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SCHOOL DIGITAL READINESS, TEACHER AI READINESS AND PEDAGOGICAL INTEGRATION IN GOVERNMENT SCHOOLS IN HIMACHAL PRADESH, INDIA

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ABSTRACT

Digital infrastructure can create the conditions for technology-supported teaching without ensuring that those conditions become regular or pedagogically purposeful classroom practice. The rapid diffusion of generative artificial intelligence (GenAI) adds a second distinction between exposure to emerging tools and professional readiness to evaluate and use them responsibly. This study examined how school digital-readiness conditions, teacher AI readiness and digital pedagogical practices were associated with classroom digital-resource utilization and teacher-perceived student learning and engagement. A quantitative cross-sectional dataset comprising 998 school-class records from 300 government high and senior secondary schools in four districts of Himachal Pradesh was linked to school-level administrative indicators through the 11-digit UDISE+ code. School context was represented by a 0-1 Digital Readiness Index (DRI) and an empirically derived four-category readiness typology; the typology was used in adjusted models to preserve distinct infrastructure configurations. Teacher AI Readiness Score (TAIRS) and Perceived Student Learning and Engagement Score (PSLES) were supported by one-factor solutions and strong McDonald's omega coefficients. Although 98.4% of records reported access to at least one functional device and 75.8% reported functional internet during teaching, regular digital-screen use was reported in 52.5%. Previous GenAI use was reported in 82.8%, but only 10.0% reported formal AI-related training and 80.5% reported no or only slight confidence in evaluating AI-generated educational content. Inquiry-oriented digital practice had the largest adjusted association with regular utilization (28.5 percentage points per category, $p < .001$). More frequent classroom utilization, inquiry-oriented practice and TAIRS were positively associated with PSLES, while Crisis Zone records remained 11.9 percentage points below Elite records after adjustment. The findings indicate that structural readiness establishes opportunity, whereas pedagogical practice and evaluative capability shape how that opportunity is translated into classroom integration.

Keywords: digital readiness; teacher AI readiness; generative artificial intelligence; digital pedagogy; classroom integration; government schools; India

1. INTRODUCTION

Digital technologies have become part of routine educational planning, yet the presence of devices, connectivity and digital content does not by itself establish that technology is being

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used regularly or meaningfully in classrooms. School digital transformation depends on the interaction of infrastructure, institutional capacity, teacher competence and pedagogical practice rather than on equipment provision alone (Timotheou et al., 2023). UNESCO (2023) similarly argues that educational technology should be judged in relation to appropriateness, accessibility and contribution to learning, not merely by whether it is available. This distinction is especially important in public-school systems where schools differ in enrolment, geography, connectivity, maintenance capacity and access to technical support. The gap between provision and practice is well documented. Teacher digital competence includes technical, pedagogical, ethical and professional judgement, not simply the operational ability to use a device (Falloon, 2020). Studies of teachers' technology adoption show that perceived usefulness, attitudes, professional learning and institutional support influence whether available resources are incorporated into teaching (Scherer et al., 2019; Cattaneo et al., 2022; Demissie et al., 2022). Indian evidence reaches a similar conclusion. Teachers may report substantial use of technology while still facing limitations in infrastructure, access to newer tools and lesson-planning support (Naik et al., 2024). Thus, structural readiness should be treated as an enabling condition rather than as evidence of classroom integration.

Generative artificial intelligence extends this problem. Tools such as ChatGPT, Gemini, Copilot and Claude can be accessed independently of formal school systems, allowing exposure to grow more rapidly than curriculum guidance or professional development. AI literacy therefore cannot be reduced to previous use. It includes understanding and application, critical evaluation of outputs and awareness of ethical concerns (Ng et al., 2021; Sperling et al., 2024). The UNESCO AI Competency Framework for Teachers places these capabilities within a broader professional model spanning a human-centred mindset, ethics, foundations and applications, AI pedagogy and professional learning (Miao & Cukurova, 2024). Intelligent-TPACK similarly emphasises that technical familiarity becomes educationally meaningful only when it is connected with pedagogy, subject content and ethical judgement (Celik, 2023). Recent teacher studies show why exposure and readiness should be separated. Teachers' perceived relevance and confidence are associated with readiness and intention to teach AI (Ayanwale et al., 2022), while teachers with previous AI experience tend to report higher readiness and perceived usefulness (Granström & Oppi, 2025). Structured professional learning can strengthen AI literacy and attitudes (Lademann et al., 2026), but training participation alone does not reveal its duration, quality, subject relevance or effect on practice. The central educational question is therefore not simply whether teachers have encountered GenAI, but whether they can evaluate its output, judge its suitability for learners and integrate it within defensible pedagogical activity.

