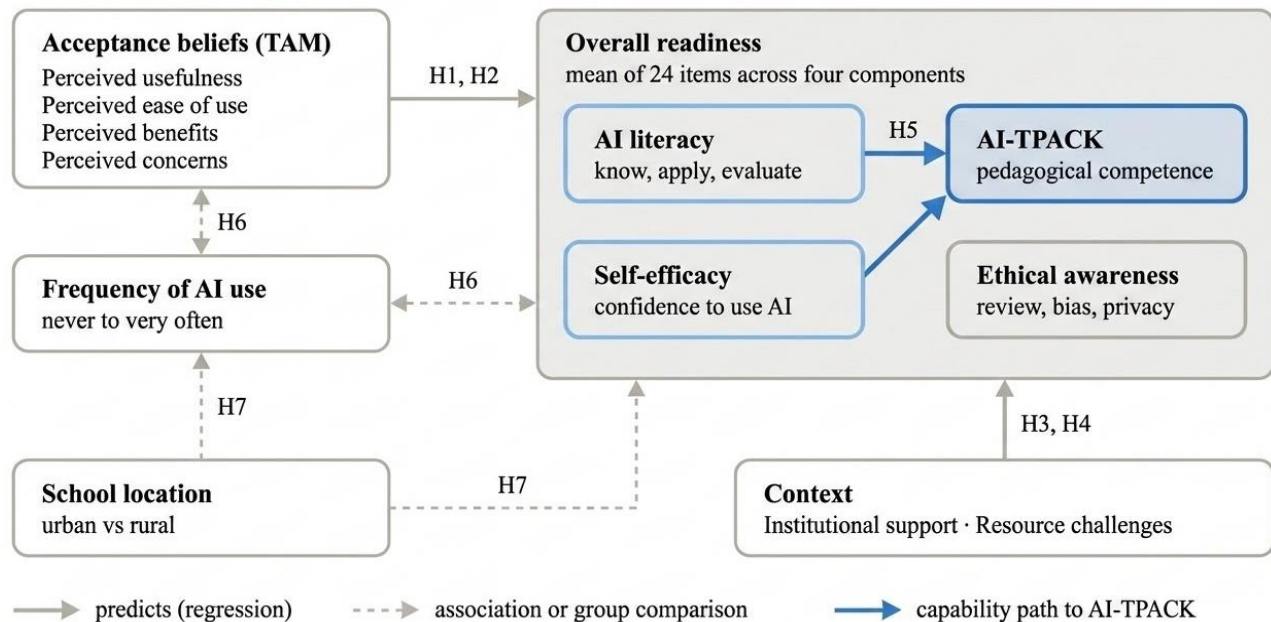
## 2.6 Hypotheses

This study separate acceptance, capability and context, and tests the following hypotheses based on the existing literature. The hypothesis **(H1)** defines as the Teachers' perceptions of AI (usefulness, ease of use and benefits) are positively associated with their overall readiness. The hypothesis **(H2)** Perceived concerns are negatively associated with overall readiness. The hypothesis **(H3)** Institutional support positively predicts overall readiness, over and above perceptions. The hypothesis **(H4)** Resource-related challenges are negatively associated with overall readiness. The hypothesis **(H5)** AI literacy and self-efficacy predict AI pedagogical competence (AI-TPACK) over and above perceptions. The hypothesis **(H6)** Frequency of AI use is positively associated with

perceptions and with readiness components. The hypothesis **(H6)** Urban teachers report higher readiness and more frequent AI use than rural teachers.

## 2.7 Conceptual Framework

the conceptual framework of this study is represent in the Figure 1 that operationalises these theories. Acceptance beliefs and contextual conditions are expected to predict overall readiness (H1–H4). Readiness is measured as the mean of four components, shown inside it. Within readiness, AI literacy and self-efficacy are expected to predict AI pedagogical competence (H5), the study's central capability path. Frequency of AI use is examined as a correlate of both acceptance beliefs and readiness (H6), and school location as a comparison variable for readiness and use (H7).

**Figure 1:** Conceptual framework of the study

Solid arrows are tested with multiple regression, dashed lines with correlations or group comparisons; the highlighted path from AI literacy and self-efficacy to AI-TPACK is the study's main theoretical claim.

### 3. Method

#### 3.1 Design

The study used an exploratory, cross-sectional, descriptive-correlational survey design with two open-ended items. Given its sample size, it is positioned as an exploratory study whose findings are intended to inform a larger confirmatory survey. The quantitative component addressed levels of readiness and perceptions, relationships among constructs, and group differences; the open-ended items captured teachers' own accounts of benefits and barriers.

#### 3.2 Participants and sampling

The study Participants were 64 English teachers teaching Grades 9–10 working the government high schools of Sindh. However, these teachers

were selected through two different sampling strategies such as convenience and snowball sampling via WhatsApp groups, Facebook pages and groups, LinkedIn and their personal contacts; the Google Forms questionnaire was administered in September to October 2026. Respondents came from 13 districts, mainly Khairpur Mirs (54.7%) and Sukkur (17.2%). Most teachers were male (68.8%), aged under 40 (87.5%), held a 16-year master's or BS degree (64.1%) and had a B.Ed. (62.5%). Most worked in rural schools (62.5%), and 79.7% had received no training on AI tools. Nearly all accessed the internet mainly through a smartphone (85.9%), and 29.7% reported no internet at their school (Table 2). A sensitivity analysis in G\*Power (Faul et al., 2009) showed that  $N = 64$  provides 80% power ( $\alpha = .05$ ) to detect correlations of  $r \geq .35$  and, in a five-predictor regression, effects of  $f^2 \geq .23$ .

In addition, the both regression models reported below exceeded this threshold by a wide margin ( $f^2 = 1.63$  and  $1.80$ ), but small correlations and group differences may have gone undetected.

