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A Privacy-Preserving Extended Reality Framework for Immersive Learning and Collaborative Virtual Environments

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Abstract

Extended reality (XR) platforms can support situated instruction, embodied practice, and synchronous collaboration, but continuous collection of gaze, motion, voice, hand pose, and spatial mapping information creates substantial privacy risks. This paper proposes a privacy-preserving extended reality framework (PPXR) combining purpose-limited sensing, on-device representation learning, federated optimization, differential privacy, secure aggregation, attribute-based authorization, and auditable collaborative session management. A threat model distinguishes curious service operators, malicious participants, compromised endpoints, and inference attacks on shared updates. The framework optimizes pedagogical utility, interactive latency, communication overhead, and privacy exposure subject to access and safety constraints. A detailed pipeline and mathematical formulation describe data minimization, noisy aggregation, trust-aware access, and adaptive quality selection. Because no original user study or deployed system measurements were supplied, numerical results are explicitly labeled as illustrative scenario calculations, not experimental observations. Under transparent assumed configurations, the privacy-first design reduces modeled centralized raw-data retention and improves a normalized privacy-risk score while imposing latency and accuracy trade-offs. The paper concludes with a falsifiable experimental protocol, limitations, and deployment considerations for responsible educational XR.

Keywords: extended reality; immersive learning; collaborative virtual environments; privacy preservation; federated learning; differential privacy; secure aggregation; access control

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1. Introduction

Extended reality is an umbrella term covering virtual, augmented, and mixed reality experiences. In education, immersive interfaces can place students inside simulated laboratories, visualize inaccessible environments, and support team-based manipulation of three-dimensional objects. The same technologies that enable these experiences also produce unusually revealing behavioral telemetry. Head orientation, hand trajectories, eye movements, body dimensions, vocal characteristics, spatial scans, and interaction timing can disclose identity, health-related traits, attention patterns, or aspects of a physical location. Unlike a

conventional learning management system, an XR classroom may continuously infer a learner's actions and environment even when the learner does not deliberately submit a record.

Collaborative virtual environments add a second layer of complexity. Multiuser systems must synchronize avatars, objects, annotations, gestures, and audio across geographically distributed endpoints. A collaboration server often acts as a broker for state updates, authentication, room membership, and persistence. When raw behavioral signals are uploaded for personalization or analytics, the operator can accumulate a longitudinal record of individual movement and participation. Peer participants may also observe or reconstruct information beyond what is needed for the lesson. These risks persist even when communications are encrypted in transit because authorized endpoints and application servers may still receive unnecessarily detailed information.

Privacy-preserving immersive learning therefore requires more than a conventional consent banner. It calls for architectural controls that determine which sensors are active, what transformations are performed locally, which features may leave a device, how long data are retained, and which actors can access a shared representation. The design must also recognize the educational consequences of privacy controls. Strong noise injection may impair gesture recognition, while aggressive redaction may make remote assistance difficult. Additional cryptographic processing can increase interaction latency, and poorly designed consent workflows may interrupt learning. A useful architecture must make these trade-offs measurable rather than claiming that privacy is free.

Federated learning offers a partial solution by keeping raw training examples at participating endpoints and exchanging model updates. Yet federated learning alone does not guarantee confidentiality: model gradients may reveal training information, participating clients may poison the model, and an aggregator may correlate repeated updates. Differential privacy can bound the influence of a participant on a released statistic or model, provided the sampling, clipping, noise scale, and composition accounting are implemented correctly. Secure aggregation can conceal individual client updates from the coordinating server under an explicit collusion and dropout model. These techniques are complementary, not interchangeable.

An XR system also needs a rigorous separation between learning analytics and real-time collaboration. Rendering a peer avatar may require a short-lived pose representation but does not necessarily require permanent storage of a full motion trace. Similarly, adapting the difficulty of a task may require an aggregate estimate of performance rather than raw gaze recordings. Data minimization is achieved by selecting the least revealing representation adequate for a defined pedagogical function. Role-based and attribute-based policies can then constrain what is transmitted to instructors, students, researchers, and administrators.

The central research question is how an immersive learning platform can preserve collaborative functionality while reducing exposure of sensitive sensor data. This manuscript answers through an integrated reference architecture rather than an unsupported claim of a completed deployment. It specifies a modular pipeline, adversary assumptions, utility and privacy objectives, privacy budget accounting, and evaluation metrics. The proposed architecture can be implemented in a prototype using XR client runtimes, an encrypted session broker, a federated training coordinator, and a privacy policy engine. Its principal contribution is the coordination of these layers under an explicit data lifecycle.