A related issue concerns the educational purpose of digital use. Digital resources may be used primarily for presentation and lesson preparation without changing student participation or knowledge construction (Abedi, 2024). More purposeful forms of integration such as inquiry, simulation, assignments, collaborative tasks and concept-focused activity—may be more closely related to student engagement than frequency alone. Evidence from student and teacher studies suggests that the quality and organisation of technology use can matter more than exposure by itself (Zhang et al., 2024). Student-related outcomes must nevertheless be interpreted carefully when they are reported by teachers rather than measured through independent achievement tests. The present study links these strands within government secondary schools in Himachal Pradesh. School-level administrative indicators were connected with class-context questionnaire records, allowing institutional readiness, teacher AI preparedness, pedagogical practice and classroom utilisation to be examined in the same analytical structure. This linkage addresses a gap in research that often studies infrastructure,

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teacher capability, AI readiness or perceived outcomes separately. It also preserves the distinction between a continuous school-level readiness score and the specific structural configurations revealed by readiness typologies.

Three research questions guided the paper: (1) What gaps exist between digital access, classroom utilisation and teacher AI preparedness? (2) How does classroom digital-resource utilisation vary across school digital-readiness typologies? and (3) Which structural, teacher-readiness and pedagogical factors are associated with regular classroom digital-resource utilisation and perceived student learning and engagement? The analysis is cross-sectional and estimates associations rather than causal effects.

2. METHODOLOGY

2.1 Design, setting and sample

A quantitative cross-sectional design integrated school-level administrative records with a structured questionnaire. The defined population comprised 1,264 government high and senior secondary schools serving Classes IX–XII in Chamba, Hamirpur, Kangra and Shimla districts of Himachal Pradesh. The districts were selected to represent contrasting administrative, demographic and geographical settings; they were not a probability sample of all 12 districts in the state. Cochran's finite-population procedure produced a minimum requirement of approximately 295 schools, which was increased to 300 to support proportional allocation and protect against incomplete responses (Cochran, 1977). Schools were selected within district × digital-readiness strata using a proportional stratified design (Lohr, 2022).

The final sample contained 101 government high schools, contributing Class IX and X records, and 199 government senior secondary schools, contributing records for Classes IX-XII. This produced 998 school-class records: 300 each for Classes IX and X and 199 each for Classes XI and XII. The observational unit was the school-class questionnaire record. It should not be interpreted as an independently identified teacher because no teacher identifier was collected and the same respondent could have reported on more than one class. The multivariable models adjusted for respondent role and used school-clustered standard errors to account for dependence among records from the same institution.

2.2 School-level digital readiness and data linkage

The 11-digit UDISE+ code linked each questionnaire record with the corresponding school-level administrative context. Codes were stored as text to preserve leading zeros. Linkage appended district, school type, total functional pedagogical devices, hardware readiness, pedagogical internet connectivity, supporting infrastructure, the Digital Readiness Index (DRI), school enrolment and digital-readiness typology. The final workbook contained 300 unique schools and 998 unique UDISE–class combinations, with no duplicate school-class keys or school/district linkage mismatches.

The DRI summarized three school-level structural dimensions on a 0–1 scale: normalised Hardware Readiness, pedagogical Internet Connectivity and supporting digital Infrastructure. The index was calculated as:

$$DRI_s = 0.50\, S^{H}{}_{,s} + 0.40\, S^{I}{}_{,s} + 0.10\, S^{f}{}_{,s} \quad (1)$$

where $S^{H}{}_{,s}$ denotes the hardware-readiness score for school s, $S^{I}{}_{,s}$ the internet-connectivity score and $S^{f}{}_{,s}$ the supporting-infrastructure score. The 300 sampled schools had a mean DRI of 0.537 (median 0.577; range 0-1). K-means clustering was applied to the three component scores—not to the mathematically aggregated DRI-and identified four structural typologies:

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Elite (Hotspots), Connected-Poor, Hardware-Ready and Crisis Zone (Coldspots). The continuous DRI was retained as a descriptive school-level readiness measure, while typology was used in the multivariable models because it preserves the particular combination of strengths and deficiencies. DRI, typology and the related Student-Device Pressure Index were not entered simultaneously to avoid redundant representation of school structural conditions.

