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Learning Analytics in Low-Connectivity Educational Environments: A Systematic Review of Offline-First and Edge Architectures

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ABSTRACT

Learning Analytics (LA) in low-connectivity educational environments remains severely underdeveloped, despite growing evidence that offline-capable infrastructure is critical for equity in the Global South. While a growing body of research explores offline-first and edge architectures for LA, these approaches remain fragmented and lack formally specified, end-to-end pipelines required for deployment in zero-connectivity environments. The dominant LA literature continues to treat reliable cloud connectivity as a design premise rather than a variable, leaving students in rural and marginalized regions without data-driven educational support during offline periods. This systematic literature review (SLR) examines peer-reviewed evidence on the integration of LA with offline-first and edge computing architectures in low-connectivity educational settings. Conducted in accordance with the PRISMA 2020 framework, a structured search across Scopus, IEEE Xplore, and ScienceDirect covering the period 2020 to 2026 yielded 1,539 records; after deduplication, screening, and full-text assessment, 35 studies were included in the final synthesis. Three research questions guided the review: (RQ1) identification of offline-first and edge-based architectural paradigms; (RQ2) evaluation of synchronization and data integrity mechanisms; and (RQ3) assessment of LA algorithms in resource-constrained contexts. Results reveal three validated offline-first paradigms, namely hardware-based local servers, progressive web applications with service worker buffers, and on-device AI inference, alongside consistent evidence that edge architectures reduce latency by up to 71.3% compared with cloud-only configurations. However, no study provided a formally specified protocol for conflict resolution in LA event logs under zero connectivity. This review formally articulates five research gaps (G1-G5) and argues that the formalization of offline-first infrastructure is a foundational prerequisite for both privacy-preserving synchronization and algorithmic advancement in resource-constrained settings.

Keywords: Eddge Computing, Learning Analytics, Offline-First Architecture, PRISMA 2020, Systematic Literature Review

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INTRODUCTION

Learning Analytics (LA) has emerged as a field centered on the measurement, collection, and analysis of learner data with the express purpose of supporting student learning and informing pedagogical decisions (Long & Siemens, 2011). The ambition to detect at-risk students early, personalize curriculum delivery, and provide educators with actionable insights has motivated the application of increasingly sophisticated technologies, including big data, personalization computing, and artificial intelligence, to realize these educational goals at an institutional scale. Lyu et al. (2025) confirmed that AI-integrated student performance prediction has been validated across more than 2,300 peer-reviewed studies, with multimodal data fusion approaches consistently outperforming single-modality methods. Similarly, (Parsaeifard et al., 2026) demonstrated that neural network models augmented with explainable AI (SHAP) can achieve up to 91% balanced accuracy when applied to interaction logs from large-scale learning management systems. However, predictive accuracy constitutes only one component of an effective LA intervention cycle. The translation of model outputs into actionable pedagogical responses, including early-warning prompts, targeted support referrals, and adaptive content adjustments, requires infrastructure capable of delivering those outputs to educators in real time or near real time. In the absence of such infrastructure, even highly accurate algorithms may fail to generate meaningful educational benefits. These achievements signal that the algorithmic foundations of modern LA have reached a level of technical maturity that, under stable connectivity conditions, could support institutional deployment, provided that complementary pedagogical integration, teacher capacity development, and evidence of measurable impact on student learning outcomes are also established alongside the technical infrastructure. The general LA literature presupposes cloud connectivity as a design premise, a characterization supported by concurrent systematic reviews such as (Amo-Filva et al., 2024; Lyu et al., 2025), which treat online institutional platforms as the assumed deployment context. This review does not seek to quantify that dominance but rather to characterize what is known about the subset of LA research that does not share this assumption and to identify the gaps that remain within it.

This connectivity requirement, however, exposes a consequential limitation in environments characterized by inconsistent or absent internet access. In rural and geographically marginalized regions, including the so-called 3T regions (frontline, outermost, and underdeveloped) in the Indonesian archipelago, intermittent connectivity is the structural norm rather than the exception. LA pipelines that depend on continuous cloud access generate no data during offline periods, deny educators actionable insights when students are most at risk, and progressively widen what (Norowi et al., 2024) conceptualized as the data divide. What distinguishes this review's framing from prior work is its treatment of connectivity not as a binary (connected vs. disconnected) but as a structural variable. The central argument is that infrastructure research has treated connectivity as an assumed constant and that resolving this assumption by designing LA pipelines that operate primarily offline is a prerequisite for educational equity in the Global South. (Syah et al., 2025) raised concerns that LA frameworks may not have been designed with offline data collection as a primary operational mode. Whether this represents a systematic gap across the published literature is a question this review addresses through structured evidence synthesis. This structural deficiency is particularly consequential in Southeast Asian secondary school contexts, where the intersection of limited infrastructure and high student vulnerability makes continuous LA monitoring an urgent need.

Prior literature addressing this gap has clustered into three approaches: hardware-based local server architectures (H. Dai et al., 2024; Rarugal & Sermona, 2024), Progressive Web Applications using Service Workers and local storage (Fibrian et al., 2025; Norowi et al., 2024), and Federated Learning frameworks that preserve data localisation (Fachola et al., 2023; Geng et al., 2024). Prior literature suggests that each of these clusters may carry characteristic limitations: hardware implementations may lack conflict-resolution protocols for offline-generated logs, PWA approaches may not fully address LA data-pipeline requirements beyond basic UI continuity, and FL frameworks may presuppose connectivity conditions inconsistent with the most underserved deployment contexts. The extent to which these limitations hold consistently across the peer-reviewed evidence base, and whether any study has addressed them in combination, is examined in this review. Whether asynchronous or store-and-forward FL architectures capable of queuing local model updates during disconnected periods could address this limitation remains an open question that this review examines as part of gap G5. Despite the theoretical availability of individual components, including offline buffering, synchronization mechanisms, and local inference, the literature, to the authors' knowledge, has not reported an integrated, formally specified pipeline that addresses all stages of offline LA operation as a coherent sequence. Whether this absence holds systematically across the peer-reviewed evidence base is a central question that this review addresses.

