

# Educational Technology in a Post-Pandemic World: Global Trends, East Asian Perspectives, and Persistent Divides (2020–2026)

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## Abstract

The COVID-19 pandemic accelerated the institutionalisation of online and hybrid education. At the same time, the subsequent diffusion of generative artificial intelligence (GenAI), learning analytics, and smart learning environments introduced new pedagogical, governance, and equity challenges. This systematic literature review synthesises 30 peer-reviewed studies published between 2020 and the review search cut-off in 2026, with particular attention to East Asian evidence in a global comparative perspective. Guided by PRISMA 2020, the review examines four mutually conditioning dimensions of post-pandemic educational technology: technological affordances, pedagogical integration, institutional capacity, and equitable participation. The synthesis shows that technology adoption and infrastructure expansion alone do not establish educational value. Meaningful outcomes depend on whether institutions translate technological capability into pedagogically appropriate course design, assessment, feedback, learner support, responsible data practices, and accessible conditions for participation. East Asian studies demonstrate rapid development in GenAI adoption, smart classrooms, learning analytics, and institutional digitalisation, but also reveal persistent rural-urban, literacy, participation, and outcome inequalities. Across contexts, the evidence further indicates that AI governance is not merely an administrative issue: policies governing transparency, privacy, accountability, academic integrity, and staff development can shape whether AI-mediated education mitigates or reproduces existing digital divides. The review advances an alignment framework in which durable and equitable educational value emerges when technological affordances are matched by pedagogical integration, institutional capacity, equitable participation, and responsible AI governance. It concludes by proposing testable propositions and a future research agenda focused on longitudinal outcomes, learner agency, privacy, institutional readiness, and comparative equity.

**Keywords:** Educational technology, post-pandemic education, Generative artificial intelligence, AI governance, Digital divide, East Asia, Systematic literature review.

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## **1. Introduction**

Educational technology entered the 2020s under conditions no research agenda had anticipated. COVID-19 moved teaching and learning online on an unprecedented scale, turning digital platforms from optional supplements into essential infrastructure while exposing persistent inequalities in connectivity, digital capability, institutional readiness, and learning outcomes. Evidence from China identified first-, second-, and third-level digital divides. At the same time, studies from Ghana, Kenya, and Ethiopia showed that access was further conditioned by affordability, digital skills, household circumstances, teacher capacity, and institutional readiness (Bati & Workneh, 2021; Guo & Wan, 2022; Kumi-Yeboah et al., 2023; Watson et al., 2023; Zhao et al., 2022). The post-pandemic period extended rather than reversed this transformation. Hybrid learning, data-driven education, smart environments, and institutional digitalisation expanded. At the same time, the diffusion of generative artificial intelligence (GenAI) shifted attention from adoption toward academic integrity, assessment, AI literacy, learner agency, governance, and educators' changing roles (Chan & Hu, 2023; Chiu et al., 2023; Darvishi et al., 2024; Xia et al., 2024). However, these streams remain only partially connected. East Asia provides a particularly important lens for understanding these developments. Chinese and other East Asian education systems combine large student populations, extensive digital infrastructure, strong state and institutional involvement, and rapidly expanding AI-enabled education. Recent studies examine university students' GenAI adoption in China, smart-classroom satisfaction, learning analytics, online educational environments, rural digital inequality, and teacher AI pedagogical knowledge (Dai et al., 2024; Kuo et al., 2026; Li, 2025; Tang et al., 2025; Tian & Lu, 2024). However, the same literature also demonstrates that infrastructure alone does not resolve inequality. Rural-urban outcome gaps, differences in digital literacy, uneven institutional implementation, and concerns over privacy and learner autonomy remain visible even in comparatively well-connected settings (Guo & Wan, 2022; Kong & Yang, 2026; Zhao et al., 2022). These developments create a need for a synthesis that treats post-pandemic educational technology as a socio-technical educational system rather than as a collection of tools or isolated adoption decisions. Existing reviews have made important contributions to artificial intelligence in education, AI literacy, learning-analytics privacy, and GenAI assessment (Casal-Otero et al., 2023; Chiu et al., 2023; Liu & Khalil, 2023; Xia et al., 2024). More recent research also shows that institutions are moving from initial enthusiasm and prohibition toward questions of responsible integration, teacher AI competence, institutional readiness, assessment redesign, and controlled but pedagogically meaningful use (Christ-Brendemühl, 2025; Fischer-Schöneborn et al., 2026; Kangwa et al., 2025; Kuo et al., 2026). However, these literatures are still insufficiently connected. In particular, digital-divide research commonly explains unequal access, skills, participation, and outcomes, whereas AI-governance research often focuses on privacy, integrity, regulation, and institutional policy. What remains underdeveloped is an account of the mechanism linking them: the extent to which governance arrangements determine whether unequal technological resources and capabilities are converted into equitable, meaningful, and educationally defensible participation in AI-mediated learning. This review addresses that gap by systematically synthesising 30 peer-reviewed studies published between 2020 and the 2026 search cut-off. It advances a four-dimensional alignment framework comprising technological affordances, pedagogical integration, institutional capacity, and equitable participation. The framework extends existing adoption-centred accounts in three respects. First, it treats adoption as an entry condition rather than evidence of educational value. Second, it positions pedagogical design and institutional capacity as conversion mechanisms through which technological possibilities may or may not become durable learning opportunities. Third, it incorporates AI governance as a cross-cutting institutional condition that can either protect or undermine equitable participation through rules governing access, transparency, data use, assessment, accountability, and professional support. The review therefore does not claim that technology produces outcomes linearly; instead, it explains why comparable tools can produce different learning, agency, and equity consequences across institutions and contexts. The review makes three bounded contributions. It first consolidates evidence that is often separated across GenAI adoption and governance, AI literacy and learning analytics, smart and online learning environments, digital equity, and teacher and institutional capacity. It second uses East

Asian evidence, especially from China and Taiwan, as a theoretically informative rather than universally representative lens. These settings reveal both the possibilities of scaled digital infrastructure and the persistence of capability and outcome divides. Third, it derives propositions that future longitudinal, experimental, quasi-experimental, multilevel, and structural-equation studies can test. Because this article is a systematic qualitative synthesis, it does not test the propositions as causal estimates; it identifies the relationships the reviewed evidence suggests examining empirically.

## **2. Literature Review: Post-Pandemic Educational Technology, Equity and AI Governance**

Post-pandemic educational-technology research spans four closely related streams: digitally mediated learning environments; AI adoption, literacy, assessment, and agency; digital inequalities in access, capability, participation, and outcomes; and institutional capacity encompassing professional learning, infrastructure, governance, privacy, and policy. The unresolved problem is not a shortage of evidence but the absence of an integrated explanation of how these conditions interact (Scheerder et al., 2017; Guo & Wan, 2022). Early pandemic research established that continuity of instruction depended on more than access to a platform. In China, digital inequalities were evident in equipment quality, network conditions, adaptability to online learning, and offline learning outcomes (Guo & Wan, 2022). Related evidence showed that rural-urban outcome differences were linked to self-efficacy, motivation, family support, and other forms of capital, indicating that access does not automatically yield equal educational benefit (Zhao et al., 2022). Research in Ghana, Kenya, and Ethiopia similarly documented the interdependence of infrastructure, affordability, training, institutional coordination, and household conditions (Bati & Workneh, 2021; Kumi-Yeboah et al., 2023; Watson et al., 2023). This body of work supports a progression from first-level divides in access to second-level divides in skills and effective use to third-level divides in outcomes. The rise of GenAI has intensified this problem rather than displaced it. Adoption research shows that perceived usefulness, effort expectancy, and learning value remain important drivers of students' willingness to use GenAI (Tang et al., 2025). However, adoption research cannot establish whether use strengthens understanding, transfer, judgement, or independent learning. Students report both practical benefits and concerns about accuracy, ethics, dependency, and legitimacy (Chan & Hu, 2023; Farinosi & Melchior, 2025). Experimental evidence further suggests that AI assistance may improve immediate task performance while weakening learner agency when support is withdrawn (Darvishi et al., 2024). Accordingly, current scholarship increasingly focuses on AI literacy, guided feedback, assessment redesign, self-regulation, and the pedagogical conditions under which AI serves as a scaffold rather than a substitute for thinking (Chiu, 2024; Delanoy & Chen, 2026; Xia et al., 2024). AI governance provides the missing institutional bridge between these two literatures. Learning analytics research has long identified risks related to privacy, data protection, transparency, surveillance, and limited student control (Jones et al., 2020; Liu & Khalil, 2023). In the GenAI context, governance also addresses legitimate use, disclosure, academic integrity, bias, assessment, accountability, and the distribution of AI-related knowledge among staff and students. Recent institutional studies indicate a shift towards controlled, literacy-oriented approaches rather than simple prohibition, though policies vary in clarity, enforceability, staff support, and sensitivity to local conditions (Christ-Brendemühl, 2025; Kangwa et al., 2025; Liu et al., 2025). Governance can therefore shape equity outcomes. Unclear, punitive, technically inaccessible, or unsupported rules may disproportionately disadvantage learners with less prior digital or AI literacy. Conversely, transparent guidance, privacy safeguards, accessible support, and educator development can help make responsible participation more broadly attainable. East Asian evidence is particularly useful for examining this relationship because it combines rapid digitalisation of education with persistent internal inequality. Studies from China document advanced experimentation with smart classrooms, online learning environments, learning analytics, and GenAI adoption (Dai et al., 2024; Li, 2025; Tang et al., 2025). Research from Taiwan also demonstrates the need to distinguish specialised AI pedagogical content knowledge from generic digital competence (Kuo et al., 2026). At the same time, research on rural education in China shows that infrastructure improvements do not eliminate inequality when digital literacy, local implementation capacity, teacher engagement,

maintenance, and family support remain uneven (Fu et al., 2024; Kong & Yang, 2026; Shen et al., 2026). East Asia should therefore not be treated as a universal model; rather, it offers a useful case for analysing how advanced technology infrastructures can coexist with unequal participation and outcomes. Taken together, this literature indicates that post-pandemic educational technology should be analysed as an alignment problem. Technological affordances create possibilities, but pedagogical integration determines how those possibilities support learning. Institutional capacity determines whether institutions can govern, resource, maintain, and scale responsible practice. Equitable participation determines whether learners and educators can access, understand, use, and benefit from the system. This review builds on this insight by synthesising these dimensions into a single framework and treating AI governance as a cross-cutting condition linking institutional capacity to equity.