Table 1. Sample coverage, school-level readiness and measurement properties

Domain	Indicator	Sample/statistic	Interpretation
Coverage	Eligible school population	1,264 schools	Four selected districts
Coverage	Participating sample	300 schools	23.7% of eligible population
Coverage	School-class records	998 records	Classes IX-XII
School readiness	Mean DRI	0.537 (median 0.577)	0–1 school-level score
Typology	Elite (Hotspots)	176 schools / 630 records; mean DRI 0.669	Most favourable structural profile
Typology	Connected-Poor	68 schools / 188 records; mean DRI 0.491	Connectivity with weaker hardware/supporting conditions
Typology	Hardware-Ready	32 schools / 120 records; mean DRI 0.262	Hardware/supporting infrastructure with limited connectivity
Typology	Crisis Zone (Coldspots)	24 schools / 60 records; mean DRI 0.069	Multidimensional structural constraint
Measurement	TAIRS: 5 items	KMO = .858; ω = .919	One factor; loadings .651–.983
Measurement	PSLES: 6 items	KMO = .944; ω = .964	One factor; loadings .850–.939

Note. DRI = Digital Readiness Index; TAIRS = Teacher AI Readiness Score; PSLES = Perceived Student Learning and Engagement Score; KMO = Kaiser–Meyer–Olkin statistic; ω = McDonald's omega. Counts describe school-class records, not unique teachers. Source: authors' calculations from the final linked dataset.

2.3 Questionnaire measures

Classroom access was represented by the number of functional pedagogical devices accessible during teaching and reported functional internet availability for the selected class. Classroom digital-resource utilisation was recorded as smartboard, projector or digital-screen use: never, 1–2 periods, 3–5 periods or more than 5 periods per week. For binary logistic regression, use during 3 or more periods per week was classified as regular utilisation; never

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or 1–2 periods per week was classified as limited utilisation. The threshold denotes recurring exposure within the school week and is a study-specific analytical distinction rather than a universal adequacy standard.

Four general pedagogical indicators were analysed separately: inquiry-oriented digital use, digital assignments, independent digital-resource searching and digital lesson planning. Their empirical structure did not support a defensible single pedagogy score. AI-related measures covered awareness of the school AI curriculum, formal AI-related professional training, the current role of AI in teaching, previous GenAI use, confidence in evaluating AI-generated educational content and perceived educational usefulness. Student-related items recorded teachers' perceptions of curiosity, retention and performance, collaboration, conceptual understanding, enthusiasm and exploration beyond the textbook.

2.4 Composite construction and construct validation

Ordinal items with different response ranges were transformed to a common 0–1 scale before aggregation:

$$z_{ij} = (x_{ij} - L_j) / (U_j - L_j) \quad (2)$$

where x_{ij} is the observed response for record i on item j and L_j and U_j are the theoretical lower and upper bounds. When conceptual coherence and empirical unidimensionality were supported, the retained items were combined using an unweighted mean:

$$C_i = (1/m) \Sigma_{j=1}{}^{m} z_{ij} \quad (3)$$

Exploratory factor analysis was based on polychoric correlations. Factorability was assessed using the KMO statistic and Bartlett's test of sphericity, and factor retention was determined through parallel analysis (Boateng et al., 2018; Watkins, 2018). The five-item TAIRS combined AI-curriculum awareness, current classroom role of AI, previous GenAI use, evaluative confidence and belief in AI's educational usefulness. Formal training remained separate. The six-item PSLES combined curiosity, perceived performance and retention, collaboration, understanding, enthusiasm and exploration beyond the textbook. McDonald's omega was used to assess internal consistency after unidimensionality had been supported (Hayes & Coutts, 2020). TAIRS and PSLES are study-specific composite measures rather than established universal scales.