For this review, key terms are defined as follows. "Low connectivity" refers to educational settings in which internet access is structurally unreliable, severely bandwidth-constrained, or prohibitively expensive, such that LA pipelines cannot assume continuous cloud communication. Intermittent connectivity refers to conditions in which network access is available for limited periods but is frequently and unpredictably interrupted, requiring systems to operate autonomously between synchronization windows. "Zero connectivity" refers to conditions in which no network access is available for extended or indefinite periods, demanding fully autonomous local operation. "Offline-first" denotes an architectural design philosophy in which full application functionality, including LA data collection, local processing, and storage, is the primary operational mode, with synchronization to a central server occurring only when connectivity is restored. Offline-capable, by contrast, denotes systems designed primarily for online operation that include a fallback mechanism to preserve limited functionality during connectivity disruptions; such systems are distinguished from offline-first architectures by the secondary, rather than primary, status of offline operation in their design. These definitions are applied consistently throughout this review.

A formally specified protocol, for this review, is defined as one that: (a) explicitly enumerates all system states and state transitions relevant to the protocol's operation; (b) defines preconditions and postconditions for each operation; and (c) has been evaluated against a documented correctness criterion. Implementations accompanied only by narrative descriptions or architecture diagrams are classified as informally specified. A formally evaluated mechanism is one assessed against explicitly stated correctness, completeness, or performance criteria derived from a prior specification, with results reported against those criteria rather than as ad hoc observations. For offline-buffered LA data specifically, the relevant integrity properties are completeness (no records lost during synchronization), ordering correctness (records are constructible in causal sequence), and deduplication correctness (no spurious duplicate records appear in the centralized store).

Research Gaps and Objectives

The limitations identified in prior literature motivate the following five research questions. The systematic evidence synthesised in this review will determine whether and to what extent each represents a genuine and consistently unaddressed gap across the published literature. G1: No study has formally specified an offline-first LA data collection protocol. G2: No study has formally evaluated a deduplication, ordering, or causal-consistency mechanism specifically designed for LA event logs generated across distributed offline sessions in intermittently connected environments. Consider the following concrete failure scenario: a student completes an assessment on two different local devices during an extended offline period; both devices independently buffer completion records. Without a formally specified merge protocol, the synchronization server may record duplicate attempt entries or assign causally incorrect timestamps to the log sequence. No included study evaluated a protocol that addresses this scenario for LA-specific event logs. G3: No study has provided a formal evaluation of data integrity mechanisms for offline-buffered LA data. G4: High-accuracy LA algorithms have been validated exclusively in well-connected higher education settings, leaving secondary school educators in developing countries without LA dashboards that meet the criteria for pedagogically meaningfulness, defined here as dashboards that produce actionable intervention prompts aligned with formative assessment workflows, are interpretable by classroom teachers without specialist data literacy, and are evaluated for impact on student learning outcomes rather than predictive accuracy alone (Clow, 2012; Hacker et al., 1998). G5: No study has addressed privacy-preserving synchronization architectures designed for primary zero-connectivity operation. Taken together, these gaps indicate that the field lacks not only technical solutions but also a coherent sequencing of the research agenda required to build them. This study addresses these gaps through a Systematic Literature Review (SLR) guided by the PRISMA 2020 framework, examining peer-reviewed evidence on the integration of learning analytics with offline-first and edge-computing architectures in low-connectivity educational environments. Three research questions guide the review: (RQ1) to identify and taxonomize offline-first and edge-based architectural paradigms developed for LA data collection in low-connectivity settings; (RQ2) to evaluate synchronization and data integrity mechanisms employed in distributed or intermittently-connected educational systems; and (RQ3) to assess LA features and algorithms that have demonstrated effectiveness in resource-constrained educational contexts. This review contributes a PRISMA-compliant taxonomy of the technical landscape, formally articulates five previously unnamed research gaps (G1–G5), and argues that offline-first infrastructure formalization is the foundational prerequisite for both privacy-preserving synchronization and algorithmic advancement in resource-constrained settings.

METHOD

This study employed a Systematic Literature Review (SLR) as its primary research design, conducted in accordance with the PRISMA 2020 framework (Page et al., 2021). The central research focus was the convergence of learning analytics and edge/offline computing architectures in educational settings characterized by limited or unstable internet connectivity. The literature search was conducted across three major academic databases: Scopus, IEEE Xplore, and ScienceDirect (Elsevier), restricted to publications from 2020 to 2026. The lower boundary of 2020 was selected for two reasons: first, 2020 marks the global inflection point at which COVID-19-induced school closures generated widespread institutional recognition of offline and low-connectivity educational infrastructure as a critical research priority, producing a substantively distinct and rapidly growing literature from that year forward; second, prior to 2020, offline educational systems research was largely confined to device-level applications without the edge-computing and LA integration that defines the scope of this review. The combined initial retrieval yielded 1,539 records (Scopus: n = 740; IEEE Xplore: n = 46; ScienceDirect: n = 753).

Search strategy and keyword construction

A structured Boolean search was applied across three conceptual keyword groups using AND logic to combine groups and OR logic within groups. Concept Group 1 (Learning Analytics): “learning analytics” OR “student monitoring” OR “educational data mining” OR “student performance prediction”. Concept Group 2 (Edge/Offline Architecture): “edge computing” OR “fog computing” OR “offline-first” OR “offline learning” OR “distributed computing” OR “federated learning” OR “local server”. Concept Group 3 (Connectivity/Equity Context): “low connectivity” OR “rural education” OR “digital divide” OR “remote learning” OR “limited bandwidth” OR “developing countries”. Negative keyword filtering was applied to exclude records from irrelevant domains, including industrial IoT, supply chain, autonomous vehicle, smart grid, healthcare, medical imaging, smart city, 5G network slicing, intrusion detection, cloud-only, always-connected, constructivism, motivation, self-regulated learning, abstract only, and poster session. Reference management and deduplication were conducted using Zotero and Rayyan. The final search was executed on 31 March 2026. Screening was conducted by a single reviewer using predefined inclusion and exclusion criteria; inter-rater reliability was therefore not calculated. Backward citation searching was not systematically performed, and forward citation searching was not performed. The inclusion and exclusion criteria were established a priori to ensure consistency and objectivity, as summarised in Table 1.