### **3. Theoretical and Conceptual Framework**

#### **3.1 From Technology Adoption to Meaningful Educational Use**

Technology-adoption models remain useful because they explain why learners and educators approach new systems as useful, usable, or worth sustained effort. In the post-pandemic literature, however, adoption is better treated as an entry condition than as the educational endpoint. Tang et al. (2025) show that performance expectancy and effort expectancy remain important for university students' intention to use GenAI, while Chan and Hu (2023) show that perceived benefits coexist with concerns about accuracy, ethics, and dependency. Experimental evidence sharpens this distinction: in a randomised study of peer feedback, Darvishi et al. (2024) found that students tended to rely on rather than learn from AI assistance. This finding raises questions about learner agency and independent performance, but it does not by itself establish long-term learning effects across educational settings. The analytical implication is that technological affordances must be separated from pedagogical value. A system can be accepted and feature-rich yet still fail to strengthen judgement, self-regulation, knowledge retention, or transfer. This review therefore treats meaningful educational use as converting technological capability into durable learning through pedagogical design, institutional support, and conditions that permit equitable participation.

#### **3.2 Digital Divide as Access, Capability, and Outcome**

Equitable participation is conceptualised as more than physical access. First-level divides concern devices, connectivity, and infrastructure; second-level divides concern skills, confidence, patterns of use, and the capacity to participate effectively; third-level divides concern unequal benefits and outcomes. Chinese evidence demonstrates this progression particularly clearly. Guo and Wan (2022) identify disparities in equipment and network quality, adaptability to online learning, and offline learning outcomes, while Zhao et al. (2022) show that self-efficacy, motivation, family support, and other forms of capital help explain rural–urban outcome differences. Fu et al. (2024), Kong and Yang (2026), and Shen et al. (2026) extend the argument beyond emergency remote learning by showing that meaningful access depends on digital literacy, sustained use, local implementation capacity, teacher engagement, and maintenance. African evidence points to the same layered mechanism under different material conditions: connectivity and affordability remain important, but institutional strategies, training, household norms, and implementation capacity shape whether access becomes participation (Bati & Workneh, 2021; Kangwa et al., 2026; Kumi-Yeboah et al., 2023; Osei-Tutu et al., 2025; Watson et al., 2023). Equity is therefore not a residual concern after technology is deployed; it determines whether technological affordances can become educational opportunities.

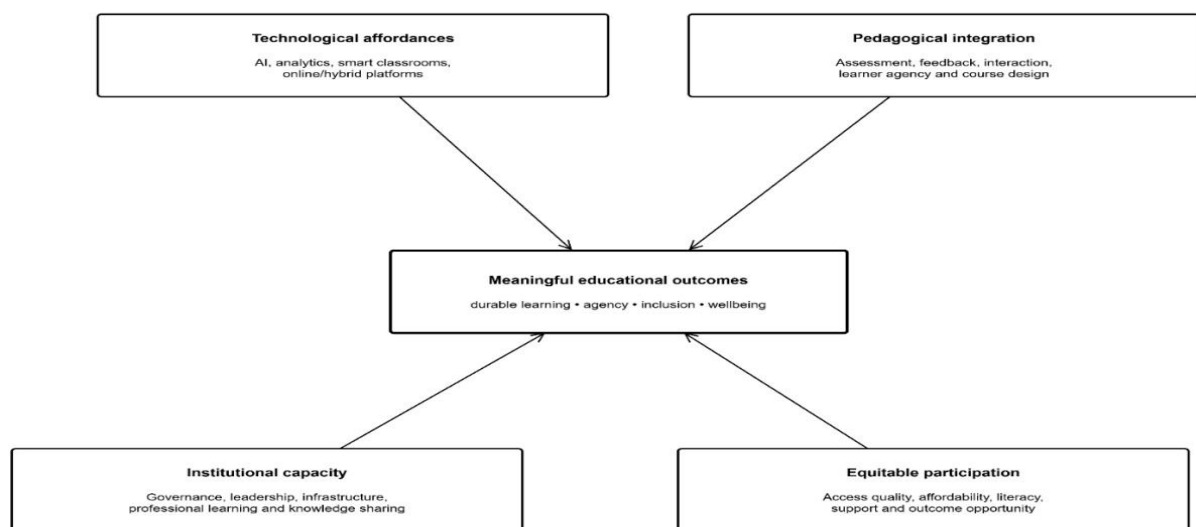
#### **3.3 Pedagogical and Institutional Capacity**

Pedagogical integration and institutional capacity are analytically distinct but empirically interdependent. Pedagogical integration concerns how technologies are embedded in learning tasks, interaction, feedback, assessment, and learner support. Dai et al. (2024) show that smart-classroom satisfaction depends strongly on user experience and perceived value, and Tian and Lu (2024) demonstrate that the perceived online educational environment and patterns of

interpersonal interaction are associated with students' ability development. In GenAI contexts, Xia et al. (2024), Chiu (2024), and Delanoy and Chen (2026) similarly direct attention from tool availability to assessment design, self-regulation, AI literacy, and guided feedback. Institutional capacity concerns whether organisations can sustain those pedagogical practices through governance, professional learning, infrastructure, leadership, and knowledge-sharing routines. This concern extends directly to AI-driven learning environments, where institutional readiness shapes educational systems' capacity to integrate emerging technologies in ways that support quality education across institutional and regional settings (Josiah et al., 2026). Koh (2020) shows the value of individualised consultation for TPACK development; Liu et al. (2025), Christ-Brendemühl (2025), and Kangwa et al. (2025) show why institutional rules and academic-integrity arrangements matter for responsible GenAI use; and Fischer-Schöneborn et al. (2026) demonstrate that schools' ICT knowledge absorptive capacity is positively associated with technology integration.

### 3.4 Proposed Post-Pandemic Educational Technology Framework

Drawing these strands together, the review advances a four-dimensional alignment framework. Technological affordances capture what AI, analytics, smart classrooms, and online or hybrid platforms make possible; pedagogical integration captures how those possibilities are translated into learning, interaction, assessment, scaffolding, and learner agency; institutional capacity encompasses the governance, professional development, infrastructure, leadership, and knowledge-sharing needed to sustain responsible use; and equitable participation concerns whether learners and educators can access, understand, use, and benefit from technology without systematic technology disadvantage. The dimensions are mutually conditioning rather than sequential: weakness in any one can constrain educational value.



**Figure 1:** Four-dimensional framework for meaningful post-pandemic educational technology use.

**Source:** Authors' construction

**Note:** The four dimensions are mutually conditioning rather than sequential. The framework therefore represents technological capability as educationally consequential only when it is pedagogically integrated, institutionally supported, and equitably accessible. It guided deductive coding and subsequent interpretation of the 30-study corpus; it is an interpretive framework rather than an estimated causal model.

Figure 1 represents this alignment. However, the framework's theoretical advance is that it does not treat technology adoption, digital inequality, or governance as separate explanatory domains. Adoption models primarily explain intention and use; digital-divide frameworks explain unequal resources, capabilities, and outcomes; governance scholarship explains how institutions regulate technological practice. The proposed alignment framework specifies their relationship. Technological affordances are necessary but insufficient possibilities. Pedagogical integration is the proximal mechanism that converts those possibilities into learning activities and assessment

practices. Institutional capacity supplies the organisational conditions for sustained implementation, while equitable participation captures the distribution of capabilities and benefits across learners and educators. AI governance operates across these dimensions by structuring acceptable use, transparency, data rights, accountability, assessment, and access to support. The framework therefore predicts that identical technologies can produce divergent outcomes when these conditions are misaligned.

### **3.5 Research Proposition for Future Empirical Testing**

As a systematic qualitative review, this study does not estimate causal relationships. The synthesis instead supports four propositions for future empirical testing:

**Proposition 1:** The association between technological affordances and meaningful educational outcomes is stronger when pedagogical integration is high, particularly when course design, feedback, assessment, and scaffolding require active learner judgement (Darvishi et al., 2024; Tian & Lu, 2024; Xia et al., 2024).

**Proposition 2:** Institutional capacity positively conditions the sustainability of educational-technology integration through professional development, governance, infrastructure maintenance, knowledge sharing, and implementation support (Fischer-Schöneborn et al., 2026; Koh, 2020; Shen et al., 2026).

**Proposition 3:** Equitable participation mediates the relationship between technological access and educational outcomes; devices and connectivity are less likely to produce durable benefits where digital or AI literacy, affordability, learner support, and local implementation capacity are weak (Guo & Wan, 2022; Kangwa et al., 2026; Zhao et al., 2022).