2.5 Statistical analysis

Frequencies, percentages, medians and interquartile ranges described the sample. The original four-category utilisation outcome did not support a stable common-slope ordinal specification, so regular utilisation was analysed with binary logistic regression (Agresti, 2018):

$$Pr(Y_i = 1 \mid X_i) = \Lambda(X_i'\beta) \quad (4)$$

Because PSLES ranged from 0 to 1 and included boundary observations, its conditional mean was estimated using fractional logit regression (Papke & Wooldridge, 1996):

$$E(P_i \mid X_i) = \Lambda(X_i'\gamma) \quad (5)$$

Here, Y_i equals 1 for regular classroom utilisation, P_i denotes PSLES and $\Lambda(t) = \exp(t)/[1 + \exp(t)]$. Both models included class-accessible devices, functional internet, TAIRS, formal AI training, inquiry-oriented use, digital assignments, digital-resource searching, digital lesson planning and digital-readiness typology. District, class level, respondent role, teaching experience and subject area were included as adjustment variables. The accessible-device count was entered as $\log_2(x + 1)$, so its marginal effect represents an approximate doubling of

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accessible devices. Results are reported as average marginal effects (AMEs) with 95% confidence intervals (Mize et al., 2019). Standard errors were clustered by school because multiple school-class records originated from the same institution (Abadie et al., 2023). The maximum variance inflation factor was 3.45 for the utilisation model and 4.59 for the PSLES model, below the adopted threshold for serious multicollinearity (Hair et al., 2019).

2.6 Ethical and interpretive safeguards

The questionnaire began with a required voluntary-consent item and did not request names, teacher codes or personal contact details. The UDISE+ code identified the school rather than an individual and was used only for verification, linkage and clustered analysis. Results are reported in aggregate. PSLES represents teacher perceptions rather than independently measured examination performance, and all regression estimates are interpreted as associations rather than causal effects.

3. RESULTS

3.1 Digital access, classroom utilisation and AI preparedness

Digital access was widespread but did not result in universal classroom use. Functional internet during teaching was reported in 756 records (75.8%), and 982 records (98.4%) reported at least one accessible functional device. The median accessible-device count was five (IQR 4.00–7.75). Smartboards, projectors or digital screens were used at least once per week in 78.3% of records, but regular use across three or more periods was reported in 52.5%; 21.7% reported no use. Weekly structured inquiry or routine student investigation with digital tools was reported in 43.7% of records. Teacher-facing preparation was more common: 91.8% reported searching for a new digital teaching resource during the previous month.

The exposure–preparedness gap was more pronounced for AI. Some previous GenAI use was reported in 82.8% of records, yet frequent or very frequent use accounted for only 12.3%. Formal AI-related professional training was reported in 10.0%. AI was used beyond non-discussion or brief textbook mention in 37.8% of class records, while active student experimentation with AI applications occurred in 1.6%. Confidence in judging whether AI-generated educational material was accurate and suitable remained limited: 80.5% reported no confidence or only slight confidence. Lack of AI awareness or training was rated as highly or most limiting in 85.3% of records.

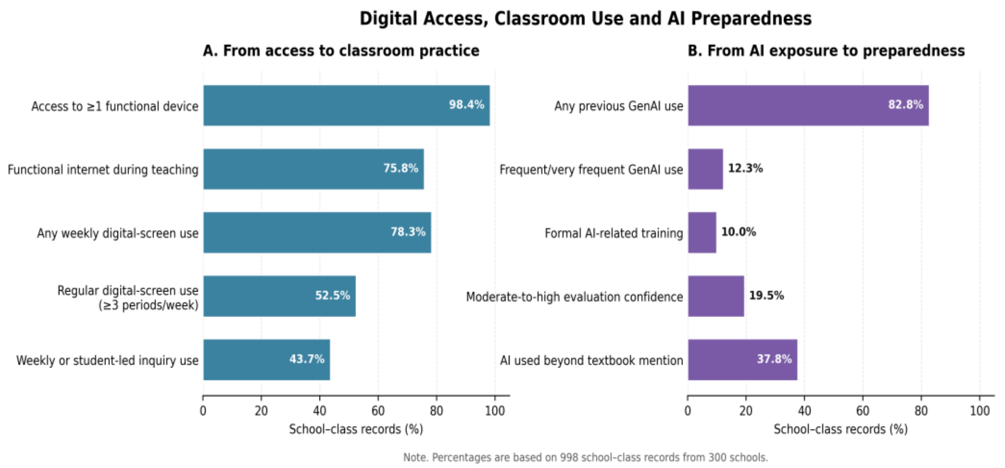

Figure 1. Digital access, classroom use and AI preparedness across the analytical records.