**Table 2:** Characteristics of Participants (N = 64)

| Characteristic                     | Category             | n           | %                  |
|------------------------------------|----------------------|-------------|--------------------|
| Gender                             | Male                 | 44          | 68.8               |
|                                    | Female               | 20          | 31.2               |
| Age (years)                        | Below 30             | 25          | 39.1               |
|                                    | 30–39                | 31          | 48.4               |
|                                    | 40–49                | 8           | 12.5               |
| Academic qualification             | BA/BSc               | 3           | 4.7                |
|                                    | MA/MSc/BS (16 years) | 41          | 64.1               |
|                                    | MPhil/MS             | 19          | 29.7               |
|                                    | PhD                  | 1           | 1.6                |
| Professional qualification         | B.Ed.                | 40          | 62.5               |
|                                    | M.Ed.                | 18          | 28.1               |
|                                    | Other / missing      | 6           | 9.4                |
| Teaching experience                | Less than 5 years    | 25          | 39.1               |
|                                    | 5–10 years           | 26          | 40.6               |
|                                    | More than 10 years   | 13          | 20.3               |
| School location                    | Urban                | 24          | 37.5               |
|                                    | Rural                | 40          | 62.5               |
| School type                        | Boys / Girls / Mixed | 21 / 7 / 36 | 32.8 / 10.9 / 56.2 |
| AI training received               | Yes                  | 13          | 20.3               |
|                                    | No                   | 51          | 79.7               |
| Main internet device               | Smartphone           | 55          | 85.9               |
|                                    | Laptop/computer      | 9           | 14.1               |
| Internet at school                 | Not available        | 19          | 29.7               |
|                                    | Sometimes available  | 25          | 39.1               |
|                                    | Always available     | 20          | 31.2               |
| AI tools used (multiple responses) | ChatGPT              | 59          | 92.2               |
|                                    | Meta AI (WhatsApp)   | 41          | 64.1               |
|                                    | Gemini               | 37          | 57.8               |
|                                    | Grammarly            | 16          | 25.0               |
|                                    | QuillBot             | 10          | 15.6               |
|                                    | Microsoft Copilot    | 8           | 12.5               |

### 3.3 Instrument

Data were collected with a structured questionnaire adapted from validated instruments (Table 3). Section A recorded teachers' background information, the AI tools used and frequency of AI use (1 = never to 5 = very often). Sections B and C used a five-point Likert scale (1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree) to measure perceptions and readiness.

Overall readiness was computed as the mean of 24 items on AI literacy, AI pedagogical competence, self-efficacy and ethical awareness. Section D asked teachers to rate eight resource-related challenges (1 = not a challenge, 5 = very serious challenge), and Section E asked two open-ended questions about the main benefit of and main barrier to using AI in teaching. Concern items were not reverse-coded and were analysed as a separate scale.

**Table 3:** *Constructs, Sources and Internal Consistency of the Scales*

| Section | Construct                            | Items | Adapted from                                    | $\alpha$ |
|---------|--------------------------------------|-------|-------------------------------------------------|----------|
| B1      | Perceived usefulness (PU)            | 6     | Davis (1989); Qureshi (2026)                    | .95      |
| B2      | Perceived ease of use (PEOU)         | 6     | Davis (1989); Qureshi (2026)                    | .94      |
| B3      | Perceived benefits                   | 4     | Sobkowiak (2026); Alzeebaree (2026)             | .90      |
| B4      | Perceived concerns                   | 4     | Sobkowiak (2026); Alzeebaree (2026)             | .81      |
| C1      | AI literacy                          | 8     | Nabhan & Habók (2026)                           | .91      |
| C2      | AI pedagogical competence (AI-TPACK) | 6     | Ren & Li (2026); Chiu (2026)                    | .94      |
| C3      | Self-efficacy for AI use             | 5     | Darko et al. (2026)                             | .88      |
| C4      | Ethical awareness                    | 5     | Isaee et al. (2026); Vellanki & Tabassum (2026) | .89      |
|         | Overall readiness (C1–C4)            | 24    | Composite: mean of C1–C4 items                  | .96      |
| C5      | Institutional support                | 5     | Isaee et al. (2026); Al-khresheh et al. (2026)  | .84      |
| D       | Resource-related challenges          | 8     | Ali et al. (2026); Qaim-ud-Din et al. (2026)    | .77      |

### 3.4 Validity and reliability

Content and face validity were established by three experts in ELT, educational technology and research methods, who judged each item's relevance, clarity and fit to Sindh's public schools. The instrument was piloted with 20 teachers outside the main sample, yielding subscale Cronbach's alpha ( $\alpha$ ) values ranging from .74 to .92, indicating satisfactory construct reliability. In the main sample, Cronbach's alpha ranged from .77 to .95 for the subscales and was .96 for overall readiness, all above the .70 criterion. Because all data were self-reported and collected with one

instrument, Harman's single-factor test was run: the first unrotated factor explained 41.9% of the variance, below the 50% threshold, suggesting that common-method variance was not dominant, although this test is a weak diagnostic and cannot rule out common-method bias (Podsakoff et al., 2003). Discriminant validity among the four readiness components was examined with the heterotrait–monotrait ratio (HTMT; Henseler et al., 2015). All values were below the .90 criterion (.61–.87), although AI literacy approached it with self-efficacy (.87) and ethical awareness (.84). An exploratory factor analysis of the 24 readiness

items (principal axis factoring, promax rotation; KMO = .88; Bartlett's  $\chi^2(276) = 1354.0$ ,  $p < .001$ ) showed that the six AI pedagogical competence items formed a distinct factor (loadings .59–.97), as did most ethical awareness items, whereas the literacy and self-efficacy items loaded across factors. Parallel analysis indicated a strong general factor (first eigenvalue = 13.12, 54.7% of variance), so the four components are best understood as related facets of a single readiness construct.