**Proposition 4:** Responsible AI governance moderates the relationship between institutional capacity and equitable participation. Transparent rules, privacy safeguards, accessible support, proportionate academic-integrity practices, and staff development are expected to reduce the risk that AI-mediated education reproduces existing inequalities (Christ-Brendemühl, 2025; Kangwa et al., 2025; Liu & Khalil, 2023; Liu et al., 2025).

These relationships are theoretically derived from the reviewed evidence rather than causally established in this study. Future studies should test them using longitudinal, multilevel, quasi-experimental, or structural-equation designs with validated measures of AI use, literacy, pedagogical integration, governance, institutional capacity, participation, and learning outcomes.

## **4. Research Methodology**

### **4.1 Systematic Literature Review (SLR) Protocol**

This systematic literature review followed the PRISMA 2020 reporting guidelines (Page et al., 2021). The review followed five stages: protocol development and research question specification; database searching; applying eligibility criteria; screening and quality assessment; and data extraction and thematic synthesis. The review protocol and its registration record were preserved, together with documentation of the search, screening, and assessment procedures. The unit of analysis was the peer-reviewed journal article. The analytical corpus excluded grey literature, policy reports, dissertations, book chapters, editorials, news items, and non-peer-reviewed conference materials.

### **4.2 Research Questions and Research Objectives for the Systematic Literature Review (SLR)**

The review objectives were designed to capture both technological change and the conditions shaping its educational consequences.

R01: To identify the principal post-pandemic educational technology trends reported between 2020 and 2026.

R02: To examine how East Asian evidence contributes to understanding AI-enabled, smart, online, and data-driven education.

R03: To analyse how digital inequality has evolved from access gaps toward capability, participation, and outcome divides.

R04: To identify the pedagogical, institutional, methodological, and geographic gaps that should shape future educational technology research.

The corresponding research questions were:

RQ1: What educational technology themes dominate peer-reviewed research in the post-pandemic period?

RQ2: What distinctive patterns emerge from East Asian research, and how do they relate to the wider global evidence base?

RQ3: How are persistent digital divides manifested in access, capability, participation, and educational outcomes?

RQ4: What methodological and theoretical limitations remain in the 2020–2026 literature?

### 4.3 Search Strategy and Study Eligibility Criteria

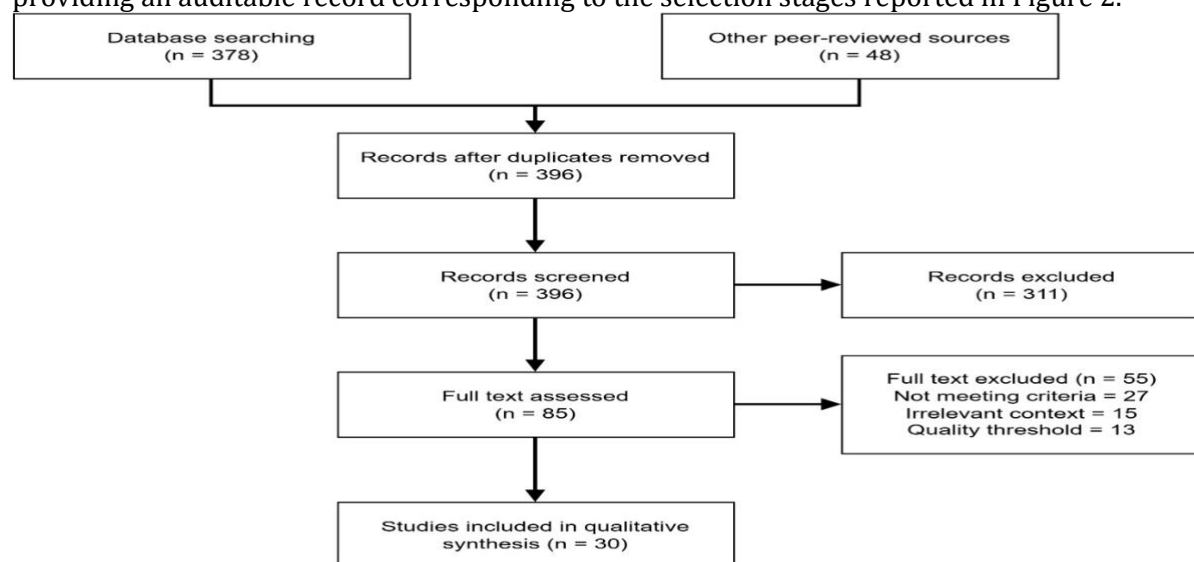
A structured search strategy was developed to identify peer-reviewed literature relevant to post-pandemic educational technology, with particular attention to emerging technologies, digital inequality, and pedagogical and institutional capacity. The strategy was organised around four interrelated concept groups: educational technology, post-pandemic digital learning, emerging technologies, and equity and capacity. Search terms were adapted to each database's indexing conventions and Boolean syntax to ensure consistent conceptual coverage while accommodating database-specific requirements. The core search expression combined terms relating to educational technologies, educational contexts, post-pandemic transformation, and equity or institutional conditions, as follows: ("educational technology" OR "digital learning" OR "online learning" OR "smart classroom" OR "artificial intelligence in education" OR "generative AI") AND (education OR teaching OR learning) AND (COVID-19 OR post-pandemic OR "digital transformation" OR adoption) AND (equity OR "digital divide" OR literacy OR teacher OR institution OR governance). To capture evidence relevant to the review's East Asian comparative focus, targeted searches additionally incorporated terms such as China, East Asia, rural education, smart education, and AI literacy. We determined study eligibility using predefined inclusion and exclusion criteria aligned with the review objectives and research questions. Eligible publications were English-language, peer-reviewed journal articles published between January 2020 and the 2026 search cut-off. Studies were required to examine educational technology within formal education or closely related learning contexts and to make a substantive contribution to at least one of the review's focal domains: artificial intelligence (AI) and generative AI (GenAI), learning analytics, smart or online learning environments, digital equity, or teacher and institutional digital capacity. We considered empirical investigations, systematic and scoping reviews, and theoretically substantive peer-reviewed studies eligible, provided their research focus and findings were directly relevant to the review questions. Conversely, the review excluded grey literature, policy and institutional reports, dissertations, book chapters, editorials, opinion pieces, and other non-peer-reviewed publications. We also excluded studies outside the specified publication period, those addressing contexts unrelated to education, or those lacking a substantive technology-mediated teaching or learning component. We removed duplicate records and publications for which we could not verify sufficient bibliographic or full-text information. Finally, we excluded studies that did not meet the predefined methodological quality threshold, in accordance with the assessment procedure detailed in Section 4.6. Together, these criteria established a consistent basis for identifying, screening, and evaluating relevant studies while maintaining the review's global comparative scope and focused attention to East Asian educational technology developments. Section 4.4 describes the databases and supplementary search procedures, while Section 4.5 reports the screening outcomes and final study selection.

### 4.4 Data Sources and Database Search

The literature search covered five databases: Scopus, Web of Science, IEEE Xplore, ScienceDirect, and SpringerLink. We used supplementary source tracing to identify additional peer-reviewed papers from reference lists and citation chains. We limited searches to 2020–2026 and English-language records. We intentionally used a broad database strategy because the review spans educational technology, educational psychology, information systems, teacher education, higher education, and digital-equity research.

#### 4.5 Article Screening and Selection Process

After deduplication, we screened titles and abstracts and assessed full texts for eligibility against predefined inclusion, exclusion, and quality criteria. The search identified 378 database records and 48 additional records through supplementary source tracing ( $n = 426$ ). After removing 30 duplicates, we screened 396 unique records and excluded 311 at the title-and-abstract stage. We assessed the remaining 85 full texts for eligibility and excluded 55: 27 for failing substantive inclusion criteria, 15 for irrelevant populations or educational contexts, and 13 for not meeting the quality threshold. The final qualitative synthesis comprised 30 studies. We documented and preserved study-level screening decisions, eligibility assessments, and reasons for exclusion, providing an auditable record corresponding to the selection stages reported in Figure 2.



**Figure 2:** PRISMA flow diagram for study identification, screening, eligibility and inclusion.

*Source:* Authors' construction

**Note:** Figure 2 reconciles the review counts across all selection stages: 426 records were identified, 30 duplicates were removed, 396 unique records were screened, 85 full texts were assessed, and 30 studies were retained after 55 full-text exclusions. The diagram therefore makes the review's evidence boundary explicit and separates the 30-study analytical corpus from methodological references such as PRISMA 2020.

#### 4.6 Quality Assessment of Studies

A structured quality assessment was applied before final inclusion. We evaluated each study against five predefined criteria (Q1–Q5; Table 1), scored from 0 (not demonstrated) to 2 (clearly demonstrated), for a maximum total score of 10. Studies scoring below 6 were excluded.

**Table 1:** Study quality evaluation criteria.

| Criterion | Description                                                           | Score |
|-----------|-----------------------------------------------------------------------|-------|
| Q1        | Clear research purpose and educational technology focus               | 0–2   |
| Q2        | Transparent and appropriate methodology or review procedure           | 0–2   |
| Q3        | Adequate description of participants, context, data, or evidence base | 0–2   |
| Q4        | Findings supported by the reported analysis                           | 0–2   |
| Q5        | Clear theoretical, pedagogical, equity, or policy contribution        | 0–2   |

*Source:* Authors' construction.

The assessment accommodated methodological differences between empirical studies and systematic or scoping reviews while examining research purpose, methodological transparency, adequacy of contextual information, evidential support, and contribution to the review questions. We documented and preserved study-level criterion scores, total scores, and corresponding eligibility decisions, enabling independent examination of how we applied the quality threshold. The instrument was designed for transparent eligibility appraisal across heterogeneous study designs, not as a validated, design-specific risk-of-bias measure.