Table 1. Outline of the Reflective Field Note Content

Code	Category	Description	Notes
INCLUSION CRITERIA			
I1	Topic	Discusses Learning Analytics, Student Monitoring, or Data-Driven Education	Mandatory relevance to LA
I2	Technology	Employs Edge Computing, Fog Computing, Offline-first, Synchronisation, Local Server, or Distributed System	Minimum one technology required
I3	Context	Addresses Low Connectivity, Rural Education, Digital Divide, or Equity	Connectivity-limited context
I4	Document Type	Peer-reviewed journal article OR conference paper containing technical data	Excludes editorials and posters
EXCLUSION CRITERIA			
E1	Wrong Domain	Edge/Fog computing for industry (manufacturing), healthcare (hospitals), or autonomous vehicles, NOT education	Most frequently encountered
E2	Full-Cloud Only	Learning analytics requiring continuous internet connectivity, without any offline solution	Not relevant to research scope
E3	Pure Pedagogy	Learning theory or student psychology without an IT architectural solution	No technical component
E4	Document Type	Poster abstract, editorial, book chapter, or non-peer-reviewed publication; or conference extended abstract without quantitative or qualitative technical data	Low methodological quality
E5	Duplicate	The same article appearing more than once across databases	Handled via Zotero deduplication

Study selection procedure

The study selection followed the four-phase PRISMA 2020 procedure: identification, screening, eligibility assessment, and final inclusion (Figure 1). Phase 1 (Identification): database searches yielded 1,539 records (Scopus: n = 740; IEEE Xplore: n = 46; ScienceDirect: n = 753); Zotero deduplication removed 41 duplicates, resulting in 1,498 unique records. Phase 2 (Screening): all 1,498 records underwent title and abstract screening; 1,396 records were excluded (E1: n = 663; E2: n = 584; E3: n = 147; E4: n = 2), leaving 118 records for full-text retrieval. Phase 3 (Eligibility): of 118 records, 53 were inaccessible and excluded due to full-text retrieval limitations; full texts were obtained primarily through institutional subscriptions, supplemented by Google Scholar searches for accessible PDF versions, and, where necessary, through individual article purchase; articles that remained inaccessible after these efforts were classified as “Full-text not retrieved”. Of the 65 full texts assessed, 30 were excluded following full-text review for the following reasons: FT1 (quality assessment below threshold or domain mismatch); n= 11); FT2 (study did not sufficiently address the review questions); n= 14); FT3 (insufficient technical detail; n= 5). Phase 4 (Inclusion): A final corpus of 35 studies was included in qualitative synthesis.

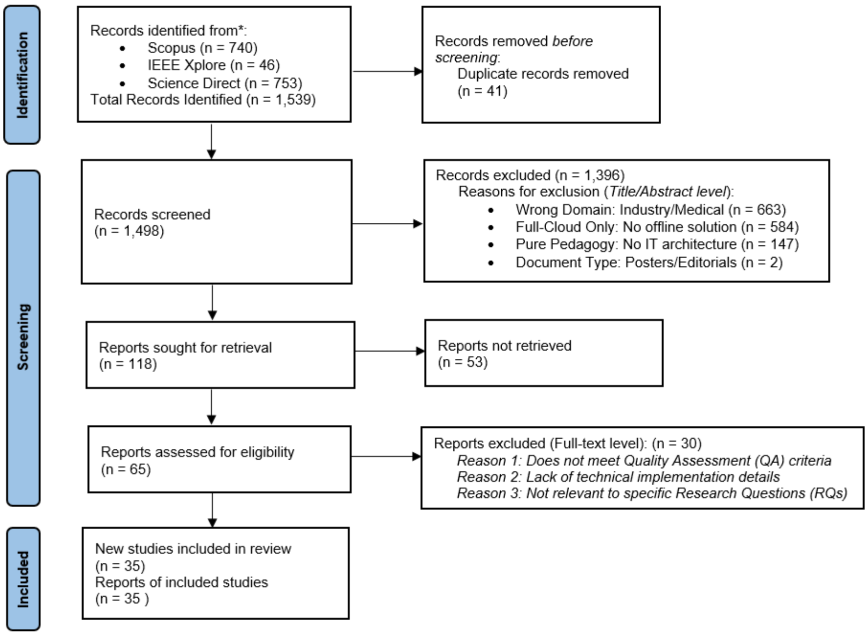

Figure 1. PRISMA 2020 Flow Diagram

Data extraction and quality assessment

A standardised data extraction protocol was applied uniformly to each of the 35 included studies, capturing bibliographic metadata, stated research objective, methodology, key technology and computing architecture, platform and tools, deployment context, principal findings and measured outcomes, identified limitations, and relevance to each research question. Each study was subjected to a formal Quality Assessment (QA) using a five-criterion rubric (Table 2). Studies scoring 5 were classified as Primary References (n = 12), those scoring 4 as Supporting References (n = 15), and those scoring 3 as Contextual References (n = 8). No study fell below the threshold of 3.