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Note. Percentages are based on 998 school-class records from 300 schools. "AI used beyond textbook mention" includes occasional AI-enabled tool use, classroom activities/projects and active exploration.

Table 2. Key descriptive findings

Domain	Indicator	n / statistic	% / scale
Classroom access	Functional internet during teaching	756	75.8
Classroom access	At least one accessible functional device	982	98.4
Digital utilisation	No digital-screen use	217	21.7
Digital utilisation	Regular use (≥3 periods/week)	524	52.5
Digital pedagogy	Weekly or student-led inquiry use	436	43.7
AI engagement	Any previous GenAI use	826	82.8
AI engagement	Frequent/very frequent GenAI use	123	12.3
AI preparation	Formal AI-related training	100	10.0
AI integration	AI used beyond brief textbook mention	377	37.8
AI evaluation	No/slight confidence evaluating AI content	803	80.5
Reported barrier	AI awareness/training highly or most limiting	851	85.3
Composite scores	TAIRS mean (SD); PSLES mean (SD)	.369 (.200); .552 (.228)	0–1 scales

Note. GenAI = generative artificial intelligence. Counts and percentages describe school-class records. Source: authors' calculations.

3.2 Variation across digital-readiness typologies

Unadjusted classroom-use profiles differed sharply across the four school typologies. Among Elite records, 74.6% reported regular digital-screen use and only 6.3% reported no use. Connected-Poor records commonly reported low-frequency use: 48.9% used a display for 1–2 periods per week and 21.3% reported regular use. Hardware-Ready records combined a median of six accessible devices with severe connectivity limitations; 63.3% reported no digital-screen use and 9.2% reported regular use. The Crisis Zone was the most restricted: 75.0% reported no use and 5.0% reported regular use. The contrasts show that hardware availability and connectivity constrained practice in different ways and that the same overall readiness problem can arise through different structural configurations.

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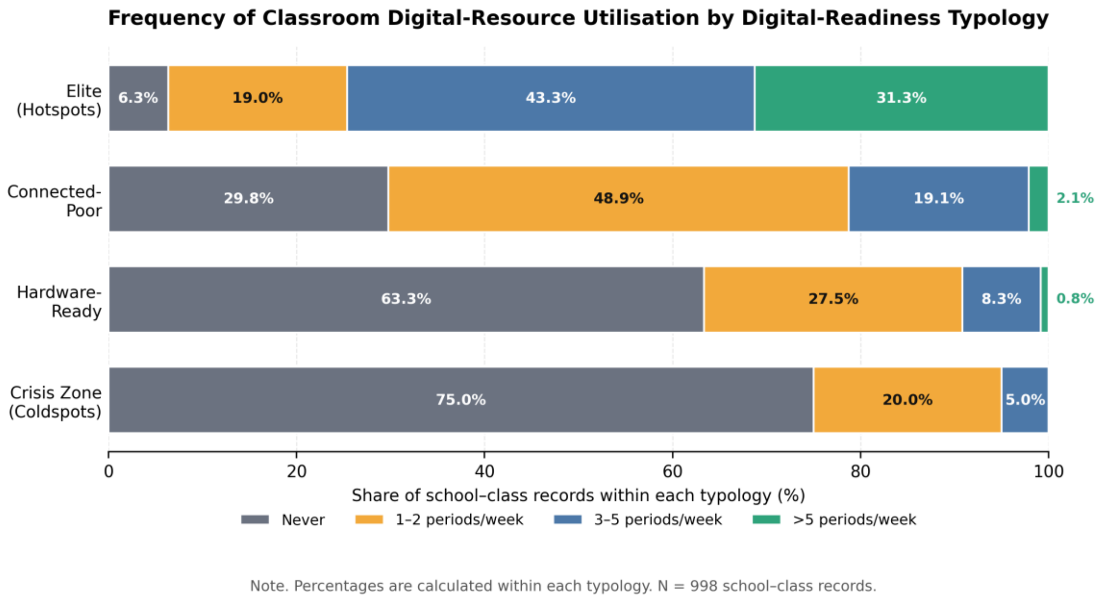

Figure 2. Frequency of classroom digital-resource utilisation by digital-readiness typology.

Note. Percentages are calculated within typology. Record-level denominators were Elite n = 630, Connected-Poor n = 188, Hardware-Ready n = 120 and Crisis Zone n = 60.