#### 4.7 Data Extraction and Coding

We extracted data using a structured form covering author and publication year, geographical context, educational level, technology focus, research design, theoretical framing, sample or evidence base, principal findings, and implications. We preserved extraction records and thematic coding documentation to support traceability between the included studies and the synthesis. Deductive coding followed the four-dimensional framework, while inductive coding captured recurring issues, including AI overreliance, assessment redesign, privacy, rural–urban inequality, digital literacy, professional development, and organisational knowledge capacity. Table 2 presents the coding framework, and Table 5 documents the analytical contributions of the 30 retained studies.

**Table 2:** Coding framework for thematic analysis.

| Category                  | Illustrative codes                                                                                  |
|---------------------------|-----------------------------------------------------------------------------------------------------|
| Technological affordances | GenAI, learning analytics, smart classrooms, online/hybrid platforms                                |
| Pedagogical integration   | feedback, assessment, interaction, learner agency, course design                                    |
| Institutional capacity    | governance, leadership, professional development, infrastructure, knowledge sharing                 |
| Equitable participation   | device/network quality, affordability, digital literacy, rural–urban gaps, gender/household factors |
| Outcomes and risks        | learning outcomes, satisfaction, engagement, privacy, academic integrity, dependency                |

*Source: Authors' construction*

#### 4.8 Data Synthesis

Because the included studies differed substantially in design, population, educational setting, technology, outcome definition, and reported statistical information, quantitative pooling and meta-analysis were not appropriate. The review therefore used a structured narrative synthesis supported by deductive and inductive thematic coding. Descriptive coding counts were used only to document the coverage of the retained corpus; they were not treated as effect sizes, prevalence estimates, tests of association, or evidence of causal importance. The synthesis instead compared the conditions under which similar technologies were associated with different forms of participation, agency, governance, and educational outcomes across contexts.

### 5. Results and Analysis

#### 5.1 Profile of the Included Studies

The 30-study corpus captures the transition from emergency online learning to a more complex post-pandemic environment shaped by GenAI, analytics, smart learning systems, hybrid delivery, and continuing digital inequality. The evidence base is methodologically diverse, including surveys, structural equation models, experiments, qualitative interviews, implementation studies, document analyses, and systematic/scoping reviews. East Asian studies are especially prominent in the corpus, reflecting the review's comparative focus and the scale of recent research on China and neighbouring systems.

**Table 3:** Characteristics of the 30 studies included in the qualitative synthesis

| No | Study                      | Context   | Focus             | Method                 | Principal contribution                                                |
|----|----------------------------|-----------|-------------------|------------------------|-----------------------------------------------------------------------|
| 1  | Tang et al. (2025).        | China     | GenAI adoption    | Survey; revised UTAUT2 | Performance and effort expectancy shape learning value and intention. |
| 2  | Chan & Hu (2023)           | Hong Kong | GenAI perceptions | Student survey         | Benefits coexist with concerns over accuracy, ethics and dependency.  |
| 3  | Farinosi & Melchior (2025) | Italy     | GenAI use         | Mixed methods          | Students favour regulated use over prohibition.                       |
| 4  | Darvishi et al. (2024).    | Australia | AI assistance     | Randomised experiment  | AI support can encourage reliance when scaffolding is removed.        |

|    |                           |               |                             |                              |                                                                                        |
|----|---------------------------|---------------|-----------------------------|------------------------------|----------------------------------------------------------------------------------------|
| 5  | Liu et al. (2025).        | China         | AI governance               | Policy analysis + interviews | Institutional governance mediates AI integration and academic values.                  |
| 6  | Chiu et al. (2023).       | Global        | AI in education             | Systematic review            | AI spans learning, teaching, assessment and administration; evidence gaps remain.      |
| 7  | Chiu (2024)               | Global/HE     | GenAI transformation        | Qualitative study            | Future-ready outcomes require AI literacy, new pedagogy and assessment.                |
| 8  | Xia et al. (2024).        | Global/HE     | GenAI assessment            | Scoping review               | Assessment should emphasise self-regulation and integrity rather than detection alone. |
| 9  | Kangwa et al. (2025).     | Global/HE     | Academic integrity          | Systematic review            | Institutional guidance is central to responsible GenAI use.                            |
| 10 | Christ-Brendemühl (2025)  | Germany       | AI guidelines               | Document analysis + workshop | Universities largely move toward controlled, literacy-oriented acceptance.             |
| 11 | Casal-Otero et al. (2023) | Global/K-12   | AI literacy                 | Systematic review            | AI literacy requires technical and critical/conceptual dimensions.                     |
| 12 | Kuo et al. (2026).        | Taiwan        | Teacher competence AI       | Scale validation             | AI pedagogical content knowledge requires distinct measurement.                        |
| 13 | Delanoy & Chen (2026)     | China         | AI literacy                 | Mixed-method intervention    | Instructor-driven GenAI feedback can develop literacy while preserving judgement.      |
| 14 | Liu & Khalil (2023)       | Global        | Learning analytics          | Systematic review            | Privacy and data protection remain unresolved implementation challenges.               |
| 15 | Jones et al. (2020).      | United States | Learning analytics/privacy  | Qualitative study            | Students report limited control and concern over institutional data practices.         |
| 16 | Li (2025)                 | China         | Learning analytics          | Empirical study              | Data-driven personalisation expands faster than governance capacity.                   |
| 17 | Dai et al. (2024).        | China         | Smart classrooms            | Survey; SEM                  | Satisfaction depends on perceived value, experience and expectations.                  |
| 18 | Tian & Lu (2024)          | China         | Online learning             | Survey; cluster/regression   | Online environment and interaction patterns predict ability development.               |
| 19 | Guo & Wan (2022)          | China         | Digital divide              | Large-scale survey           | Divides persist in network quality, adaptability and offline learning outcomes.        |
| 20 | Zhao et al. (2022).       | China         | Outcome divide              | Survey; decomposition        | Self-efficacy, motivation and support explain rural-urban outcome gaps.                |
| 21 | Shen et al. (2026).       | China         | Rural digital inclusion     | Implementation research      | Local implementation capacity determines whether infrastructure closes divides.        |
| 22 | Kong & Yang (2026)        | China         | Rural inequality digital    | Student/teacher survey       | Digital literacy remains essential even when infrastructure improves.                  |
| 23 | Fu et al. (2024).         | China         | Children's digital learning | Qualitative interviews       | Meaningful access, not device ownership alone, structures rural-urban inequality.      |
| 24 | Watson et al. (2023).     | Kenya         | EdTech equity               | Exploratory mixed methods    | Household and gender-related social factors shape technology participation.            |
| 25 | Kumi-Yeboah et al. (2023) | Ghana         | Digital divide              | Qualitative interviews       | Connectivity, platforms and training are complementary institutional responses.        |
| 26 | Bati & Workneh (2021)     | Ethiopia      | ICT implementation          | Design-reality gap           | Policy ambition exceeds school infrastructure, coordination and training capacity.     |

|    |                                  |             |                        |                              |                                                                                       |
|----|----------------------------------|-------------|------------------------|------------------------------|---------------------------------------------------------------------------------------|
| 27 | Osei-Tutu et al. (2025)          | Africa      | Access/equity/quality  | Systematic review            | Infrastructure and regional disparities continue to constrain equitable HE.           |
| 28 | Kangwa et al. (2026).            | Africa      | Digital transformation | SEM; multi-region sample     | Access works through support, literacy and engagement rather than technology alone.   |
| 29 | Koh (2020)                       | New Zealand | Teacher TPACK          | Action research              | Individual consultation supports TPACK through modelling and pedagogical realignment. |
| 30 | Fischer-Schöneborn et al. (2026) | Germany     | Institutional capacity | Representative school survey | ICT knowledge absorptive capacity predicts technology integration.                    |

*Source: Authors' construction.*

## 5.2 Artificial Intelligence: From Adoption to Governance and Agency

The most visible post-2022 change is the rapid normalisation of GenAI in higher education, but the studies differ in what they treat as the central educational problem. Tang et al. (2025) retain an adoption lens, showing that performance and effort expectancy shape learning value and behavioural intention in China. Chan and Hu (2023) and Farinosi and Melchior (2025) move closer to lived use: students recognise efficiency and learning support while simultaneously expressing concerns about accuracy, ethics, dependency, and the legitimacy of use. Chiu et al. (2023) place these developments within a broader AIED landscape spanning learning, teaching, assessment, and administration. Read through the four-dimensional framework, these studies show strong technological affordances but also expose the limits of adoption as a proxy for educational value. The important analytical question is whether institutions and educators can convert accessible GenAI into pedagogically defensible practices without weakening agency or widening participation gaps. A second strand makes pedagogical integration the decisive mechanism. Darvishi et al. (2024) provide experimental evidence that AI assistance can support immediate performance while encouraging reliance, demonstrating that an affordance can be productive at the task level yet problematic for durable learning. Chiu (2024) accordingly argues for changes in learning outcomes, pedagogy, AI literacy, and assessment, while Xia et al. (2024) show that assessment redesign should foreground self-regulation and integrity rather than detection alone. Delanoy and Chen (2026) add an instructional mechanism: instructor-driven GenAI feedback can build AI literacy when learners must exercise judgement over machine output. Together, these studies reposition pedagogy as the conversion layer between AI capability and learner agency. Governance has consequently become part of the pedagogical problem rather than a separate administrative concern. Liu et al. (2025) show that Chinese universities are institutionalising AI within a state-led policy environment while faculty remain attentive to integrity, bias, and overreliance. Christ-Brendemühl (2025) documents a parallel movement in German university guidance toward controlled, literacy-oriented acceptance, and Kangwa et al. (2025) identify institutional guidance as central to balancing academic integrity with legitimate GenAI use. Institutional capacity therefore shapes the boundary conditions under which educators can integrate technological affordances pedagogically. Governance that is too weak leaves uncertainty and privacy/integrity risks unresolved; purely restrictive governance can suppress opportunities for guided learning and AI literacy. Figure 3 shows the shift evident in the GenAI literature from adoption and acceptance to agency and durable outcomes.