Three design principles guide the framework. First, raw sensor information should be processed at the device whenever feasible and discarded after extracting task-specific features. Second, a learner should be able to

participate in essential instructional activities without accepting unrelated analytics. Third, privacy controls should be evaluated alongside instructional outcomes, accessibility, latency, energy, and system robustness. These principles are particularly important in classrooms because power differences between students and institutions can undermine the meaningfulness of nominal consent.

The paper differentiates identity privacy, content confidentiality, and behavioral inference resistance. Identity privacy concerns whether a user can be linked across sessions. Content confidentiality concerns who can read room artifacts and messages. Behavioral inference resistance concerns whether fine-grained telemetry reveals traits beyond the learning task. A system may achieve one property and fail another. For example, pseudonymous avatars do not prevent gait-based reidentification, and encrypted streams do not prevent an authorized peer from observing a disclosed room scan.

In practical deployments, governance matters as much as algorithms. Institutions must define retention periods, lawful bases for processing, access-review procedures, breach responses, and ways to accommodate learners who cannot or do not wish to use a particular sensor. Educators should be able to distinguish feedback based on robust performance indicators from speculative emotional or cognitive inferences. Privacy notices should state exactly which signals are used, whether data train a model, and whether model updates are shared beyond the institution.

The remainder of this paper reviews foundational research on XR learning and privacy-enhancing technologies, introduces the proposed system and its mathematical objectives, presents a transparent illustrative comparison, and outlines a rigorous future validation study. The results are scenario-based demonstrations of how metrics can be reported; they are not presented as measurements from students or deployed XR hardware. This distinction is necessary for reproducibility and research integrity.

2. Literature Review

Immersive learning research has explored experiential training, visualization, simulation, and collaboration. Radianti et al. (2020) systematically reviewed immersive virtual reality in higher education and described educational design opportunities as well as the need for stronger evaluation practices. Merchant et al. (2014) synthesized evidence on virtual reality-based instruction and found that learning outcomes depend on implementation characteristics. These studies motivate assessment of actual learning gains rather than assuming that immersion itself produces improvement.

Collaborative virtual environments extend individual simulation to shared workspaces. Learners can jointly manipulate artifacts, practice communication, and observe embodied demonstrations. However, collaboration quality depends on consistency of object state, intelligible spatial audio, and responsiveness to gestures. The networking literature highlights the importance of end-to-end latency and jitter for interactive media. In privacy-preserving XR, every added encryption, filtering, or aggregation stage must therefore be evaluated against perceptual and instructional constraints.

XR sensing creates privacy challenges distinct from ordinary web analytics. Eye tracking may reveal attention and interest; motion patterns can act as biometric signatures; and scene reconstruction may capture private surroundings. Miller et al. (2020) showed the identification potential of head and hand motion data in virtual reality. Such evidence suggests that removing explicit names from telemetry is insufficient. Privacy

controls should limit the fidelity, persistence, and linkability of behavior traces even when user identifiers are pseudonymous.

Privacy by design, articulated by Cavoukian (2011), provides a useful governance foundation: preventive controls, default protections, and lifecycle accountability should be embedded in system architecture. Nissenbaum's (2010) contextual integrity framework additionally emphasizes whether information flows conform to the norms of the educational setting. A student may reasonably expect an instructor to observe task completion, but not expect the institution to retain high-frequency gaze trajectories for unrelated profiling.

Differential privacy formalizes a guarantee about the influence of one participant on a randomized output. Dwork et al. (2006) established foundational results; Dwork and Roth (2014) provide a broad treatment of mechanisms and composition. In a learning analytics context, differential privacy can protect aggregate dashboards or federated model updates. However, the guarantee applies only to the specified mechanism and adjacency relation. It does not automatically protect live avatar streams, audio, or information deliberately disclosed to peers.

Federated optimization, popularized by McMahan et al. (2017), enables training from decentralized client data. This is attractive for XR because devices can compute local embeddings and performance statistics. Nevertheless, privacy leakage from gradients remains a concern. Zhu et al. (2019) demonstrated gradient-based reconstruction attacks under certain conditions. Thus, federated optimization should be combined with clipping, calibrated noise, secure aggregation, and protections against malicious or compromised clients.