3.3 Teacher AI readiness and perceived student responses

TAIRS had a mean of .369 (SD .200) and a median of .350. The formal-training item was not included in the score. Records without formal AI training had a mean TAIRS of .326 (SD .154), whereas trained records had a mean of .756 (SD .146). Among the trained subgroup, 84.0% rated the training as very useful or extremely useful. The large descriptive separation should not be interpreted as a causal training effect because respondents already interested in AI may have been more likely to undertake training and the cross-sectional data do not establish temporal order.

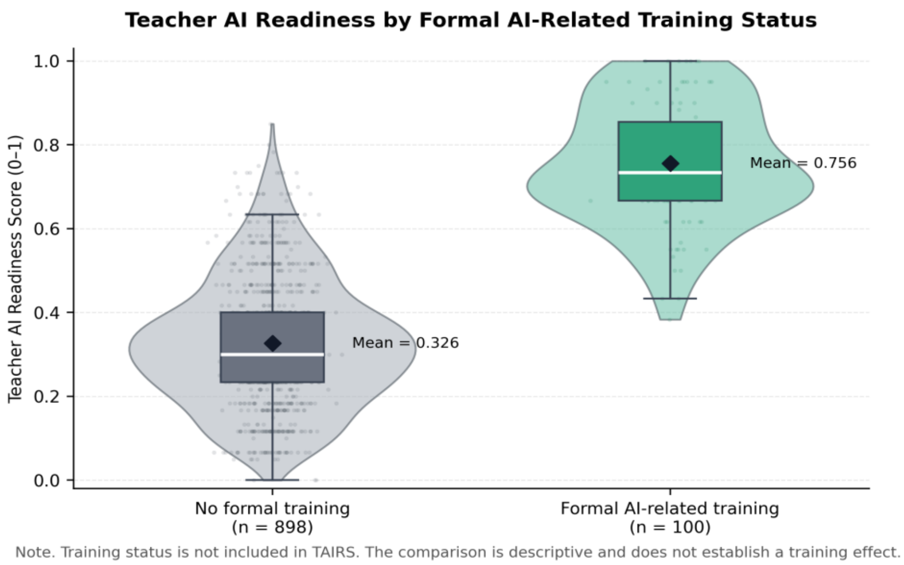

Figure 3. Teacher AI Readiness Score by formal AI-related training status.

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Note. Training status is not included in TAIRS. Diamonds show group means and box centres show medians. The comparison is descriptive and does not establish a causal training effect.

PSLES had a mean of .552 (SD .228) and a median of .583. Follow-up questions or curiosity were reported often or almost always in 55.1% of records, and at least slight improvement in performance or retention was perceived in 92.4%. The pattern was not uniformly favourable. Agreement or strong agreement was 50.9% for enthusiasm, 44.6% for understanding difficult concepts, 37.1% for peer collaboration and 33.0% for exploration beyond the textbook. These responses indicate perceived benefits alongside substantial neutral or negative experience.

3.4 Adjusted associations

Inquiry-oriented digital use was the strongest adjusted correlate of regular classroom utilisation. A one-category increase—from passive display toward occasional simulation, weekly problem solving or routine student investigation—was associated with a 28.5-percentage-point increase in the probability of regular use (95% CI 26.0–30.9, $p < .001$). Independent digital-resource searching showed a small inverse association (AME −4.0 points, 95% CI −5.5 to −1.5, $p = .002$). Accessible devices, functional internet, TAIRS, formal training, digital assignments and lesson planning did not show statistically distinguishable independent associations with regular use after adjustment.

Relative to Elite records, Connected-Poor records had a 6.2-percentage-point lower adjusted probability of regular utilization (95% CI −10.3 to −2.1, $p = .003$). The adjusted differences for Hardware-Ready and Crisis Zone records were not statistically significant. Model-adjusted probabilities were 54.6% for Elite, 51.6% for Hardware-Ready, 48.5% for Connected-Poor and 53.2% for Crisis Zone records. The reduction from the much larger unadjusted typology contrasts indicates that part of the raw difference was associated with variation in pedagogy, class access and respondent characteristics rather than structural typology alone.