Evidence on Outcomes should feed back into adoption, design and governance decisions

Cross-cutting risks: Overreliance, inaccurate output, privacy, academic integrity, unequal AI literacy level

**Figure 3:** Analytical pathway from GenAI adoption to agency and durable educational outcomes.

*Source: Authors' construction*

This figure summarises the shift evident in the GenAI literature. Acceptance and perceived usefulness remain relevant, but the evidence increasingly moves through questions of affordance, instructional design, and institutional governance toward learner agency and durable outcomes. The dashed feedback loop emphasises that evidence about dependency, integrity, privacy, and learning transfer should reshape subsequent design and governance decisions rather than be treated as downstream side effects.

### **5.3 AI Literacy, Learning Analytics, and Data Governance**

The expansion of AI has heightened the importance of literacy as both a pedagogical capability and an equity resource. Casal-Otero et al. (2023) show that K-12 AI literacy includes technical engagement alongside conceptual and critical understanding, while Kuo et al. (2026) developed and validated a 26-item, four-factor AIPACK scale to assess teachers' AI-related instructional knowledge in Taiwan, providing a context-specific instrument for studying AI knowledge and its pedagogical integration. Delanoy and Chen (2026) show how guided GenAI feedback can develop learner literacy while preserving human judgement. Across these studies, AI literacy is not merely another technology skill: it determines whether users can interrogate outputs, understand limitations, and participate on more equal terms in AI-mediated learning. Learning analytics provides an important precursor to current GenAI governance debates. Liu and Khalil (2023) identify persistent privacy, data-protection, transparency, and stakeholder-participation concerns, while Jones et al. (2020) show how students can experience institutional analytics as continuous tracking with limited meaningful control. Li (2025) illustrates the same tension in the Chinese context: data-driven personalisation expands the technological capacity to tailor support, but governance arrangements must keep pace with the scale and sensitivity of data use. These studies connect technological affordances directly to institutional capacity and equitable participation because consent, transparency, and data literacy influence who can exercise meaningful agency in data-intensive environments.

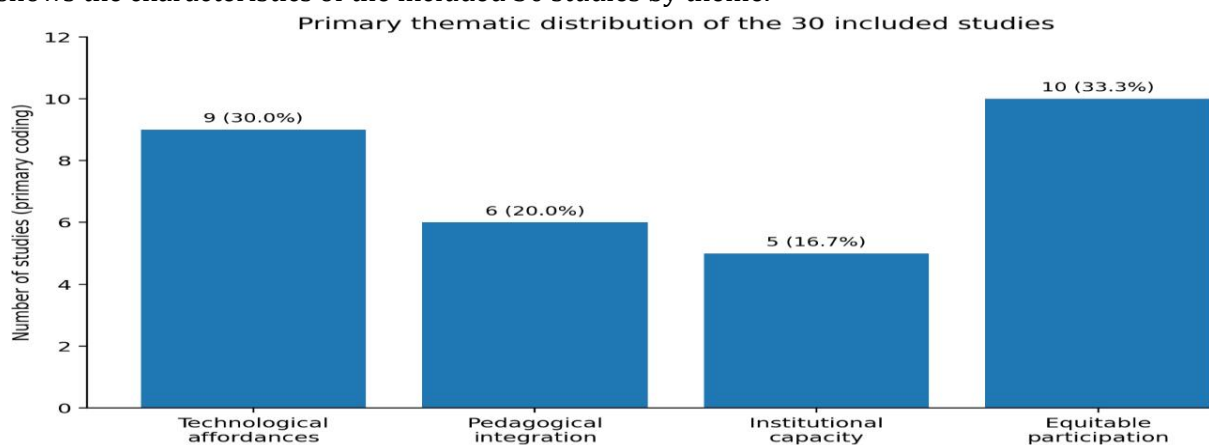
### **5.4 Smart Classrooms and the Post-Pandemic Online Learning Environment**

Post-pandemic educational technology is also characterised by a shift from emergency access to the quality of digitally mediated learning environments. Dai et al. (2024), drawing on 1,979 Chinese college students, show that smart-classroom satisfaction depends on perceived value, user experience, and expectations rather than technological novelty alone. Tian and Lu (2024), studying 1,010 international students across 41 Chinese universities, similarly show that perceived online educational environments and interaction patterns are associated with ability development. Together, these studies demonstrate that smartness is not a property of installed equipment. Technological affordances become educationally meaningful through interaction design, timely support, participation structures, and the extent to which learners can inhabit digital spaces as genuine learning environments.

### **5.5 Persistent Digital Divides: From Connectivity to Meaningful Outcomes**

The strongest cross-cutting finding is that digital inequality persists even as basic access expands. Guo and Wan (2022) show that pandemic online learning in China reproduced differences in equipment and network quality, adaptability, and offline learning outcomes. Zhao et al. (2022) identify a third-level rural-urban outcome divide and demonstrate that self-efficacy, intrinsic motivation, parental support, and other forms of capital explain important parts of the gap. These findings make equitable participation analytically inseparable from pedagogy: learners need not only a connection, but also the capabilities and support required to convert digital participation into learning outcomes. Recent rural-China research extends the argument from emergency access to implementation capacity. Fu et al. (2024) show that meaningful access depends on productive and sustained use rather than device ownership alone; Kong and Yang (2026) identify digital literacy as a continuing source of inequality even where infrastructure improves; and Shen et al. (2026) show that local champions, maintenance capacity, teacher engagement, institutional culture, and contextual fit shape whether cloud-based infrastructure produces actual participation. These studies are critical because they connect all four themes: a technological

affordance may be present, but its pedagogical use depends on local institutional capacity. Its equity effect depends on whether disadvantaged learners can participate meaningfully. African evidence reveals similar mechanisms under different infrastructural conditions, preventing the framework from being read as an East Asia-specific model. Kumi-Yeboah et al. (2023) show that Ghanaian universities combined connectivity support, platforms, and training to address the digital divide, illustrating the complementarity of infrastructure and institutional action. Watson et al. (2023) demonstrate that EdTech participation among Kenyan girls is shaped by household and gender-related social conditions as well as material resources. Bati and Workneh (2021) identify a design–reality gap in Ethiopian secondary schools, where infrastructure delays, weak coordination, and limited capacity building constrained implementation. Osei-Tutu et al. (2025) synthesise persistent disparities in access, quality, and regional outcomes in African higher education, while Kangwa et al. (2026) show that technology access operates through institutional support, digital literacy, and engagement. The regional evidence therefore reinforces a common mechanism without implying identical conditions: equitable participation is produced through the interaction of material access, institutional capacity, and pedagogical opportunity. Figure 4 shows the characteristics of the included 30 studies by theme.



**Figure 4:** Primary thematic distribution of the 30 studies included in the qualitative synthesis.

To describe the scope of the retained corpus, we assigned each study a dominant analytical focus for Figure 4. The figure maps study coverage rather than effect magnitude, evidential strength, or theoretical importance. The corpus includes work on equitable participation, technological affordances, pedagogical integration, and institutional capacity, with substantial overlap across these dimensions. This overlap reinforces the rationale for an integrated alignment framework: studies rarely support an interpretation in which adoption, pedagogy, governance, and equity operate independently. Several studies informed more than one analytical dimension; the figure therefore marks explicitly coded overlaps without inferring additional roles or assigning quantitative weights.

### 5.6 Teacher and Institutional Capacity

Teacher capability remains a decisive condition of post-pandemic technology integration because pedagogical integration is enacted through professional judgement. Koh (2020) demonstrates that one-to-one instructional consultation can support TPACK development through modelling, pedagogical realignment, and deepening practice, challenging professional-development models built around one-off technical workshops. Kuo et al. (2026) extend this logic into the AI era by distinguishing AI pedagogical content knowledge from generic technology competence. Across the corpus, teacher capacity is therefore best understood as an adaptive professional capability: educators must decide when technology adds value, how to scaffold its use, how to verify outputs, and when non-digital approaches remain pedagogically preferable. Institutional capacity matters as much because individual expertise is hard to sustain without organisational routines. Fischer-Schöneborn et al. (2026), using a representative sample of 411 German schools, show that ICT knowledge absorptive capacity positively affects technology integration and mediates the relationship between external knowledge and integration; knowledge sharing and collaboration

condition this process. This organisational perspective converges with the governance studies of Liu et al. (2025), Christ-Brendemühl (2025), and Kangwa et al. (2025), and with Shen et al.'s (2026) implementation evidence from rural China. Sustainable integration is strongest where institutions can acquire external knowledge, adapt it to local needs, support teachers, govern data and AI use, maintain infrastructure, and circulate effective practice beyond isolated innovators.