Bonawitz et al. (2017) proposed practical secure aggregation for privacy-preserving machine learning, enabling a server to obtain aggregate updates without directly seeing each participating client contribution under the protocol assumptions. In educational XR, secure aggregation can reduce exposure during model training across classrooms. Yet it does not eliminate risks from a compromised client, colluding parties beyond the threat threshold, or information inferred from the final global model.

Access control provides a complementary boundary. Attribute-based access control, standardized in NIST guidance by Hu et al. (2014), supports decisions based on subject, object, action, and environment attributes. This is more flexible than fixed roles when a virtual laboratory has instructors, students, observers, and external assessors. Policies can prohibit export of a room scan, allow temporary access to a shared object, or restrict recordings to a particular consented instructional activity.

Privacy-preserving systems also face usability and fairness questions. Differential privacy noise may affect learners unequally when sensor quality, device performance, or participation frequency differ. Federated training may amplify non-independent data distributions across devices or institutions. Secure aggregation can increase communication and recovery complexity. A comprehensive study should therefore report subgroup performance, device classes, dropout rates, privacy accounting, and accessibility outcomes rather than only an overall accuracy number.

Existing approaches often address isolated concerns: XR learning effectiveness, anonymization of tracking data, federated model training, or encrypted communications. The gap motivating this work is an integrated, operationally specified framework that links local sensing, collaborative state sharing, analytics, policy enforcement, and auditable deletion. The proposed design does not claim to invent differential privacy or

secure aggregation; its contribution is the orchestration and evaluation blueprint for an educational XR setting.

3. Research Methodology

3.1 Design objectives and research model

The study adopts a design-science methodology. A reference architecture is specified, measurable hypotheses are stated, and an evaluation plan compares centralized processing with privacy-aware alternatives. The target application is a multiuser virtual laboratory in which learners manipulate shared objects, receive adaptive hints, and optionally contribute anonymized model updates. The unit of privacy protection for analytics is a learner session; a separate per-user policy governs live collaboration. No empirical participant data are assumed in the illustrative results.

3.2 System boundaries and threat model

The trust boundary separates the headset or desktop client, collaboration broker, analytics coordinator, institution identity service, and authorized peers. Threats include a curious server logging movement traces, a peer requesting unauthorized scene data, an eavesdropper observing network traffic, a compromised client uploading malicious updates, and membership inference against a published model. The baseline assumes trusted device operating systems and authenticated keys; compromised endpoints and side-channel leakage remain residual risks. Secure aggregation requires a stated threshold of honest participants and is not a substitute for endpoint hardening.

3.3 Local capture and feature minimization

Raw gaze, head pose, hand pose, microphone input, and room geometry enter a local sensor gateway. Each stream is mapped to an explicit pedagogical purpose and consent state. The gateway selects coarse task events such as completed manipulation, gesture category, or dwell-time band. Raw samples are kept in a volatile buffer only as long as necessary for local inference; session-level retention follows a configurable institutional policy. Learners may disable optional gaze analytics without losing access to the core lesson. A separate ephemeral state channel transmits the minimum pose information necessary to render collaborative actions.

3.4 Privacy-aware collaborative synchronization

A session broker authenticates participants and applies attribute-based authorization before forwarding state updates. Sensitive spatial meshes are reduced to task-relevant geometry; personal background objects are masked locally. Shared artifacts are encrypted during transport and at rest where persistence is authorized. Ephemeral avatar data use short retention and distinct session identifiers to reduce cross-session linkage. The broker records policy decisions and data categories, but avoids storing raw behavioral trajectories in its audit log.

3.5 Federated adaptation and protection

An on-device encoder estimates task progress and interaction patterns. Local training computes an update on consented examples; update norms are clipped to bound sensitivity. Clients then participate in secure

aggregation, and Gaussian noise is added under a defined privacy accountant. The coordinator receives only the protected aggregate and distributes an updated model. Model release is gated by validation, poisoning checks, and a minimum participant threshold. When too few clients participate, the system skips the update rather than relaxing privacy controls silently.

3.6 Adaptive rendering and optimization

The client chooses rendering detail, telemetry frequency, and collaboration fidelity based on available bandwidth, battery state, task requirements, and a minimum privacy policy. The optimizer penalizes delay and bandwidth consumption while rewarding task completion and collaborative consistency. Privacy constraints are hard limits, not optional reward terms. For example, a high-bandwidth room scan cannot be uploaded simply because it improves visual fidelity if consent or authorization is absent.