PSLES was positively associated with both frequency and purpose of digital use. A one-category increase in classroom utilisation corresponded to a 3.7-percentage-point increase in PSLES. Inquiry-oriented practice had the largest pedagogical association (7.3 points), followed by digital assignments (4.1) and digital lesson planning (2.6). A .10-point increase in TAIRS corresponded to a 1.6-point increase in PSLES, and an approximate doubling of class-accessible devices plus one corresponded to a 1.3-point increase. Formal AI training, functional internet and digital-resource searching did not retain statistically significant independent associations with PSLES. Structural differences remained evident: PSLES was lower than in Elite records by 4.1 points in Hardware-Ready, 2.2 points in Connected-Poor and 11.9 points in Crisis Zone records.

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Table 3. Average marginal effects for regular classroom utilisation and PSLES

Predictor	Regular-use AME, pp (95% CI)	p	PSLES AME, pp (95% CI)	p
Classroom utilisation: one-category increase	—	—	3.7 (2.2, 5.2)	<.001
Accessible devices: approximate doubling + 1	−0.2 (−2.1, 1.8)	.877	1.3 (0.3, 2.4)	.015
Functional internet: yes vs no	4.7 (−0.8, 10.3)	.096	0.6 (−2.5, 3.6)	.712
TAIRS: 0.10-point increase	−0.3 (−1.7, 1.2)	.717	1.6 (0.9, 2.3)	<.001
Formal AI-related training: yes vs no	0.2 (−8.7, 9.1)	.965	−3.9 (−7.8, 0.1)	.055
Inquiry-oriented digital use: one-category increase	28.5 (26.0, 30.9)	<.001	7.3 (5.6, 9.0)	<.001
Digital assignments: one-category increase	1.1 (−2.4, 4.6)	.543	4.1 (2.7, 5.6)	<.001
Digital-resource searching: one-category increase	−4.0 (−5.5, −1.5)	.002	1.4 (−0.5, 3.3)	.148
Digital lesson planning: one-category increase	−1.5 (−4.0, 1.0)	.252	2.6 (1.2, 3.9)	<.001
Hardware-Ready vs Elite	−3.0 (−9.8, 3.7)	.377	−4.1 (−7.4, −0.7)	.017
Connected-Poor vs Elite	−6.2 (−10.3, −2.1)	.003	−2.2 (−4.3, −0.1)	.039
Crisis Zone vs Elite	−1.5 (−11.2, 8.3)	.770	−11.9 (−15.8, −8.0)	<.001

Note. AME = average marginal effect; pp = percentage points; CI = confidence interval. Models also adjust for district, class level, respondent role, teaching experience and subject area. Standard errors are clustered by school. Source: authors' analysis of the final linked dataset.

4. DISCUSSION

4.1 Structural readiness creates opportunity, not integration

The first contribution is the empirical separation of school readiness from classroom use. Nearly every record reported access to a functional device, but regular digital-screen use occurred in only slightly more than half of the records. The DRI provided a concise school-level summary of structural opportunity, while the typologies showed why a single score is insufficient for operational interpretation. Connected-Poor and Hardware-Ready schools illustrate the point: the former generally combined connectivity with weaker hardware/supporting conditions, whereas the latter combined stronger hardware/supporting

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infrastructure with limited connectivity. Their instructional constraints are therefore not interchangeable even when both are described as less favourable than Elite schools.

The pronounced unadjusted differences in classroom utilisation across typologies confirm that structural conditions matter. Yet the adjusted model substantially narrowed these gaps. Only the Connected-Poor difference remained statistically distinguishable from Elite records after accounting for class-accessible devices, teacher readiness, pedagogical practices and respondent characteristics. This supports a more precise interpretation of infrastructure: it shapes what is feasible, but it does not fully explain what teachers do with available resources. Similar research has shown that school preparedness and professional learning interact in shaping instructional integration and that strong infrastructure alone does not ensure classroom uptake (Amemasor et al., 2025; Cattaneo et al., 2022).

4.2 GenAI exposure has outpaced professional preparedness

The second contribution is the scale of the AI exposure–preparedness gap. More than four-fifths of the school-class records reported some previous GenAI use, but only one-tenth reported formal AI-related professional training. At the same time, four-fifths of records indicated no or only slight confidence in evaluating AI-generated educational content. This distinction is educationally important because fluent AI output may still be inaccurate, biased, contextually inappropriate or unsuitable for a particular age group. Previous use therefore cannot be treated as evidence of readiness for responsible educational application. The finding aligns with conceptions of AI literacy that combine knowledge, application, evaluation and ethics rather than exposure alone (Ng et al., 2021; Sperling et al., 2024).