### 5.7 Narrative Synthesis: Conditions for Meaningful Post-Pandemic Educational Technology

The thematic findings support the four-part framework proposed in Section 3.4, but they also show that the dimensions overlap in practice. Technological affordances have expanded rapidly through GenAI, analytics, smart classrooms, and scalable online platforms; yet the strongest studies do not treat capability as impact. Pedagogical integration determines whether affordances become learning opportunities through interaction, assessment, feedback, scaffolding, and learner agency. Institutional capacity determines whether such practices can be governed, resourced, learned, and sustained. Equitable participation determines who can convert access into meaningful educational benefit. The synthesis therefore rejects a linear technology-to-outcome model in favour of an alignment model: educational value is strongest when capability, pedagogy, organisational support, and participation conditions reinforce one another, and weakest when one dimension is treated as substitutable for the others.

**Table 4:** Evidence synthesis for the proposed post-pandemic educational technology framework

| Dimension                 | What the evidence shows                                                                                                             | Representative studies                                                              |
|---------------------------|-------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|
| Technological affordances | AI, analytics and smart systems expand personalisation, feedback and access, but availability does not establish educational value. | Tang et al. (2025); Dai et al. (2024); Li (2025)                                    |
| Pedagogical integration   | Design, interaction, assessment and learner agency determine whether tools support durable learning.                                | Darvishi et al. (2024); Xia et al. (2024); Tian & Lu (2024)                         |
| Institutional capacity    | Governance, professional development, leadership and knowledge-sharing enable sustained integration.                                | Liu et al. (2025); Koh (2020); Fischer-Schöneborn et al. (2026)                     |
| Equitable participation   | Divides increasingly concern quality, literacy, support and outcomes rather than connectivity alone.                                | Guo & Wan (2022); Zhao et al. (2022); Kumi-Yeboah et al. (2023); Shen et al. (2026) |

*Source:* Authors' construction.

Figure 5 provides a study-level crosswalk between the 30 retained studies and the framework roles reported in Table 5. We used multi-label coding only where Table 5 explicitly assigns a study to two dimensions; we did not infer additional roles. The coding yields 43 study-theme assignments: institutional capacity (14), equitable participation (13), pedagogical integration (10), and technological affordances (6). Thirteen studies have two explicit roles, and 17 have one. These counts describe evidence coverage rather than effect magnitude or theoretical importance, but the documented overlap supports the framework's treatment of technology, pedagogy, institutional capacity, and equity as interdependent dimensions.

In Figure 5, a filled cell indicates an explicitly assigned framework role; a blank cell indicates the role was not assigned there. The Figure provides a study-level crosswalk between the 30 retained studies and the framework roles reported in Table 5. We used multi-label coding only where Table 5 explicitly assigns a study to two dimensions; we inferred no additional roles. The matrix displays thematic overlap without implying effect sizes, weights, or unreported secondary coding. The coding yields 43 study-theme assignments: institutional capacity (14), equitable participation (13), pedagogical integration (10), and technological affordances (6). Thirteen studies have two explicit roles, and 17 have one. These counts describe evidence coverage rather than effect magnitude or theoretical importance, but the documented overlap supports the framework's treatment of technology, pedagogy, institutional capacity, and equity as interdependent dimensions.

|                                      | Technological affordances | Pedagogical integration | Institutional capacity | Equitable participation |
|--------------------------------------|---------------------------|-------------------------|------------------------|-------------------------|
| 1. Tang, Yuan & Qu (2025)            | ✓                         |                         |                        |                         |
| 2. Chan & Hu (2023)                  | ✓                         | ✓                       |                        |                         |
| 3. Farinosi & Melchior (2025)        |                           |                         | ✓                      |                         |
| 4. Darvishi et al. (2024)            |                           | ✓                       |                        |                         |
| 5. Liu, Fang & Lan (2025)            |                           |                         | ✓                      |                         |
| 6. Chiu et al. (2023)                | ✓                         | ✓                       |                        |                         |
| 7. Chiu (2024)                       |                           | ✓                       |                        |                         |
| 8. Xia et al. (2024)                 |                           | ✓                       |                        |                         |
| 9. Kangwa, Msafiri & Fute (2025)     |                           |                         | ✓                      |                         |
| 10. Christ-Brendemühl (2025)         |                           |                         | ✓                      |                         |
| 11. Casal-Otero et al. (2023)        | ✓                         |                         |                        | ✓                       |
| 12. Kuo et al. (2026)                |                           | ✓                       | ✓                      |                         |
| 13. Delanoy & Chen (2026)            |                           | ✓                       |                        |                         |
| 14. Liu & Khalil (2023)              |                           |                         | ✓                      | ✓                       |
| 15. Jones et al. (2020)              |                           |                         | ✓                      | ✓                       |
| 16. Li (2025)                        | ✓                         |                         | ✓                      |                         |
| 17. Dai et al. (2024)                | ✓                         | ✓                       |                        |                         |
| 18. Tian & Lu (2024)                 |                           | ✓                       |                        |                         |
| 19. Guo & Wan (2022)                 |                           |                         |                        | ✓                       |
| 20. Zhao et al. (2022)               |                           |                         |                        | ✓                       |
| 21. Shen et al. (2026)               |                           |                         | ✓                      | ✓                       |
| 22. Kong & Yang (2026)               |                           |                         |                        | ✓                       |
| 23. Fu, Zeng & Kang (2024)           |                           |                         |                        | ✓                       |
| 24. Watson et al. (2023)             |                           |                         |                        | ✓                       |
| 25. Kumi-Yeboah et al. (2023)        |                           |                         | ✓                      | ✓                       |
| 26. Bati & Workneh (2021)            |                           |                         | ✓                      | ✓                       |
| 27. Osei-Tutu et al. (2025)          |                           |                         |                        | ✓                       |
| 28. Kangwa et al. (2026)             |                           |                         | ✓                      | ✓                       |
| 29. Koh (2020)                       |                           | ✓                       | ✓                      |                         |
| 30. Fischer-Schöneborn et al. (2026) |                           |                         | ✓                      |                         |

**Figure 5:** Thematic coverage of the 30 retained studies

**Source:** Authors' construction from Table 5 coding of the 30 studies retained in the systematic review.

## 6. Discussion

### 6.1 From Emergency Digitalisation to Institutionalised Educational Technology

The principal transition across the 2020–2026 evidence is from emergency digital access toward the institutionalisation of technology across teaching, assessment, support, data systems, and governance. The analytical problem has consequently shifted from whether technologies are adopted to what follows adoption: whether pedagogical practices sustain learning and agency, whether institutions can govern and support implementation, and whether learners can convert access into durable benefit. GenAI makes this distinction particularly visible because perceived usefulness and immediate performance gains can coexist with dependency, uncertainty, and weak independent performance (Chan & Hu, 2023; Darvishi et al., 2024). Post-pandemic EdTech should therefore be understood as a socio-technical educational system rather than a sequence of tool-adoption decisions.

### 6.2 East Asian Perspectives and Context-Dependent Digital Divide

East Asian evidence shows both the potential for scaled educational digitalisation and the persistence of inequality within technologically advanced systems. Chinese studies document extensive GenAI, smart-classroom, analytics, and online-learning development, while Taiwanese research shows increasing specialisation in teacher AI pedagogical knowledge (Dai et al., 2024; Kuo et al., 2026; Li, 2025; Liu et al., 2025; Tang et al., 2025). However, rural–urban differences persist in network quality, literacy, self-efficacy, family support, implementation capacity, and learning outcomes (Guo & Wan, 2022; Kong & Yang, 2026; Zhao et al., 2022). The theoretical implication is that digital inequality changes form as infrastructure matures: disparities increasingly concern quality of use, capability, institutional support, and conversion of participation into outcomes. Comparative African evidence strengthens this interpretation without implying that regions face identical conditions. Infrastructure and affordability remain prominent constraints, but studies from Ghana, Kenya, and Ethiopia also identify training, household conditions, institutional coordination, and implementation capacity as determinants of meaningful participation (Bati & Workneh, 2021; Kumi-Yeboah et al., 2023; Watson et al., 2023). Across contexts, therefore, technology is necessary but insufficient; its educational value depends on social, pedagogical, and institutional complements.

### **6.3 Theoretical Implications**

The synthesis makes three theoretical moves. First, it separates technological affordance from educational value: availability, acceptance, and immediate performance do not establish durable learning, learner agency, or equitable participation (Chan & Hu, 2023; Darvishi et al., 2024). Second, it positions pedagogical integration as the conversion mechanism through which technological capability becomes educational activity, making course design, assessment, feedback, interaction, and scaffolding explanatory rather than merely implementation variables. Third, it treats institutional capacity and equitable participation as mutually conditioning, with AI governance operating across them through rules governing legitimate use, transparency, privacy, accountability, assessment, and access to support (Christ-Brendemühl, 2025; Fischer-Schöneborn et al., 2026; Koh, 2020; Shen et al., 2026). Figure 1 therefore presents an alignment model: comparable technologies can produce different educational outcomes because pedagogy, institutional capacity, governance, and participation conditions differ across settings.

### **6.4 Practical and Policy Implications**

For educators, professional learning should connect AI-related pedagogical knowledge directly to instructional practice (Koh, 2020; Kuo et al., 2026) and learning outcomes. This capability-oriented approach aligns with evidence linking digital innovation skills to entrepreneurial readiness among higher-education commerce students (Emmanuel et al., 2025). Teachers need support to determine when AI adds educational value, verify outputs, design tasks requiring explanation and judgment, and assess learning processes rather than final products alone. AI literacy should therefore encompass critical evaluation, responsible disclosure, source verification, and judgment about when AI should not be used. For institutions, technology procurement should be matched by governance and implementation capacity. Policies should state which uses are permitted, how AI use should be disclosed, how privacy and data responsibilities will be protected, how academic-integrity concerns will be addressed, and where staff and students can obtain support. Institutions should avoid policies that are exclusively punitive or detection-led, because such approaches can increase uncertainty and may disadvantage students with less access to informal guidance. For policymakers, equity indicators should extend beyond device ownership and nominal connectivity. Monitoring should include connection quality, affordability, accessibility, digital and AI literacy, teacher support, meaningful participation, data rights, and learning outcomes. Rural and disadvantaged communities may need continuing maintenance, local support, accessible training, and context-sensitive implementation rather than one-time hardware provision. Figure 1 provides a practical diagnostic tool: policymakers can use its four dimensions to identify whether an observed problem reflects technology access, pedagogical design, institutional capacity, governance, or unequal capability to participate.