### 3.5 Data screening

No scale items were missing, although two cases showed questionable response patterns: one respondent gave the same rating to every attitude item (straight-lining), while another rated usefulness, ease of use and benefits at 1–2 but every readiness and support item at 5. Rather than excluding them on arbitrary grounds, both cases were retained and their influence was checked in a sensitivity analysis. Shapiro–Wilk tests showed that most scales departed from normality. Because parametric tests are robust to moderate departures of this kind, they were used for the main analyses, and results were checked with non-parametric equivalents, heteroscedasticity-consistent (HC3) standard errors and bootstrapped confidence intervals (Hayes & Cai, 2007).

### 3.6 Data analysis

Analyses were conducted in IBM SPSS Statistics 27. Mean scores were interpreted as low (1.00–2.33), moderate (2.34–3.66) or high (3.67–5.00). Relationships were examined with Pearson correlations, and correlations involving the single-item frequency measure were checked with Spearman's  $\rho$ . Two multiple regression models were estimated. **Model A** predicted overall readiness from acceptance beliefs and context. Because perceived usefulness and ease of use were very highly correlated ( $r = .89$ ), they were combined into a single TAM composite in both models. **Model B** was a two-step hierarchical regression predicting AI pedagogical competence from the TAM composite and perceived benefits (Step 1) and then AI literacy and self-efficacy (Step

2), so that the change in  $R^2$  tested H5 directly. Multicollinearity was assessed with variance inflation factors (VIF) and condition indices (Hair et al., 2019). Urban and rural teachers were compared with independent-samples t-tests, with Levene's test, Welch's correction, Cohen's  $d$  and Hedges'  $g$ . For comparisons involving small or unequal groups (gender, training, experience, device and frequency of use), Mann–Whitney U and Kruskal–Wallis H tests were used, with effect size  $r = |z|/\sqrt{N}$ . Open-ended responses were coded inductively following Braun and Clarke (2006) and reported as theme frequencies.

## 4. Results

### 4.1 Readiness, perceptions and AI use (RQ1)

Teachers reported high overall readiness ( $M = 3.88$ ,  $SD = 0.72$ ). Among its components, ethical awareness was highest ( $M = 4.03$ ) and AI pedagogical competence lowest ( $M = 3.75$ ), with AI literacy ( $M = 3.94$ ) and self-efficacy ( $M = 3.78$ ) in between (Table 4). Perceptions were favourable: ease of use ( $M = 3.95$ ), usefulness ( $M = 3.83$ ) and benefits ( $M = 3.73$ ) were all high, while concerns were moderate ( $M = 3.47$ ).

Item-level scores sharpen this picture. The highest-rated usefulness item concerned preparing teaching materials ( $M = 4.02$ ), and the lowest concerned giving feedback on students' writing ( $M = 3.56$ ). Within pedagogical competence, teachers felt most able to use AI for grammar and vocabulary ( $M = 3.88$ ) and least able for speaking and listening ( $M = 3.61$ ). The strongest ethical belief was that teachers should always review AI-generated content before classroom use ( $M = 4.25$ ). The strongest concern was students' over-dependence on AI ( $M = 3.83$ ); the weakest was that AI does not suit Pakistani culture and English ( $M = 2.80$ ).

AI use was common but not intensive ( $M = 3.38$ ,  $SD = 0.90$  on a five-point scale). Some 42.2% of teachers used AI often or very often, 43.8% sometimes and 14.1% rarely or never. ChatGPT was used by 92.2% of teachers and Meta AI, available inside WhatsApp, by 64.1%.

**Table 4:** Means, Standard Deviations and Pearson Correlations Among Study Variables (N = 64)

| Variable                     | M    | SD   | 1     | 2     | 3     | 4     | 5     | 6     | 7     | 8    | 9    | 10  |
|------------------------------|------|------|-------|-------|-------|-------|-------|-------|-------|------|------|-----|
| 1. Perceived usefulness      | 3.83 | 1.05 | —     |       |       |       |       |       |       |      |      |     |
| 2. Perceived ease of use     | 3.95 | 0.95 | .89** | —     |       |       |       |       |       |      |      |     |
| 3. Perceived benefits        | 3.73 | 0.93 | .65** | .66** | —     |       |       |       |       |      |      |     |
| 4. Perceived concerns        | 3.47 | 0.96 | .22   | .23   | .33** | —     |       |       |       |      |      |     |
| 5. AI literacy               | 3.94 | 0.74 | .61** | .67** | .58** | .14   | —     |       |       |      |      |     |
| 6. AI pedagogical competence | 3.75 | 0.86 | .51** | .50** | .58** | .08   | .75** | —     |       |      |      |     |
| 7. Self-efficacy             | 3.78 | 0.82 | .48** | .53** | .62** | .05   | .78** | .75** | —     |      |      |     |
| 8. Ethical awareness         | 4.03 | 0.85 | .42** | .45** | .54** | .27*  | .76** | .56** | .61** | —    |      |     |
| 9. Institutional support     | 2.99 | 0.98 | .03   | .05   | .20   | -.19  | .33** | .39** | .44** | .22  | —    |     |
| 10. Challenges               | 3.88 | 0.74 | .34** | .33** | .25*  | .19   | .44** | .36** | .34** | .35* | .06  | —   |
| 11. Frequency of AI use      | 3.38 | 0.90 | .49** | .49** | .48** | .39** | .33** | .21   | .13   | .31* | -.22 | .12 |

**Note.** \* $p < .05$ . \*\* $p < .01$  (two-tailed). All scales range from 1 to 5. For challenges, higher scores mean more serious challenges. Frequency of AI use: 1 = never, 5 = very often. Overall readiness (mean of variables 5–8, 24 items):  $M = 3.88$ ,  $SD = 0.72$ .