Table 2. Quality Assessment Criteria and Scoring Guide

Criterion	Code	Description
Clear Research Objective	Q1	The study clearly states its research objective, research questions, or intended contributions
Implementation or Experiment	Q2	The study includes a real-world implementation, prototype deployment, or controlled experiment
Evaluation with Measurable Metrics	Q3	The study reports quantitative or qualitative evaluation outcomes (e.g., accuracy, latency, F1-score, user satisfaction)
Educational and Connectivity Context	Q4	The study is situated in an educational context involving limited connectivity, rural/remote settings, digital divide, or offline deployment
Replicability	Q5	The study provides sufficient technical detail (architecture diagrams, algorithms, hardware specifications, datasets) to enable replication

Criterion	Code	Description
Scoring Guide		Each criterion scored 0 (not met) or 1 (met). Score 5 = Primary Reference; Score 4 = Supporting Reference; Score 3 = Contextual Reference; Score 2 or below = Excluded

Data analysis

Data analysis employed thematic synthesis, proceeding across three stages: (1) descriptive coding of key findings, technology types, deployment contexts, and outcomes per study; (2) comparative analysis across studies to identify interpretive themes representing recurring patterns; and (3) mapping of analytical themes onto the research questions to generate overarching propositions. Descriptive statistics were calculated to characterise the evidence base.

RESULTS & DISCUSSION

Result

The systematic search yielded 1,539 records. Following deduplication (n = 41), 1,498 articles were selected for title-and-abstract screening. Of these, 1,396 were excluded based on predefined criteria (E1: n = 663; E2: n = 584; E3: n = 147; E4: n = 2). A total of 118 articles were assessed for full-text eligibility; 53 were inaccessible and excluded. Of the 65 full-texts assessed, 30 were excluded. The final corpus comprised 35 peer-reviewed studies.

The temporal distribution of included studies reveals a marked acceleration in research activity from 2024 onward, consistent with the post-pandemic surge in offline and edge computing applications in education. No articles from 2020 met all the inclusion criteria at the full-text stage. In 2021, 2 articles (5.7%) were published, while 2022 and 2023 each contributed 4 studies (11.4% each). The years 2024 and 2025 each contributed the largest cohorts, with 11 studies each (31.4% each), reflecting the maturation of offline-first and edge LA as a distinct research cluster. The year 2026 contributed 3 studies (8.6%), consistent with the search cutoff in the first quarter. Figure 2 illustrates the full annual distribution, and Table 3 provides a detailed breakdown of the dominant technology clusters per period.

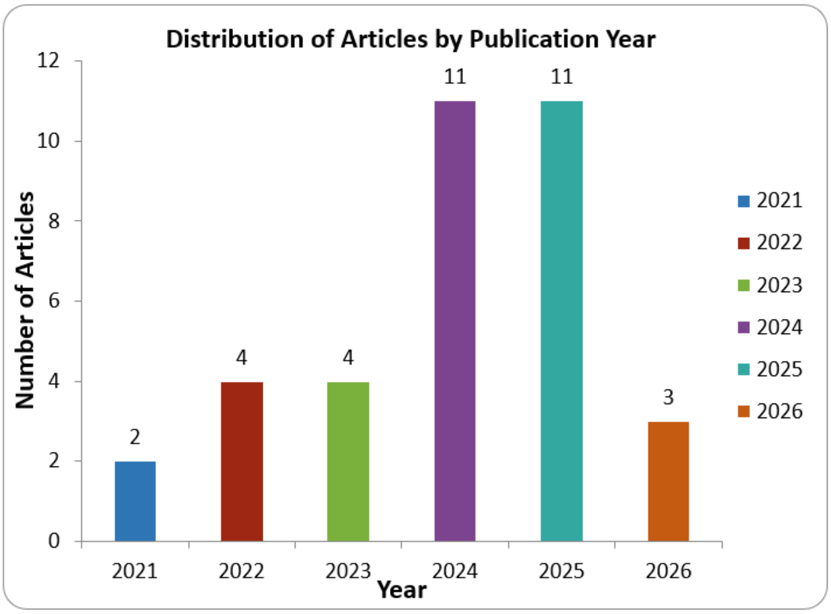

Figure 2. Distribution of Article

Table 3. Distribution of Included Studies by Publication Year

Year	n	%	Dominant Technology Cluster
2021	2	5.7%	FL baseline, fault-tolerant edge systems
2022	4	11.4%	Edge-cloud stream analytics, MEC blueprint, Fog Computing
2023	4	11.4%	Federated LA, QoE prediction, task offloading, knowledge tracing
2024	11	31.4%	Offline-first PWA, Intranet LMS, FedCampus, disengagement ML, edge recommendation
2025	11	31.4%	EdgePrompt, AIED Unplugged, 6G-MEC, Regional Computing, energy-efficient edge
2026	3	8.6%	IoT-MEC real-time feedback, Smart Campus edge governance
Total	**35**	**100%**	

Regarding database distribution, the majority of included articles originated from Scopus (n= 28, 80.0%), with ScienceDirect contributing 7 studies (20.0%) and IEEE Xplore contributing no articles at the final synthesis stage due to full-text retrieval limitations. The dominance of Scopus-indexed publications reflects the interdisciplinary positioning of this research area at the junction of educational technology, distributed systems, and equity policy, which tends to attract Scopus-indexed interdisciplinary journals rather than core IEEE venues. Across the 35 studies, the technology landscape was dominated by Edge/MEC computing (n= 11, 31.4%), Federated Learning (n= 9, 25.7%), and offline-first or local server architectures (n = 7, 20.0%), as detailed in Table 4.