### **6.5 Methodological Gaps and Future Research**

Cross-sectional surveys remain common, particularly in technology-acceptance research, limiting causal inference and the ability to distinguish initial enthusiasm from sustained educational value. Longitudinal, experimental, and quasi-experimental research should test whether AI use changes learning strategies, agency, achievement, and well-being over time and whether AI scaffolding produces durable learning rather than short-term task gains. Comparative studies should use common validated measures and test measurement invariance before interpreting cross-national differences, including comparisons of East Asian models across differently resourced institutional settings. Future research should also connect literatures that currently develop in parallel. AI-adoption research should engage digital-divide theory; analytics research should connect technical capability to privacy and governance; teacher-competence research should model institutional conditions; and AI-integrity research should evaluate learning outcomes rather than policy alone. Cross-regional work should examine institutional readiness, governance, and quality-education objectives together, including how institutional partnerships and South-South cooperation shape adaptation across different resource and governance settings (Josiah et al., 2026; Koroma et al., 2026).

## 6.6 Contribution of the 30 Included Studies to the Four-Theme Synthesis

Table 5 provides a transparent study-level audit of the synthesis by identifying each retained study's principal framework role and analytical contribution. Several studies inform two dimensions, consistent with the overlap displayed in Figure 5.

**Table 5:** Analytical contribution of all 30 included studies to the four-theme framework.

| Study                       | Principal framework role                            | Critical contribution to the synthesis                                                                                                                                     |
|-----------------------------|-----------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Tang et al. (2025).         | Technological affordances                           | Explains GenAI adoption conditions and shows why acceptance remains an entry condition rather than an outcome.                                                             |
| Chan & Hu (2023).           | Technological affordances / pedagogical integration | Connects perceived GenAI benefits with accuracy, ethics and dependency concerns.                                                                                           |
| Farinosi & Melchior (2025). | Institutional capacity                              | Shows student preference for regulated use, informing managed rather than prohibitive integration.                                                                         |
| Darvishi et al. (2024).     | Pedagogical integration                             | Provides experimental evidence of reliance on AI assistance in peer feedback, highlighting the need to distinguish supported task performance from independent capability. |
| Liu et al. (2025).          | Institutional capacity                              | Shows how policy and university governance shape AI integration in China.                                                                                                  |
| Chiu et al. (2023).         | Technological affordances / pedagogical integration | Maps AI roles across learning, teaching, assessment and administration and identifies evidence gaps.                                                                       |
| Chiu (2024).                | Pedagogical integration                             | Frames GenAI transformation around new learning outcomes, pedagogy, assessment and AI literacy.                                                                            |
| Xia et al. (2024).          | Pedagogical integration                             | Supports assessment redesign around self-regulation and integrity rather than detection.                                                                                   |
| Kangwa et al. (2025).       | Institutional capacity                              | Synthesises institutional guidance needed to balance integrity with productive GenAI use.                                                                                  |
| Christ-Brendemühl (2025)    | Institutional capacity                              | Documents movement toward controlled, literacy-oriented institutional acceptance of GenAI.                                                                                 |
| Casal-Otero et al. (2023)   | Technological affordances / equitable participation | Defines AI literacy as technical plus critical understanding, linking capability to participation.                                                                         |
| Kuo et al. (2026).          | Pedagogical integration / institutional capacity    | Establishes AI pedagogical content knowledge as a distinct teacher competence.                                                                                             |
| Delanoy & Chen (2026).      | Pedagogical integration                             | Shows guided GenAI feedback can develop AI literacy while preserving human judgement.                                                                                      |
| Liu & Khalil (2023).        | Institutional capacity / equitable participation    | Identifies privacy, data protection, transparency and stakeholder-participation gaps in analytics.                                                                         |
| Jones et al. (2020).        | Equitable participation / institutional capacity    | Provides student evidence on surveillance, control and institutional data practices.                                                                                       |
| Li (2025)                   | Technological affordances / institutional capacity  | Links data-driven personalisation to unresolved governance capacity in China.                                                                                              |
| Dai et al. (2024).          | Technological affordances / pedagogical integration | Shows smart-classroom value depends on user experience, expectations and perceived value.                                                                                  |
| Tian & Lu (2024).           | Pedagogical integration                             | Shows online environment and interaction patterns are associated with ability development.                                                                                 |
| Guo & Wan (2022).           | Equitable participation                             | Demonstrates first-, second-, and third-level divides in Chinese online learning.                                                                                          |
| Zhao et al. (2022)          | Equitable participation                             | Explains rural-urban outcome gaps through self-efficacy, motivation, support and capital.                                                                                  |
| Shen et al. (2026).         | Institutional capacity / equitable participation    | Shows local implementation capacity determines whether cloud infrastructure reduces rural divides.                                                                         |
| Kong & Yang (2026).         | Equitable participation                             | Shows digital literacy remains consequential after infrastructure improves.                                                                                                |
| Fu et al. (2024).           | Equitable participation                             | Reframes access as productive, sustained use rather than device ownership.                                                                                                 |
| Watson et al. (2023)        | Equitable participation                             | Shows household and gender-related social factors shape Kenyan girls' EdTech participation.                                                                                |
| Kumi-Yeboah et al. (2023)   | Institutional capacity / equitable participation    | Shows connectivity, platforms and training operate as complementary responses in Ghana.                                                                                    |
| Bati & Workneh (2021).      | Institutional capacity / equitable participation    | Identifies design-reality gaps in infrastructure, coordination and capacity building in Ethiopia.                                                                          |
| Osei-Tutu et al. (2025)     | Equitable participation                             | Synthesises persistent disparities in access, quality, and regional outcomes in African higher education.                                                                  |

|                                   |                                                  |                                                                                                             |
|-----------------------------------|--------------------------------------------------|-------------------------------------------------------------------------------------------------------------|
| Kangwa et al. (2026).             | Equitable participation / institutional capacity | Shows access operates through support, digital literacy and engagement in African higher education.         |
| Koh (2020)                        | Pedagogical integration / institutional capacity | Shows sustained consultation can build TPACK through modelling and pedagogical realignment.                 |
| Fischer-Schöneborn et al. (2026). | Institutional capacity                           | Demonstrates the organisational role of ICT knowledge absorptive capacity in integrating school technology. |

*Source: Authors' construction.*

### 6.7 Limitation, Transparency and Reproducibility

Several limitations should be considered when interpreting the findings. First, the review was restricted to English-language peer-reviewed journal publications identified through five databases and supplementary reference-list and citation-chain searching. This introduces potential language, database-coverage, and publication biases. Second, the review period extends from January 2020 to the 2026 search cut-off, encompassing both emergency remote education and subsequent post-pandemic developments. Where appropriate, these phases are distinguished rather than treated as a uniform educational context. Third, the retained studies are heterogeneous in research design, educational setting, technology, population, and geographical context. Accordingly, the qualitative synthesis identifies recurring mechanisms and contextual relationships rather than estimating pooled effects or establishing causality. The five-criterion quality assessment provided a consistent basis for evaluating eligibility across different study designs, although it was not intended to replace validated design-specific risk-of-bias instruments. Methodological transparency and reproducibility were strengthened by preserving database-specific search dates, complete executed search strings, protocol-registration documentation, study-level screening and eligibility decisions, data-extraction records, and criterion-level quality assessments. These records establish an auditable account of study identification, selection, appraisal, and synthesis, enabling independent examination of the procedures underlying the 30-study corpus. Their preservation supports procedural reproducibility while recognising that subsequent searches may yield different results because database indexing and coverage change. Finally, the East Asian focus is analytically purposeful rather than regionally representative. China and Taiwan are more prominently represented than several other East Asian settings, while African studies provide a selective comparative perspective. The framework therefore requires further testing across additional geographical, institutional, and resource contexts before broader generalisability can be established. These limitations qualify the scope of interpretation without diminishing the review's contribution to understanding the relationships among technological affordances, pedagogical integration, institutional capacity, AI governance, and equitable participation.

### 7. Conclusion

This review shows that post-pandemic educational technology is fundamentally an alignment problem rather than an adoption problem. Across the 30 retained studies, technological capability produced educational value only in relation to pedagogical design, institutional capacity, governance, and learners' ability to participate meaningfully. East Asian evidence is especially instructive because advanced digital infrastructure coexists with persistent inequalities in literacy, implementation capacity, participation, and outcomes. In contrast, comparative African evidence demonstrates how similar mechanisms operate under different material constraints. The principal contribution is the four-dimensional alignment framework in Figure 1, which links technological affordances, pedagogical integration, institutional capacity, and equitable participation while positioning AI governance as a cross-cutting condition. For policy and practice, investments in platforms and AI should therefore be matched by teacher development, assessment redesign, accessible learner support, privacy safeguards, transparent governance, and local implementation capacity. Future research should test the proposed relationships longitudinally and experimentally, examine learner agency and learning transfer rather than adoption alone, and compare governance quality and equity outcomes across institutions using common validated measures. The central policy lesson is that educational

technology becomes inclusive not through technological provision alone, but through the institutional and pedagogical conditions that convert access into meaningful learning.