#### 4.2 Challenges and institutional support (RQ2)

Institutional support was the lowest-rated dimension in the study ( $M = 2.99$ ) and the only one in the moderate band. Fewer than three in ten teachers agreed that technical help was available at school (28.1%) or that their school had clear guidelines on AI (28.1%), and only 35.9% said their head encouraged AI use. Support from colleagues

was the strongest source of help (65.6% agreement; Table 5). Resource challenges were rated as serious ( $M = 3.88$ ). The most serious were lack of technical support ( $M = 4.06$ ), lack of devices ( $M = 4.03$ ), lack of training ( $M = 4.00$ ) and the absence of a clear departmental policy ( $M = 3.98$ ). Heavy workload was rated as the least serious challenge ( $M = 3.56$ ), although still moderate to high.

**Table 5: Institutional Support Items and Resource Challenges (N = 64)**

| Item                                                           | M    | SD   | % agree (4–5) |
|----------------------------------------------------------------|------|------|---------------|
| <b>Institutional support</b>                                   |      |      |               |
| Colleagues share ideas and help each other in using AI tools   | 3.53 | 1.17 | 65.6          |
| The education department provides training on using AI tools   | 3.20 | 1.32 | 43.8          |
| My school head encourages teachers to use AI tools             | 2.98 | 1.20 | 35.9          |
| My school has clear guidelines on the use of AI tools          | 2.67 | 1.24 | 28.1          |
| Technical help is available in my school                       | 2.56 | 1.36 | 28.1          |
| <b>Challenges (ranked)</b>                                     |      |      |               |
| 1. Lack of technical support at school                         | 4.06 | 1.07 | —             |
| 2. Lack of computers, multimedia or other devices              | 4.03 | 1.22 | —             |
| 3. Lack of training on AI tools                                | 4.00 | 1.20 | —             |
| 4. No clear policy or permission from the education department | 3.98 | 1.15 | —             |
| 5. High cost of mobile data or internet packages               | 3.88 | 1.15 | —             |
| 6. No, or unreliable internet at school                        | 3.80 | 1.16 | —             |
| 7. Electricity shortage or load shedding                       | 3.70 | 1.35 | —             |
| 8. Lack of time due to workload and syllabus pressure          | 3.56 | 1.23 | —             |

**Note.** Support items: 1 = strongly disagree, 5 = strongly agree. Challenges: 1 = not a challenge, 5 = very serious challenge.

### 4.3 Relationships and predictors (RQ3)

**Correlations.** Three patterns stand out in Table 4. First, the readiness components were strongly interrelated ( $r = .56-.78$ ), and AI literacy correlated with pedagogical competence ( $r = .75$ ) and self-efficacy ( $r = .78$ ). Second, institutional support was related to the capability components (pedagogical competence  $r = .39$ , self-efficacy  $r = .44$ , AI literacy  $r = .33$ ) but not to any acceptance belief ( $r = .03-.20$ ) or to frequency of use ( $r = -.22$ ,  $p = .082$ ). Third, frequency of AI use was associated with acceptance beliefs (usefulness  $r = .49$ , ease of use  $r = .49$ , benefits  $r = .48$ ) and with AI literacy ( $r = .33$ ) and ethical awareness ( $r = .31$ ), but not with pedagogical competence ( $r = .21$ ,  $p = .100$ ) or self-efficacy ( $r = .13$ ,  $p = .296$ ). Frequent users also reported more concerns ( $r = .39$ ), although this association was not significant with Spearman's  $\rho$  (.24,  $p = .056$ ); all other associations with frequency of use kept the same direction and significance under Spearman's  $\rho$ . Contrary to expectations,

challenges correlated positively with every readiness component ( $r = .34-.44$ ).

### Model A: predictors of overall readiness.

Acceptance beliefs and context together explained 62% of the variance in overall readiness,  $R^2 = .62$ , adjusted  $R^2 = .58$ ,  $F(5, 58) = 18.73$ ,  $p < .001$  (Table 6). Perceived benefits ( $\beta = .35$ ,  $p = .004$ ), the TAM composite ( $\beta = .30$ ,  $p = .011$ ), institutional support ( $\beta = .29$ ,  $p = .002$ ) and challenges ( $\beta = .23$ ,  $p = .012$ ) were significant positive predictors; concerns were not ( $\beta = -.02$ ,  $p = .789$ ). In a hierarchical version of the model, adding support and challenges to the perception variables increased  $R^2$  from .50 to .62,  $\Delta R^2 = .12$ ,  $F$  change (2, 57) = 9.42,  $p < .001$ . Benefits, support and challenges remained significant with HC3 robust standard errors, with 5,000-sample bootstrapped confidence intervals, and after removing the two cases with questionable response patterns ( $n = 62$ ,  $R^2 = .74$ ), in which all four predictors remained significant (TAM

composite  $\beta = .37$ , benefits  $\beta = .42$ , institutional support  $\beta = .18$ , challenges  $\beta = .16$ ; all  $p < .05$ ).

**Table 6:** Multiple Regression Predicting Overall Readiness (Model A,  $N = 64$ )

| Predictor                                       | B     | SE   | $\beta$ | t     | p    | 95% CI for B  | VIF  |
|-------------------------------------------------|-------|------|---------|-------|------|---------------|------|
| (Constant)                                      | 0.60  | 0.41 |         | 1.46  | .149 | [-0.22, 1.42] |      |
| <b>TAM composite (usefulness + ease of use)</b> | 0.22  | 0.08 | .30     | 2.62  | .011 | [0.05, 0.39]  | 1.97 |
| <b>Perceived benefits</b>                       | 0.27  | 0.09 | .35     | 2.96  | .004 | [0.09, 0.45]  | 2.11 |
| <b>Perceived concerns</b>                       | -0.02 | 0.07 | -.02    | -0.27 | .789 | [-0.15, 0.12] | 1.24 |
| <b>Institutional support</b>                    | 0.21  | 0.06 | .29     | 3.32  | .002 | [0.08, 0.34]  | 1.15 |
| <b>Challenges</b>                               | 0.22  | 0.08 | .23     | 2.58  | .012 | [0.05, 0.39]  | 1.16 |

**Note.**  $R^2 = .62$ , adjusted  $R^2 = .58$ ,  $F(5, 58) = 18.73$ ,  $p < .001$ . Dependent variable: overall readiness (24 items).