Table 4. Technology Distribution Across the 35 Included Studies

Technology Category	n	%	Representative Studies
Edge / Mobile Edge Computing (MEC)	11	31.4%	(Alshemaimri et al., 2025; Giannou & Mamalis, 2022; Jin et al., 2026; Mohiuddin et al., 2022; Shen et al., 2025; X. Wang et al., 2022)
Federated Learning (FL)	9	25.7%	(Amo-Filva et al., 2024; Fachola et al., 2023; Geng et al., 2024; Jiao, 2025; Piccialli et al., 2025; Preuveneers et al., 2021; R. Wang et al., 2025)
Offline-First / Local Server	7	20.0%	(H. Dai et al., 2024; Fibrian et al., 2025; Monteiro Santos et al., 2024; Norowi et al., 2024; Rarugal & Sermona, 2024; Rasulova et al., 2025; Syah et al., 2025)
Explainable AI / ML (SHAP, ECOC, KT)	6	17.1%	(Jiao, 2025; Parsaeifard et al., 2026; Shitaya et al., 2024; Yang et al., 2024; J. Zhang et al., 2025; M. Zhang et al., 2023)
IoT-Integrated Learning Analytics	5	14.3%	(Gao & Zhan, 2024; Li, 2026; Tan & Lin, 2023; X. Wang et al., 2022; Yu & Tian, 2025)
Progressive Web App (PWA)	3	8.6%	(Fibrian et al., 2025; Monteiro Santos et al., 2024; Norowi et al., 2024)
On-Device AI / Quantized LLM	3	8.6%	(Monteiro Santos et al., 2024; Piccialli et al., 2025; Syah et al., 2025)
Fog Computing (Multi-layer)	3	8.6%	(Amo-Filva et al., 2024; X. Dai et al., 2022; Giannou & Mamalis, 2022)

Quality assessment scores ranged from 3 to 5 out of 5. Twelve studies received the maximum score of 5 and were classified as Primary References; 15 studies scored 4 (Supporting References); and 8 studies scored 3 (Contextual References). No study fell below the threshold of 3, confirming the methodological adequacy of the final corpus.

RQ1: Offline-First and Edge-Based Architectural Paradigms

Six studies were directly relevant to RQ1. Three distinct implementation paradigms were identified. The first paradigm, hardware-based local server architectures, was described by (H. Dai et al., 2024), who deployed a Raspberry Pi' Learning Box' running Moodle LMS in a zero-connectivity setting in Australia's remote Northern Territory, enabling asynchronous synchronisation via Rsync and UUID-based conflict resolution. (Rarugal & Sermona, 2024) deployed a Remote LMS using PHP/MySQL and the Network File System on a local intranet for hinterland schools in the Philippines, achieving Technology Acceptance Model (TAM) scores of 83%-97% among 46 participants. (Rasulova et al., 2025) demonstrated an energy-efficient Raspberry Pi 4 platform that consumes only 1.8W of active power, with offline availability satisfaction rated 4.8/5 in an off-grid rural language-learning context.

The second paradigm, Progressive Web Applications, was represented by (Fibrian et al., 2025), who architected an offline-first gamified LMS using React, Service Workers, and IndexedDB, and by (Norowi et al., 2024), whose BURDLE application demonstrated that 67.7% of rural Malaysian users consumed fewer than 50 MB of mobile data over two weeks. The third paradigm, on-device AI inference, was exemplified by (Monteiro Santos et al., 2024), who benchmarked quantized language models on a Samsung Galaxy A34 smartphone, reporting a mean response time of 1.35 minutes for TinyLlama-1.1B with a 622 MB storage footprint, and by (Syah et al., 2025), who developed the EdgePrompt framework for K-12 schools in Indonesia's 3T regions. Complementary evidence on on-device efficiency was provided by (Piccialli et al., 2025), who evaluated edge-optimized neural network architectures and demonstrated the viability of inference workloads on consumer-grade mobile hardware under zero-connectivity conditions, reinforcing the paradigm's applicability to resource-constrained educational deployment.

RQ2: Synchronisation and Data Integrity Mechanisms

Seven studies addressed RQ2. (Alshemaimri et al., 2025) demonstrated through EdgeCloudSim simulation that a regional computing paradigm reduced end-to-end latency from 707.1 ms to 203.11 ms, representing a 71.3% reduction, while eliminating the 600% congestion surge observed during peak-hour cloud loads at 2,000 concurrent devices and reducing per-transaction cost from USD 5.36 to USD 1.14. Multi-layer fog computing architectures corroborated this scalability advantage. (Giannou & Mamalis, 2022) demonstrated that a three-tier fog hierarchy sustained quality of experience thresholds under variable load conditions, while (X. Dai et al., 2022) showed that edge-cloud stream analytics pipelines reduced data staleness by decoupling ingestion latency from centralized processing cycles.

(Mohiuddin et al., 2023) validated an edge-centric MEC architecture in a real-world university deployment, achieving an average response latency of 0.3 seconds, compared to 0.7 seconds for standard mobile cloud configurations, representing a 57% improvement. (Jin et al., 2026) reported that their ASTEN+SIDS MEC scheduling model achieved a mean latency of 152.3 ms, compared with 243.5 ms for random scheduling, with F1 = 85.44% and AUC = 90.15%. (Shen et al., 2025) further established that 6G-aided MEC architectures can provide edge recommendation services with sub-100 ms latency, positioning edge-native inference as a practical complement to offline-first buffering strategies in intermittently connected schools.

Concerning synchronization mechanisms specifically for LA data, (H. Dai et al., 2024) implemented Rsync with UUID-based deduplication, which appropriately addresses the duplicate-record problem characteristic of append-only LA logs, where the same record may arrive via multiple synchronization paths. However, the study does not address the correctness of ordering or causal consistency reconstruction for logs generated across distributed offline sessions, which represents a distinct and open problem: ensuring that the chronological and causal sequence of student interactions is faithfully recoverable even when those interactions were recorded on separate devices during overlapping offline periods. (Fibrian et al., 2025) employed IndexedDB buffering with Service Worker-triggered synchronisation upon reconnection, acknowledging that concurrent offline edits could produce unresolved conflicts. It should be noted that Fibrian et al.'s system was a gamified LMS with collaborative content features; the conflict type they describe relates to shared content editing rather than independent LA event log generation. Whether this conflict type applies to append-only LA interaction logs, where each user generates independent records, requires explicit verification before it is treated as equivalent to an LA logging conflict. (M. Wang & Xie, 2024) demonstrated hybrid real-time synchronisation to maintain course content consistency, and (Zaini et al., 2021) established fault-tolerance strategies, achieving 99.9% uptime despite unstable Indonesian infrastructure. No investigation across all RQ2 studies evaluated a formally specified protocol addressing the deduplication, causal ordering, or consistency of LA event logs under intermittent or zero connectivity. The gap is most precisely characterised not as the absence of collaborative editing conflict resolution, a paradigm more appropriate to shared document systems, but as the absence of a formally evaluated merge-and-ordering protocol for the append-only, multi-device, multi-session log-generation scenario characteristic of offline LA deployments.