## References

- Bati, T. B., & Workneh, A. W. (2021). Evaluating integrated use of information technologies in secondary schools of Ethiopia using design-reality gap analysis: A school-level study. *The Electronic Journal of Information Systems in Developing Countries*, 87(1), e12148. <https://doi.org/10.1002/isd2.12148>
- Casal-Otero, L., Catala, A., Fernández-Morante, C., Taboada, M., Cebreiro, B., & Barro, S. (2023). AI literacy in K-12: A systematic literature review. *International Journal of STEM Education*, 10, 29. <https://doi.org/10.1186/s40594-023-00418-7>
- Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education*, 20, 43. <https://doi.org/10.1186/s41239-023-00411-8>
- Chiu, T. K. F. (2024). Future research recommendations for transforming higher education with generative AI. *Computers and Education: Artificial Intelligence*, 6, 100197. <https://doi.org/10.1016/j.caeai.2023.100197>
- Chiu, T. K. F., Xia, Q., Zhou, X., Chai, C. S., & Cheng, M. (2023). Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education. *Computers and Education: Artificial Intelligence*, 4, 100118. <https://doi.org/10.1016/j.caeai.2022.100118>
- Christ-Brendemühl, S. (2025). Leveraging generative AI in higher education: An analysis of opportunities and challenges addressed in university guidelines. *European Journal of Education*, 60(1), e12891. <https://doi.org/10.1111/ejed.12891>
- Dai, Z., Wang, L., Peng, X., Zhao, L., & Xiong, J. (2024). A model for assessing student satisfaction with smart classroom environment in higher education. *Journal of Computer Assisted Learning*, 40(6), 2901–2916. <https://doi.org/10.1111/jcal.13045>
- Darvishi, A., Khosravi, H., Sadiq, S., Gašević, D., & Siemens, G. (2024). Impact of AI assistance on student agency. *Computers & Education*, 210, 104967. <https://doi.org/10.1016/j.compedu.2023.104967>
- Delanoy, N., & Chen, D. (2026). Instructor-Driven GenAI Feedback as a Pathway to AI Literacy in Postsecondary Courses in China. *European Journal of Education*, 61(2), e70578.
- Emmanuel, K., Saidu, S.E., Koroma, A.B., Bangura, M., Josiah, E., Mansaray, S.G., & Mansaray, A. (2025). The role of digital innovation skills in shaping entrepreneurial readiness among commerce students at the University of Makeni. *International Journal of Social Sciences and Management Review*, 8(5), 496–515. <https://doi.org/10.37602/IJSSMR.2025.8530>
- Farinosi, M., & Melchior, C. (2025). 'I use ChatGPT, but should I?' A multi-method analysis of students' practices and attitudes towards AI in higher education. *European Journal of Education*, 60(2), e70094. <https://doi.org/10.1111/ejed.70094>
- Fischer-Schöneborn, S., Brown, C., Aydin, B., MacGregor, S., & Pietsch, M. (2026). ICT knowledge absorptive capacity: A critical factor for technology integration in schools. *British Journal of Educational Technology*, 57(1), 138–162. <https://doi.org/10.1111/bjet.13608>
- Fu, L., Zeng, Y., & Kang, X. (2024). Bridging the urban–rural gap: A qualitative examination of perceived access, barriers, risks and opportunities of children's digital learning during the COVID-19 pandemic. *Child & Family Social Work*, 29(1), 1–11. <https://doi.org/10.1111/cfs.13045>
- Guo, C., & Wan, B. (2022). The digital divide in online learning in China during the COVID-19 pandemic. *Technology in Society*, 71, 102122. <https://doi.org/10.1016/j.techsoc.2022.102122>
- Jones, K. M. L., Asher, A., Goben, A., Perry, M. R., Salo, D., Briney, K. A., & Robertshaw, M. B. (2020). 'We are being tracked at all times': Student perspectives of their privacy in relation to learning analytics in higher education. *Journal of the Association for Information Science and Technology*, 71(9), 1044–1059. <https://doi.org/10.1002/asi.24358>
- Josiah, E., Mansaray, S. G., Saidu, S.E., Bangura, M., Mansay, A., & Kamara, E. (2026). AI-driven learning systems and the future of quality education: A cross-regional analysis of

- institutional readiness for SDG 4. *Journal of Scientific Reports*, 12(1), 189–206. <https://doi.org/10.58970/JSR.1164>
- Kangwa, D., Msafiri, M. M., & Fute, A. (2025). Exploring the factors that promote a balance between academic integrity and the effective use of GenAI tools in higher education: A systematic review. *Journal of Computer Assisted Learning*, 41(5), e70109. <https://doi.org/10.1111/jcal.70109>
- Kangwa, D., Msafiri, M. M., Charles, K., & Fute, A. (2026). Advancing Sustainable Development Goal 4 through systemic digital transformation in African higher education. *Sustainable Development*. Advance online publication. <https://doi.org/10.1002/sd.71178>
- Koh, J. H. L. (2020). Three approaches for supporting faculty technological pedagogical content knowledge (TPACK) creation through instructional consultation. *British Journal of Educational Technology*, 51(6), 2529–2543. <https://doi.org/10.1111/bjet.12930>
- Kong, Q., & Yang, L. (2026). Digital divide in rural education in Chinese schools: Exploring issues and opportunities. *European Journal of Education*, 61(1), e70436. <https://doi.org/10.1111/ejed.70436>
- Koroma, A.B., Sekyi, D., Josiah, E., Marrah, S.A., & Jalloh, I.C. (2026). Governance and partnership in the China-Africa relationship: Rethinking institutional development and South-South bilateral cooperation. *Open Journal of Political Science*, 16 (2), 126–157. <https://doi.org/10.4236/ojps.2026.162009>
- Kumi-Yeboah, A., Kim, Y., & Armah, Y. E. (2023). Strategies for overcoming the digital divide during the COVID-19 pandemic in higher education institutions in Ghana. *British Journal of Educational Technology*, 54(6), 1441–1462. <https://doi.org/10.1111/bjet.13356>
- Kuo, B.-C., Wu, P.-C., Fan, Y.-C., & Liao, C.-H. (2026). Constructing and validating the AIPACK scale: Measuring teachers' AI pedagogical content knowledge. *European Journal of Education*, 61(1), e70464. <https://doi.org/10.1111/ejed.70464>
- Li, W. (2025). University learning analytics in the age of big data: The case of the Chinese educational system. *European Journal of Education*, 60(2), e70121. <https://doi.org/10.1111/ejed.70121>
- Liu, Q., & Khalil, M. (2023). Understanding privacy and data protection issues in learning analytics using a systematic review. *British Journal of Educational Technology*, 54(6), 1715–1747. <https://doi.org/10.1111/bjet.13388>
- Liu, X., Fang, Y., & Lan, X. (2025). Regulations, technology policies and universities' attitudes to artificial intelligence in China. *Higher Education Quarterly*, 79(4), e70055. <https://doi.org/10.1111/hequ.70055>
- Osei-Tutu, A. A. Z., Odame, E. D., Bawa, J., & Amponsah, S. (2025). A collection of voices on higher education access, quality and equity in Africa: A systematic review. *Review of Education*, 13(3), e70115. <https://doi.org/10.1002/rev3.70115>
- Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., ... Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, 372, Article n71. <https://doi.org/10.1136/bmj.n71>
- Scheerder, A., Van Deursen, A., & Van Dijk, J. (2017). Determinants of Internet skills, uses and outcomes. A systematic review of the second-and third-level digital divide. *Telematics and Informatics*, 34(8), 1607–1624.
- Shen, Y., Huang, G., Le, H., Yu, S., Xu, M., Ouyang, J., Fan, Y., & Wang, Q. (2026). 'Cloud for Youth': Implementation research of cloud-based solutions for bridging the digital divide in rural China. *British Journal of Educational Technology*, 57(3), 844–868. <https://doi.org/10.1111/bjet.70037>
- Tang, X., Yuan, Z., & Qu, S. (2025). Factors influencing university students' behavioural intention to use generative artificial intelligence for educational purposes based on a revised UTAUT2 model. *Journal of Computer Assisted Learning*, 41(1), e13105. <https://doi.org/10.1111/jcal.13105>

- Tian, M., & Lu, G. (2024). Online space for learning: Perceived educational environment typology, interpersonal interaction typology, and their relationship to international students' ability development in Chinese universities. *Higher Education Quarterly*, 78(4), e12560. <https://doi.org/10.1111/hequ.12560>
- Watson, J., Baier, J., Mughogho, W., & Millrine, M. (2023). An exploratory investigation into the factors related to EdTech use among Kenyan girls. *British Journal of Educational Technology*, 54(4), 1006–1024. <https://doi.org/10.1111/bjet.13307>
- Xia, Q., Weng, X., Ouyang, F., Lin, T.J., & Chiu, T. K. F. (2024). A scoping review on how generative artificial intelligence transforms assessment in higher education. *International Journal of Educational Technology in Higher Education*, 21, 40. <https://doi.org/10.1186/s41239-024-00468-z>
- Zhao, L., Cao, C., Li, Y., & Li, Y. (2022). Determinants of the digital outcome divide in e-learning between rural and urban students: Empirical evidence from the COVID-19 pandemic based on capital theory. *Computers in Human Behaviour*, 130, 107177. <https://doi.org/10.1016/j.chb.2021.107177>

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