**Model B: predictors of AI pedagogical competence.** A hierarchical regression tested whether AI literacy and self-efficacy predicted pedagogical competence over and above perceptions (H5; Table 7). In Step 1, the TAM composite and perceived benefits explained 37% of the variance,  $R^2 = .37$ , adjusted  $R^2 = .35$ ,  $F(2, 61) = 17.80$ ,  $p < .001$ , with benefits the only significant predictor ( $\beta = .42$ ,  $p = .004$ ; TAM composite  $\beta = .24$ ,  $p = .079$ ). Adding AI literacy and self-efficacy in Step 2 raised  $R^2$  to .64,  $\Delta R^2 = .27$ ,  $F$  change (2, 59) = 22.62,  $p < .001$ , and the final model was significant, adjusted  $R^2 = .62$ ,  $F(4, 59) = 26.52$ ,  $p < .001$ . In the

final model, AI literacy ( $\beta = .41$ ,  $p = .005$ ) and self-efficacy ( $\beta = .36$ ,  $p = .010$ ) were the only significant predictors, whereas the TAM composite ( $\beta = -.02$ ,  $p = .851$ ) and benefits ( $\beta = .13$ ,  $p = .250$ ) were not. Multicollinearity was acceptable (all VIF  $\leq 3.31$ ), and both capability predictors remained significant with HC3 robust standard errors (AI literacy  $p = .012$ ; self-efficacy  $p = .040$ ). One standardised residual exceeded  $|3|$  (-3.55); without this case the pattern was unchanged and slightly stronger ( $n = 63$ ,  $R^2 = .70$ ,  $\Delta R^2 = .30$ ; AI literacy  $\beta = .42$ ,  $p = .002$ ; self-efficacy  $\beta = .38$ ,  $p = .003$ ).

**Table 7:** Hierarchical Multiple Regression Predicting AI Pedagogical Competence (Model B,  $N = 64$ )

| Predictor                 | B     | SE   | $\beta$ | t     | p     | Tolerance | VIF  |
|---------------------------|-------|------|---------|-------|-------|-----------|------|
| <b>Step 1</b>             |       |      |         |       |       |           |      |
| (Constant)                | 1.47  | 0.39 |         | 3.72  | <.001 |           |      |
| <b>TAM composite</b>      | 0.22  | 0.12 | .24     | 1.78  | .079  | .55       | 1.81 |
| <b>Perceived benefits</b> | 0.39  | 0.13 | .42     | 3.03  | .004  | .55       | 1.81 |
| <b>Step 2</b>             |       |      |         |       |       |           |      |
| (Constant)                | 0.05  | 0.37 |         | 0.14  | .887  |           |      |
| <b>TAM composite</b>      | -0.02 | 0.11 | -.02    | -0.19 | .851  | .43       | 2.31 |
| <b>Perceived benefits</b> | 0.13  | 0.11 | .13     | 1.16  | .250  | .45       | 2.22 |
| <b>AI literacy</b>        | 0.48  | 0.17 | .41     | 2.91  | .005  | .30       | 3.31 |
| <b>Self-efficacy</b>      | 0.37  | 0.14 | .36     | 2.66  | .010  | .34       | 2.94 |

**Note.** Step 1:  $R^2 = .37$ , adjusted  $R^2 = .35$ ,  $F(2, 61) = 17.80$ ,  $p < .001$ . Step 2:  $R = .80$ ,  $R^2 = .64$ , adjusted  $R^2 = .62$ , SE of estimate = 0.53,  $F(4, 59) = 26.52$ ,  $p < .001$ ;  $\Delta R^2 = .27$ ,  $F \text{ change}(2, 59) = 22.62$ ,  $p < .001$ . Dependent variable: AI pedagogical competence (AI-TPACK).

#### 4.4 Group differences (RQ4)

Urban teachers tended to use AI more often than rural teachers ( $M = 3.67$ ,  $SD = 0.96$  vs  $M = 3.20$ ,  $SD = 0.82$ ),  $t(62) = 2.06$ ,  $p = .044$ ,  $d = 0.53$ , 95% CI [0.02, 1.04], a medium effect (Table 8). Levene's test was not significant ( $p = .142$ ), so the pooled test

is reported; with Welch's correction the difference was marginal,  $t(42.7) = 1.98$ ,  $p = .054$ . Urban and rural teachers did not differ in AI literacy, pedagogical competence, challenges (Table 8), overall readiness, self-efficacy, ethical awareness or institutional support (Mann-Whitney  $p = .325-.989$ ).