RQ3: LA Algorithms in Resource-Constrained Contexts

Eleven studies addressed RQ3. For disengagement prediction, (Parsaeifard et al., 2026) achieved 91% balanced accuracy and an AUC of 0.96 using a Neural Network with SHAP applied to Moodle quiz interaction logs from 565 students across 42 courses. (Shitaya et al., 2024) demonstrated 95% accuracy for dropout prediction using a Neutrosophic Deep Learning model applied to attendance, grades, and discipline records, outperforming conventional Fuzzy Deep Learning at approximately 85%. For performance prediction, (Yang et al., 2024) applied Error-Correcting Output Code with Shapley values to behavioural logs, achieving an F-score of 0.7497 and outperforming Random Forest (0.6634) and ANN (0.6237) benchmarks. (M. Zhang et al., 2023) developed Counterfactual Monotonic Knowledge Tracing, which outperformed all eight baseline knowledge tracing algorithms across five public benchmark datasets. (J. Zhang et al., 2025) achieved 91% knowledge gap detection accuracy from more than 12,000 behavioural logs using Big Data and AI analytics. (Chen, 2024) demonstrated cloud-edge collaborative filtering for learning resource recommendations, reducing central-server load while maintaining accuracy.

In IoT-integrated LA contexts, (Yu & Tian, 2025) demonstrated that sensor-driven interaction data collected through IoT-enabled classrooms could feed real-time engagement prediction models with accuracy comparable to that of LMS-derived logs, broadening the data source ecology available to offline-aware LA pipelines. (Gao & Zhan, 2024) corroborated this finding by evaluating graph-based recommendation algorithms on IoT-sourced educational interaction datasets, achieving recommendation precision gains of up to 12.3% over collaborative filtering baselines. (Li, 2026) reported that an IoT-MEC integrated architecture enabled real-time student feedback delivery with an average round-trip latency of 87 ms in a smart campus deployment. (Tan & Lin, 2023) developed a QoE prediction model integrating Cloud-Edge and IoT for virtual education evaluation. (Shen et al., 2025) extended this line of evidence by evaluating edge-native recommendation algorithms under simulated 6G-MEC conditions, reporting AUC improvements of 8.4% relative to cloud-only baselines when edge preprocessing was applied to behavioural feature extraction. Across all eleven RQ3 studies, high-accuracy LA algorithms were validated exclusively on well-connected university platforms, with no study providing a pedagogically evaluated offline-first LA dashboard for secondary school educators in Southeast Asian contexts.

Discussion

The synthesis of 35 peer-reviewed studies establishes three overarching findings whose most consequential implication is educational rather than technical: the infrastructure gap in low-connectivity LA constitutes a systematic denial of data-informed educational support to the students most at risk of dropout and disengagement. The technical findings, including validated architectural paradigms, latency benchmarks, and algorithmic accuracy, provide the evidence base for that educational claim. The first is the existence of three technically validated offline-first architectural paradigms, namely hardware-based local servers, Progressive Web Applications with Service Worker buffers, and on-device AI inference, each representing a distinct trade-off between deployment cost, maintenance complexity, and offline AI capability. The second is that edge and MEC computing architectures consistently outperform centralised cloud configurations on metrics critical to low-connectivity deployments: latency reduction of up to 71.3% (Alshemaimri et al., 2025), improved throughput stability under peak load, and cost-per-transaction efficiency (Mohiuddin et al., 2022, 2023). The third, and theoretically most significant, is that the LA and AI literature has produced highly accurate predictive algorithms achieving 91% to 95% accuracy on disengagement and dropout indicators. However, these algorithms have been validated exclusively on well-connected institutional platforms, creating a structural gap at the intersection of offline data collection and algorithmic application. These findings collectively map a field that is technically advancing rapidly at the infrastructure and algorithmic layers in isolation, without yet integrating those layers for the deployment context of zero-connectivity secondary schools in the Global South, where the gap is most consequential.

The convergence of offline-first and edge computing evidence provides technical support for extending the Edge Intelligence framework to educational LA contexts. To be educationally meaningful, however, this extension must be mediated through frameworks that address pedagogical adoption, specifically how edge-distributed LA outputs are translated into teacher action. The Technology Acceptance Model scores reported by (Rarugal & Sermona, 2024; Rasulova et al., 2025) suggest that adoption barriers are primarily infrastructural, which positions Edge Intelligence as a relevant technical vehicle for closing the equity gap, provided that its deployment is accompanied by teacher-facing interface design grounded in formative assessment theory. The quantitative latency advantage demonstrated by (Alshemaimri et al., 2025) and (Mohiuddin et al., 2023) aligns precisely with the theoretical proposition that computational proximity to data generation reduces latency non-linearly as user density increases, a property most valuable in the high-density, low-bandwidth environments characteristic of rural secondary schools. Fog computing deployments across multi-layer architectures (X. Dai et al., 2022; Giannou & Mamalis, 2022) provide further empirical confirmation that computational disaggregation across device, local edge, and cloud tiers sustains QoE thresholds under load fluctuations, a critical property for educational environments where peak usage coincides with scheduled class sessions. The offline-first findings further support the applicability of the Eventual Consistency model from distributed systems theory to educational technology. Under this model, all nodes operate autonomously, with system-wide consistency achieved through periodic synchronisation governed by formal conflict-resolution policies. (R. Wang et al., 2025) partially addressed communication overhead through Fed-ICL, while (Shen et al., 2025) validated 6G-MEC reinforcement learning scheduling outperforming centralised cloud. However, neither study implements conflict resolution for LA event logs under sustained zero connectivity. To enable educators to receive consistent and causally ordered student interaction logs across distributed offline sessions, a prerequisite for reliable early warning systems and formative feedback loops, distributed systems mechanisms such as Conflict-free Replicated Data Types (CRDTs), specifically grow-only set variants suited to append-only logs, and vector clocks for causal ordering reconstruction require translation into the educational LA domain. These mechanisms have not yet been formally specified for LA event log architectures, constituting the technical core of gaps G1 and G2. Operational transformation, a mechanism designed specifically for concurrent text editing in shared document systems, does not apply to append-only LA log architectures and is therefore excluded from this agenda.