The trained subgroup reported much higher TAIRS, and most trained records rated their training favourably. This pattern is consistent with evidence that structured professional learning can strengthen AI literacy, confidence and attitudes (Lademann et al., 2026). It cannot establish that training caused the difference. Training participation may reflect prior interest or access, and the binary training indicator used here does not capture content, duration, subject relevance, follow-up support or quality. The near-threshold negative coefficient for training in the PSLES model should therefore not be read as evidence that professional development is ineffective. Training is better understood as one possible pathway through which awareness, evaluative confidence and pedagogical capability may develop.

4.3 Pedagogy links resources with perceived student outcomes

The third contribution concerns the purpose of technology use. Inquiry-oriented practice had a much larger association with regular utilisation than device counts, internet availability or formal AI training. It was also the strongest pedagogical correlate of PSLES. Digital assignments and lesson planning were associated with perceived learning and engagement even though they did not independently predict the binary regular-use threshold. These findings separate frequency from educational purpose: using a display more often is not equivalent to organising simulation, investigation, experimentation, creation or concept-focused activity. This distinction is consistent with evidence that the quality of technology integration can be more informative for engagement than frequency alone.

TAIRS also contributed information to PSLES after structural and pedagogical variables were considered. A higher score—reflecting awareness, practical engagement, evaluative confidence and recognition of educational relevance—was associated with more favourable teacher-reported student responses. The association does not establish that AI readiness caused better learning. It does, however, suggest that teachers' capacity to judge and use AI-related resources may form part of the wider professional competence needed for purposeful

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digital teaching. The sizeable Crisis Zone difference in PSLES further shows that teacher capability and pedagogy do not eliminate structural disadvantage. School readiness and teacher capacity operate as complementary, not competing, explanations.

5. IMPLICATIONS FOR POLICY AND PRACTICE

Four implications follow from the findings. First, digital planning should move beyond binary provision targets. Monitoring should distinguish whether resources are functional, accessible to classes and used regularly. A school-level readiness score is useful for comparison, but typology-specific diagnosis is needed before deciding what intervention is appropriate. Connected-Poor schools require better access to functional devices and equitable scheduling; Hardware-Ready schools require dependable connectivity and robust offline resource strategies; Crisis Zone schools require coordinated minimum packages spanning devices, connectivity, maintenance and staff support. Second, professional development for AI-supported teaching should move beyond demonstrations of tools. Training should include verification of generated content, hallucination and bias awareness, privacy and data protection, age and curriculum suitability, prompt design, subject-specific lesson planning and clear boundaries for student use. Third, training should be sustained rather than treated as a one-time event. Follow-up mentoring, peer learning and opportunities to redesign actual lessons are more likely to connect professional learning with classroom practice than short exposure sessions. Fourth, evaluation frameworks should distinguish access, frequency and pedagogical depth. A school may possess devices and still require support to shift from presentation toward inquiry, assignments, student investigation and purposeful AI-supported learning.

6. CONCLUSION AND FUTURE RESEARCH

The study demonstrates why digital readiness, classroom utilization and AI preparedness should not be treated as interchangeable. The participating schools generally reported broad access to functional devices and substantial internet availability, yet regular classroom use was far less universal. The school-level DRI captured relative structural readiness, while the four typologies revealed distinct combinations of hardware, connectivity and supporting infrastructure that require different institutional responses. The AI findings show an equally important gap. GenAI exposure was already widespread, but formal preparation and confidence in evaluating AI-generated educational content remained limited. The strongest adjusted association with regular digital-resource utilization came from inquiry-oriented pedagogy rather than from infrastructure or training exposure alone. Perceived student learning and engagement were associated with more frequent utilization, inquiry-oriented practice, digital assignments, lesson planning and teacher AI readiness, while the Crisis Zone retained a substantial adjusted disadvantage. The practical challenge is therefore no longer simply to place technology in schools. It is to build the institutional and professional capacity required to use digital and AI-supported resources critically, pedagogically and consistently. Future research should follow schools and educators longitudinally, record the content and duration of AI-related professional development, incorporate classroom observation and network-quality measures, and link teacher reports with independent student assessments. Replication across the remaining districts of Himachal Pradesh and other Indian states would also test the transferability of the readiness typologies and study-specific composite measures.

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