**Table 8:** Urban–Rural Comparisons (Independent-Samples *t*-Tests)

| Variable                  | Urban M (SD), n = 24 | Rural M (SD), n = 40 | t (62) | p    | Cohen's d [95% CI] |
|---------------------------|----------------------|----------------------|--------|------|--------------------|
| Frequency of AI use       | 3.67 (0.96)          | 3.20 (0.82)          | 2.06   | .044 | 0.53 [0.02, 1.04]  |
| AI literacy               | 4.03 (0.73)          | 3.89 (0.75)          | 0.69   | .493 | 0.18 [−0.33, 0.69] |
| AI pedagogical competence | 3.83 (0.87)          | 3.70 (0.87)          | 0.59   | .555 | 0.15 [−0.35, 0.66] |
| Challenges                | 3.96 (0.76)          | 3.83 (0.73)          | 0.68   | .500 | 0.18 [−0.33, 0.68] |

**Note.** Hedges'  $g$  for frequency of AI use = 0.53, 95% CI [0.02, 1.03].

Other characteristics made little difference. Readiness and its components did not differ by gender, age, teaching experience, internet availability at school, or prior AI training (all  $p > .05$ ). Teachers who had received AI training ( $n = 13$ ) were no readier than those who had not ( $Mdn = 3.79$  vs  $4.00$ ,  $U = 311.0$ ,  $p = .738$ ). Two differences emerged. Teachers who used AI more frequently reported higher AI literacy,  $H(2) = 6.16$ ,  $p = .046$ ,  $\varepsilon^2 = .10$ . The nine teachers whose main device was a laptop reported higher overall readiness ( $Mdn = 4.33$  vs  $3.92$ ,  $U = 139.5$ ,  $p = .038$ ,  $r = .26$ ), self-efficacy ( $p = .008$ ,  $r = .33$ ) and institutional support ( $p = .004$ ,  $r = .36$ ) compared to smartphone users. Because these tests were not corrected for multiple

comparisons and the laptop group was small, they are treated as exploratory.

#### 4.5 Teachers' own accounts

Fifty-two of the 64 teachers answered the open-ended questions (Table 9). The most common benefit was help with lesson planning, materials and activities (38.5%), followed by support for specific language skills and by saving time (26.9% each). The most frequently named barrier was poor internet or network connectivity (53.8%), followed by lack of training or know-how (32.7%) and lack of devices, infrastructure or technical support (28.8%). A smaller group (7.7%) mentioned school policies that ban mobile phones or require permission to use them in class.

**Table 9:** Themes in Open-Ended Responses (*n* = 52)

| Theme                                                                          | n  | %    |
|--------------------------------------------------------------------------------|----|------|
| <b>Main benefit</b>                                                            |    |      |
| Lesson planning, materials and activities                                      | 20 | 38.5 |
| Language-skill support (grammar, vocabulary, pronunciation, writing, speaking) | 14 | 26.9 |
| Saving time, quick answers and assessment preparation                          | 14 | 26.9 |
| Personalized learning and instant feedback                                     | 9  | 17.3 |
| More engaging, interactive lessons                                             | 6  | 11.5 |
| Teacher knowledge and professional growth                                      | 3  | 5.8  |
| <b>Main barrier</b>                                                            |    |      |
| Internet and network problems                                                  | 28 | 53.8 |
| Lack of training, guidance or know-how                                         | 17 | 32.7 |
| Lack of devices, infrastructure or technical support                           | 15 | 28.8 |
| Cost of paid tools and mobile data                                             | 6  | 11.5 |
| Concerns about AI itself (creativity, dependence, accuracy)                    | 6  | 11.5 |
| Electricity and load shedding                                                  | 4  | 7.7  |
| Policy, permission or mobile-phone bans                                        | 4  | 7.7  |
| Lack of time                                                                   | 2  | 3.8  |

#### 4.6 Summary of hypothesis tests

| Hypothesis                                                       | Result                                                                            |
|------------------------------------------------------------------|-----------------------------------------------------------------------------------|
| H1. Perceptions positively associated with readiness             | Supported (TAM composite and benefits)                                            |
| H2. Concerns negatively associated with readiness                | Not supported                                                                     |
| H3. Institutional support predicts readiness                     | Supported                                                                         |
| H4. Challenges negatively associated with readiness              | Not supported; the association was positive                                       |
| H5. AI literacy and self-efficacy predict pedagogical competence | Supported                                                                         |
| H6. Frequency of use associated with perceptions and readiness   | Partly supported (perceptions, literacy, ethics; not competence or self-efficacy) |
| H7. Urban teachers are more ready and more frequent users        | Partly supported (use only)                                                       |

## 5. Discussion

This study aimed to examine the preparedness of English teachers in resource-constrained public high schools in Sindh to adopt AI tools and the

factors influencing their preparedness. Four things stand out: teachers are willing but unsupported; acceptance and capability have different antecedents; engagement brings constraints into

view rather than being blocked by them; and the urban–rural divide is not about capacity, but opportunity to use AI.

### 5.1 Willing, self-taught and unsupported

The research findings of this study highlights teacher's high readiness and favourable perceptions, however the institution was weakest dimension regarding the AI use, four out of five teachers were untrained and never received any specific training regarding AI usage in classroom. In addition, school teachers and colleagues constituted as the main source of support rather than school administration. This pattern of willing individuals operating in a weak system matches global research studies findings in which institutional support receives the lowest ratings in readiness studies of teachers AI integration (Isaee et al., 2026), as well as in Pakistan evidence of reactive, policy-light responses to AI (Ishaq et al., 2026; Qaim-ud-Din et al., 2026).

This readiness level exceeds the moderate findings reported in Vietnam (Hang, 2025) and in reviews of EFL teachers (Wulan & Santosa, 2026). Two explanations are plausible. Freely available smartphone-based tools such as ChatGPT and Meta AI within WhatsApp have lowered barriers to entry, which suggests that AI readiness may now develop informally through personal use. Second, since recruitment occurred online, teachers already using AI may have been more likely to participate, potentially inflating the estimate. Among the readiness dimensions, ethical awareness received the highest ratings from teachers, while pedagogical competence received the lowest. The pattern resembles, in attenuated form, the "aware incompetence" described by Hang (2025). While teachers recognize the necessity of verifying AI output before implementation, they report reduced self-efficacy in integrating AI into pedagogical practices, specifically concerning feedback and the domains of speaking and listening. Research consistently reflects this trend: Chinese secondary EFL teachers possess more technological knowledge of AI than they apply in their pedagogy (An et al. 2025), while Pakistani Urdu teachers demonstrate positive

attitudes that outpace their actual readiness (Abid et al. 2026).