The Federated Learning literature introduces a complementary Privacy-by-Design framework. (Geng et al., 2024) demonstrated real-world FL deployment with Differential Privacy at campus scale; (Fachola et al., 2023) proved that local FLEA training on Moodle data produces accuracy equivalent to centralised training; (Preuveneers et al., 2021) validated Secure Multiparty Computation for privacy-safe engagement analytics; and (Amo-Filva et al., 2024) concluded in a systematic review of 43 fog/edge privacy studies that 36 are transferable to LA contexts. (Piccialli et al., 2025) surveyed the feasibility of FL and Edge Learning for resource-constrained LLMs, confirming their deployment viability on limited-compute devices. However, current FL frameworks assume periodic connectivity for synchronous aggregation rounds, which conflicts with the zero-connectivity requirement identified in RQ1. This tension is not irresolvable: asynchronous federated optimisation approaches, in which local model updates are queued during disconnected periods and transmitted upon eventual reconnection, have been proposed in the distributed ML literature as a design pathway that does not require synchronous aggregation. G5, therefore, targets the intermittent-connectivity scenario specifically, not sustained zero connectivity; the latter demands a distinct architecture based on purely local inference without aggregation, which remains a separate and longer-term research direction. The theoretical contribution of this synthesis is therefore to articulate the necessary sequencing: offline-first data-collection infrastructure must formally precede the privacy-preserving synchronisation architecture.

When compared with existing systematic reviews, the present findings both corroborate and extend the current knowledge base. (Amo-Filva et al., 2024), whose SLR examined LA privacy in fog and edge computing across 43 studies, identified Federated Learning as the dominant privacy mechanism, a finding corroborated here, where FL appeared in 9 of 35 included studies (25.7%). However, by focusing on privacy mechanisms within fog and edge environments, (Amo-Filva et al., 2024) did not explicitly address offline-primary data collection, the condition in which no connectivity exists for even intermittent synchronisation, as a distinct design requirement. The present review demonstrates that this offline-primary condition remains an unresolved foundational gap beneath the privacy architecture examined by (Amo-Filva et al., 2024) treated data availability as a solved problem; the present review demonstrates that it is not, revealing the absence of an offline-first pipeline as the more foundational gap. The fog computing studies included here, namely (Giannou & Mamalis, 2022) and (X. Dai et al., 2022), further demonstrate that multi-layer fog architectures address latency disaggregation but do not address offline-primary operation, reinforcing the conclusion that existing infrastructure research treats connectivity as an assumption rather than a variable. (Lyu et al., 2025), in a concurrent SLR of AI for student performance prediction in blended learning, treat 'offline behavioural data' as survey or manual observation data, a conceptualisation that differs fundamentally from LMS interaction logs collected during genuine zero-connectivity sessions. The IoT-integrated LA evidence contributed by (Yu & Tian, 2025), (Gao & Zhan, 2024), and (Li, 2026) further enriches the comparison by demonstrating that sensor-sourced behavioural data achieves LA accuracy parity with LMS logs. However, none of these studies evaluates data collection or model inference under offline conditions. Compared to developing-country-focused studies such as (Norowi et al., 2024) for Malaysia and (Syah et al., 2025) for Indonesia, the present synthesis provides a broader architecture taxonomy incorporating MEC, Fog Computing, and Regional Computing alongside PWA and on-device AI, confirming that the most contextually relevant deployment environments are precisely those where current LA frameworks perform most poorly.

Three findings emerged that were not anticipated at the outset of the review. First, the marked dominance of Scopus-indexed publications (80.0% of included studies) over IEEE Xplore publications was unexpected for a topic at the intersection of distributed systems and educational technology, domains where IEEE venues are typically the primary venues. This pattern most plausibly reflects the interdisciplinary character of offline-first LA as a research category, which has attracted publication in Scopus-indexed educational technology and information systems journals before attracting systematic attention from core IEEE systems conferences. Second, the near-complete absence of secondary school contexts was unexpected, given that the digital divide disproportionately affects secondary students in low-income regions: only 4 of 35 included studies targeted secondary-level or below, and all 4 addressed infrastructure design rather than LA algorithmic evaluation, indicating a systematic misalignment between research attention and educational equity priorities. Third, several technically sophisticated studies, including the 6G-MEC architecture of (Jin et al., 2026) and the edge recommendation system of (Shen et al., 2025), scored as contextually relevant despite deploying infrastructure that is, by definition, inaccessible to the most underserved educational environments. Similarly, the on-device AI evaluations by (Piccialli et al., 2025) and (Monteiro Santos et al., 2024) presuppose access to mid-range smartphones costing USD 300 to USD 500, a hardware assumption that excludes the majority of secondary school students in 3T regions. These cases collectively highlight a recurring tension between technical sophistication and ecological validity that future SLR designs in this domain should explicitly address through dedicated ecological relevance criteria.