### 5.2 Acceptance drives use; literacy and confidence drive capability

The central contribution of this study is to presents the distinction between acceptance and the capability. Favourable perceptions correlated with the frequency of teachers' use of AI, as well as with the general readiness, but did not correlate with pedagogical competence when pedagogical competence was controlled for by pedagogical AI literacy and self-efficacy. Self-efficacy and pedagogical competence were, on the other hand, not related to the frequency of use. It's important to note that just liking AI is not enough for a teacher to be able to teach with it, as is using it frequently.

This pattern is an explanation of attitude–practice gap reported across contexts (Gurel Cennetkusu, 2026; Laoha et al., 2025). This conclusion is in line with the result of instrumental use (Dwipayani & Santosa 2026) which is a result of the positive psychological readiness of EFL teachers without technical and pedagogical competence. It is also congruent with the evidence that the level of AI literacy is the strongest predictor for readiness to implement (Isaee et al., 2026) and that self-efficacy influences the implementation of AI in structured or surface manner (Ofori & Debreli, 2026).

Large K-12 studies point the same way: AI-TPACK and self-efficacy, not attitudes, predicted the quality of AI-supported teaching (Du et al., 2026), and self-efficacy was the strongest predictor of AI-TPACK readiness (Xie & Luo, 2026). The open-ended answers point the same way: teachers mostly used AI to prepare lessons and materials and to save time, while pedagogically demanding uses such as feedback on writing and speaking practice were the least developed. Indonesian language teachers showed the same instrumental pattern, using WhatsApp and PowerPoint for delivery rather than for pedagogy (Hidayah et al., 2026). Sultan's (2026) finding that the value of ChatGPT for Pakistani ESL teachers depended on prompting skill suggests one concrete form this literacy takes.

For theory, the finding suggests that TAM explains the adoption of AI as a personal productivity tool but is insufficient to explain readiness for AI-integrated pedagogy. Readiness models should therefore treat acceptance and capability as distinct, with AI literacy and self-efficacy, consistent with the Intelligent-TPACK view (Chiu, 2026; Ren & Li, 2026), as the proximal antecedents of pedagogical competence. The modest overlap between the two is visible elsewhere: TPACK explained only 11.4% of the variance in AI acceptance among Turkish secondary teachers (Çakır & Güner, 2026).

### **5.3 Institutional support builds capability, not attitudes**

Institutional support predicted overall readiness and was correlated with pedagogical competence, self-efficacy and AI literacy, but not with any perception or with frequency of use. Support therefore appears to work on what teachers can do rather than on what they think of AI.

This is consistent with structural evidence which showed that institutional support predicted EFL teachers' pedagogical competence in using AI (Al-khresheh et al., 2026), organisational support predicted digital teaching competence for English teachers in Pakistan (Raza et al., 2026), and support predicted high school English teachers' technology integration competence (Haryanto et al., 2026). It also provides an understanding of why support may be weak and why use is still common, as it is tied to personal attitudes and there are freely available tools, while the deeper capability that schools could build is left to chance. The training figures also require careful interpretation. Few teachers have been AI trained (20.3%), with 43.8% saying AI training is provided by the education department, implying a few teachers are being trained, or teachers just rated the department's general provision instead of their personal training. It is important to note that there is no difference between the trained and untrained teachers either. The test had limited power since there were just 13 trained teachers, but the outcome also calls into question the type of training the trained teachers received. Professional development influences

classroom uses primarily through teachers' beliefs (Liu et al., 2026), and short professional development workshops that are just focused on tools may not impact pedagogical integration (Susanti et al., 2026). In this study, the teacher education students showed a similar gap between their self-efficacy about knowledge and ethics of AI, and their pedagogical and assessment competence. The same gap was found among the teacher education students in an AI literacy course described by Le et al. (2026). Although professional development focuses on internal factors like knowledge and confidence, other factors like support and resources in the institution are not addressed, whereas TPACK-based professional development has helped teachers accept generative AI (Ferraioli et al., 2026; Shrestha & Yi, 2026). Future research should document the content, length, and format of AI training and not just its presence.

### **5.4 Engagement brings constraints and concerns into view**

Contrary to Hypothesis 4, teachers who rated challenges of resources as highest and reported as higher readiness. In addition, teachers' frequency of AI uses was also positively correlated with concerns: teachers who used AI more often reported more concerns. For that situation one possible explanation, offered post hoc, is that constraints and risks become visible through engagement. Teachers who rarely use AI tools infrequently encounter unreliable school internet, limited devices or inaccurate AI-generated content; those who use them often meet these problems firsthand. In Ertmer's (1999) terminology, first-order barriers are felt most strongly by teachers who have already overcome the second-order barrier of reluctance. On this reading, the challenges reported here are not causes of low readiness but obstacles that ready teachers meet during implementation. Because the design is cross-sectional, this interpretation should be tested in future research, for example by controlling for frequency of use. This cautiousness is in line with the teachers' "positive but cautious" attitude in other parts of the world (Alzeebaree, 2026), and

such concerns should be addressed in ways that guide teachers rather than discourage them.

### 5.5 The urban–rural divide is in opportunity, not capacity

The research findings regarding the rural teachers also highlight the similar readiness on every component, however, they tended to use AI less often (a medium effect that was marginal under Welch's correction). Internet problems were the barrier named most often, and almost a third of teachers had no internet facilities at school. This divide in Sindh therefore appears to lie in the opportunity to use Artificial intelligence (AI) rather than in teachers' knowledge, confidence or attitudes. This increases nuance to Pakistani evidence of large rural–urban gaps in internet access (Ali et al., 2026) and to the argument that the digital divide in South Asia is shifting from access to meaningful use (Sahito et al., 2026). Access limits the depth of Engagement, a research study by Indonesian teachers with limited digital access were limited to surface-level participation in professional learning communities (Fahrudin et al., 2026), and rural United States teachers named bandwidth as their main barrier despite high confidence (Kormos, 2026).

The stakes for learners are considerable high: Tiwari and Yadav (2026) found that rural Indian Secondary ESL students scored well below their urban peers on every English Skills, and that students digital self-efficacy rose and fell with their proficiency. This study tentative advantage of laptop users reported higher readiness, self-efficacy and support points in same way. The device through which teachers reach Artificial intelligence may shape what they can do with it. A smartphone may serve personal productivity well enough, but it may be less suited to integrating AI into lesson.

Teachers also showed little concern that AI might not suit Pakistani culture and English used in Pakistan ( $M = 2.80$ ). Awareness that AI tools favour native-speaker English was the lowest-rated ethical items. This sits uneasily with critical scholarship arguing that such AI tools encode native-speaker norms and may marginalise

Pakistani English (Abbasi et al., 2026; Khan & Ali, 2026). This study suggests that teachers AI literacy is largely functional rather than critical. This may know how to use the tools a gap that professional development should address.

## 6. Implications

**For policy.** The School Education and Literacy Department, Sindh, should issue clear guidance on teachers' and students' use of AI tools, including when mobile phones may be used for teaching. Only 28.1% of teachers reported clear school guidelines, and the absence of a departmental policy was the fourth most serious challenge. Guidance that permits and frames AI use would remove an institutional barrier at almost no cost.

**For professional development.** Training should go beyond convincing teachers of the value of AI, because attitudes did not predict pedagogical competence once AI literacy and self-efficacy were considered. Effective programmes would foster critical AI literacy (evaluating output, recognising bias toward native-speaker English, prompting) and would develop self-efficacy through hands-on mastery experiences with tasks teachers find most challenging: feedback on writing and speaking/listening practice. Training should also be designed for smartphones and low-bandwidth connections, since this is how most teachers reach AI tools.

**For schools.** Colleagues were teachers' most available source of support. This support can be formalised through teacher learning circles or WhatsApp-based communities of practice in which teachers exchange prompts, materials and lessons, as university English teachers in Punjab already do informally (Raza et al., 2026). Lack of technical support, the most serious challenge reported, could be addressed even with one trained focal person per school or cluster.

**For equity.** Since rural teachers are as ready as urban teachers but use AI less, investment should target opportunities: school connectivity, subsidised data packages for teachers and offline-capable tools. Otherwise, AI risks widening the gap between schools that can use it and those that cannot (Sridhar et al., 2026).

**For theory.** Readiness frameworks for Artificial intelligence in education should discriminate the teacher's acceptance from capability to use in the classroom. TAM-based models explain adoption but should be paired with AI literacy and self-efficacy when the outcome of interest is pedagogical practice.

## 7. Limitations and Future Research

This study is limited by several limitations. First limitation of this small ( $N = 64$ ) and Teachers who already used AI may also have been more willing to respond. Second, all data were self-reported and collected with one instrument; although Harman's test did not indicate dominant common-method variance, self-reports of readiness may overstate actual capability. Third, the cross-sectional design does not permit causal claims; the paths tested are associations. Fourth, the sample was too small for confirmatory factor analysis, so the factor structure of the adapted scales should be tested in a larger sample; the high correlations among AI literacy, self-efficacy and pedagogical competence ( $r = .75-.78$ ) also mean that their distinctiveness needs confirmation (HTMT for literacy and self-efficacy = .87). Fifth, frequency of AI use was a single ordinal item, several subgroup tests were not corrected for multiple comparisons, and the trained and laptop groups were small. Finally, the open-ended responses were coded by one researcher. Future research should use a probability sample drawn from SEMIS records, test the measurement model with confirmatory factor analysis and structural equation modelling, and combine surveys with classroom observation and analysis of AI-generated teaching materials. This study suggests

several directions for further research. First, intervention studies should test whether building AI literacy and self-efficacy improves teachers' pedagogical competence with Artificial Intelligence. Second, longitudinal studies may reveal changes in teachers' use of AI over time, including the trajectory of personal uses of AI to classroom applications. Third, Female teachers working in the rural areas deserve separate attention because they may face additional constraints of mobility and access (Ullah & Shah, 2026) that shape their engagement with AI differently from male and urban colleagues.

## 8. Conclusion

The English teachers in this study, drawn from Sindh's public high schools, are largely ready to use AI tools: they see them as useful and easy to use, are aware of their ethical risks, and most already use them. They have done so largely on their own, through smartphones and free tools, with little training, guidance or technical support. The findings of this study suggest that favourable attitudes are linked to how often teachers use AI but not whether they can teach with it. Capability rests instead on AI literacy and self-efficacy; and institutional support is associated with capability rather than attitudes. Rural teachers appeared as ready as their urban colleagues but had fewer opportunities to use Artificial Intelligence. Therefore, there need to support teachers through clear guideline, technical help, reliable internet connectivity, and continues professional development opportunities that supports teachers in development of literacy and confidence needed to turn personal use into sound classroom practice.

## Declarations

**Ethics approval.** The study was conducted independently and was not reviewed by an institutional ethics committee. It involved an anonymous, voluntary online survey of adult professionals, collected no identifying information and posed minimal risk to participants.

**Consent to participate.** All participants of this study gave informed consent before completing the questionnaire and their Participation was voluntary and anonymous. These teachers could withdraw at any time without consequence. No names of teachers or schools were recorded in the research study.

**Data availability.** The anonymized dataset and SPSS syntax are available from the corresponding author on reasonable request.

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