This review makes three principal scientific contributions. First, it provides, to the authors' knowledge, a comprehensive PRISMA-compliant taxonomy of offline-first and edge-computing architectural paradigms specifically for educational LA that is among the first of its kind, organising 35 peer-reviewed studies into five coherent thematic clusters and demonstrating how these clusters address the three governing research questions. Second, the review formally identifies and documents five research gaps (G1–G5) that constitute the theoretical frontier of the field: G1, the absence of formally specified LA collection protocols under sustained zero connectivity; G2 and G3, the absence of formally evaluated conflict resolution and data integrity mechanisms for LA event logs; G4, the absence of pedagogically evaluated offline-first LA dashboards in secondary school settings in the Global South; and G5, the absence of privacy-preserving synchronisation architectures designed for zero-connectivity primary operation. Of these, G1 through G3 represent gaps that prior syntheses have not explicitly articulated as numbered, replicable research objectives, constituting a novel contribution to the research agenda. Third, the review establishes the necessary sequencing of this research agenda: offline-first infrastructure formalisation (G1 and G2) is the prerequisite for privacy-preserving synchronisation (G5) and adaptive algorithmic advancement (G4), a reordering of priorities that differs significantly from the prevailing assumption in the literature that infrastructure is solved and algorithm design is the frontier.

For practitioners in resource-constrained settings, the consistently high user acceptance across offline-first implementations, with TAM scores of 83% to 97% (Rarugal & Sermona, 2024) and offline availability satisfaction of 4.8/5 (Rasulova et al., 2025), indicates that adoption barriers are primarily infrastructural rather than attitudinal. Modest hardware investments, with a Raspberry Pi 4 costing approximately USD 35-55, can enable full LMS functionality without internet access. For system developers, the most actionable finding is the consistent superiority of edge-distributed architectures:

71.3% latency reduction via Regional Computing (Alshemaimri et al., 2025), 57% via edge-centric MEC (Mohiuddin et al., 2023), and approximately 80% energy savings via edge-optimised hardware (Rasulova et al., 2025). Developers building for low-connectivity markets should adopt a three-tier architecture spanning the device, a local edge server, and the cloud, with offline-first synchronisation libraries preferred over real-time cloud synchronisation. For policymakers, the systematic underrepresentation of secondary school contexts despite their disproportionate exposure to connectivity barriers indicates a structural misalignment between research funding patterns and equity priorities. National digital education frameworks in Indonesia, the Philippines, and Malaysia should incorporate offline-first LA capability as a minimum technical standard rather than an advanced optional feature, a policy position directly supported by the empirical evidence synthesised here.

The present review acknowledges several limitations that bound the generalisability of its conclusions. The database coverage excluded Google Scholar and Web of Science, potentially omitting relevant grey literature, which may partially explain the 80.0% concentration of included studies in Scopus-indexed journals. The language restriction to English-language publications excluded studies in Bahasa Indonesia, Filipino, Malay, and Chinese, languages in which directly relevant regional studies are likely published. A further limitation of direct relevance to the educational framing of this review is the exclusion of educational psychology literature, specifically self-regulated learning, motivation, and formative assessment research, from the search strategy. This exclusion was methodologically necessary to maintain focus on technical architectural papers. However, it means the review cannot make strong empirical claims about the pedagogical meaningfulness of the infrastructure it describes. Claims regarding pedagogical utility, notably G4, are therefore theoretical propositions requiring empirical validation in future research rather than findings supported by the evidence synthesised here. The temporal boundary of 2020 to 2026 excludes foundational offline educational systems work published before 2020. The quality assessment assigned equal weight to all five QA criteria; a weighted scheme prioritising Q4 and Q2 might have produced a different classification of primary versus supporting references. Addressing these limitations, future research should prioritise, in the immediate term, empirically specifying and evaluating offline-first LA collection protocols and conflict resolution mechanisms for educational event logs under sustained zero connectivity in secondary school settings in Southeast Asia (G1 and G2); in the medium term, conducting pedagogical utility evaluations of offline-first LA dashboards with in-service teachers in resource-constrained Indonesian contexts (G4); and in the longer term, developing Federated Learning frameworks capable of queuing local model updates during disconnected periods and transmitting them upon eventual reconnection, an approach targeting intermittent-connectivity environments. Sustained zero-connectivity deployments require a distinct, longer-term architecture based on purely local inference without aggregation, and should be treated as a separate research direction from the asynchronous FL agenda and merging them upon eventual reconnection (G5). Additionally, the creation of a validated benchmark dataset for LA algorithms on data collected under intermittent-connectivity conditions, through a multi-institutional initiative in rural Southeast Asia, would constitute a standalone scientific contribution of significant value to the field.

CONCLUSION

This PRISMA-compliant systematic literature review of 35 studies examines the integration of learning analytics (LA) with offline-first and edge-computing architectures in low-connectivity educational settings. The synthesis validates three primary offline-first paradigms—local hardware servers, Progressive Web Applications, and on-device AI—while demonstrating that edge deployments significantly reduce latency and maintain high user acceptance. Despite these advances, the study highlights critical structural limitations, noting that current IoT-based engagement models and Federated Learning (FL) frameworks still erroneously presume at least periodic internet access. Crucially, the review contributes to the field by articulating fundamental theoretical gaps rather than mere engineering flaws: the absence of formalized offline data collection protocols, event log conflict resolution mechanisms, pedagogically evaluated dashboards for Global South secondary schools, and privacy-preserving synchronization for zero-connectivity environments. By establishing a sequenced research agenda that prioritizes infrastructure formalization over adaptive algorithmic design, the study provides a foundational roadmap that corrects the broader literature's assumptions. Consequently, the authors urge subsequent empirical research and pedagogical evaluations to focus on offline-first LA pipelines in Southeast Asia, advocating for long-term FL solutions capable of handling disconnected model updates and recommending that these capabilities become mandatory technical standards in the national digital education policies of Indonesia, the Philippines, and Malaysia.

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