3.7 Measurement protocol

A reproducible study should randomize comparable learning groups to centralized and privacy-preserving implementations, balance prior experience, and preregister primary outcomes. Learning gain is measured by pretest and posttest with a matched assessment rubric; collaboration is measured by task completion and independent quality ratings. Technical measurements include end-to-end motion-to-photon latency, network bytes, client energy, model utility, membership-inference attack success, and retention volume. Results should include confidence intervals, sample sizes, device specifications, and privacy accountant settings.

3.8 Governance, deletion, and auditability

Consent is purpose-specific, revocable for future processing, and logged with a policy version. A retention controller deletes raw transient buffers, expires collaboration events, and applies institutional schedules to authorized artifacts. Deletion of historical contributions from an already trained model may require retraining or machine unlearning; the architecture does not falsely promise immediate reversal of previous learning. An independent auditor can inspect policy rules, cryptographic configuration, aggregate telemetry, and access logs without obtaining learners' raw sensor traces.

3.9 Mathematical formulation and editable equations

$$F = \alpha U + \beta C - \gamma L - \eta B - \kappa R$$

Equation 1. F is the design objective; U denotes normalized learning utility; C denotes collaboration quality; L is normalized latency; B is communication burden; R is privacy risk. The Greek coefficients are nonnegative weights selected before evaluation. This scalarization is used only among configurations satisfying mandatory privacy policies.

$$g = (1 / n) \Sigma g_i$$

Equation 2. g is the mean model update, n is the number of participating clients, and g_i is the protected update from client i. In deployment, secure aggregation computes the sum without exposing individual contributions to the server under the assumed protocol.

$$g_i^c = g_i \, min(1, C / \|g_i\|_2)$$

Equation 3. g_i^c is a clipped update; C is the maximum allowed norm; and $\| \cdot \|_2$ is the Euclidean norm. Clipping bounds the contribution of a single participant before noise calibration.

$$\hat{g} = (1 / n) (\Sigma g_i^c + Z)$$

Equation 4. $\hat{g}$ is the released aggregate; Z is Gaussian noise drawn according to the specified sensitivity, sampling scheme, and privacy accountant. Noise magnitude cannot be inferred from this equation alone.

$$P[M(D) \in S] \leq exp(\varepsilon) P[M(D') \in S] + \delta$$

Equation 5. M is the randomized analytics mechanism; D and D′ are neighboring datasets differing in one protected learner session; S is an output event; ε and δ are the differential privacy parameters. The definition holds only when the implementation and accounting satisfy its assumptions.

$$L = (1 / N) \Sigma (t_r - t_s)$$

Equation 6. L is mean observed interaction latency across N events; t_s is the event generation timestamp; t_r is the corresponding rendered update timestamp. Clock synchronization and percentile latency must also be reported.

$$G = (S_p - S_r) / (S_m - S_r)$$

Equation 7. G is normalized learning gain; S_p is posttest score; S_r is pretest score; S_m is maximum possible score. When pretest scores approach the maximum, report raw gain as well.

$$R = w_1 E + w_2 I + w_3 T$$

Equation 8. R is a transparent composite risk indicator; E is normalized exposure of raw signals, I is modeled inference susceptibility, T is normalized retention exposure, and weights sum to one. This score is a scenario heuristic, not a differential privacy guarantee.

3.10 Implementation workflow

Authenticated learner enters XR session

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Consent and task policy select permitted sensors

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On-device filtering and feature extraction

↓

Authorized ephemeral state sent to collaboration broker

↓

Local learning updates clipped and protected

↓

Secure aggregation and privacy accounting

↓

Validated model and adaptive hints returned

↓

Retention expiry, deletion and audit review

Figure 1. Text-based editable workflow. The collaboration path and federated analytics path branch after local feature extraction; no raw sensor stream is required to enter the analytics coordinator.

4. Results and Discussion: Illustrative Scenario Analysis

IMPORTANT: The following figures are constructed assumptions for method demonstration. They are not observations, benchmark results, or evidence that the proposed system has been implemented. A real evaluation must replace them with measurements and disclose uncertainty.

Scenario	Risk index	Latency ms	Retained data %	Model utility	Inference risk
Centralized baseline	85	42	100	0.82	0.78
Local filtering only	58	51	35	0.8	0.45
Federated plus secure aggregation	34	67	18	0.79	0.29
Full proposed framework	18	76	8	0.77	0.17

Table 1. Hypothetical values on a common task and device profile. Risk index and inference risk are modeled dimensionless scales, retained data are percentages relative to the centralized baseline, and model utility is an assumed normalized score. Lower is better for risk, latency, retention, and inference risk; higher is better for utility.

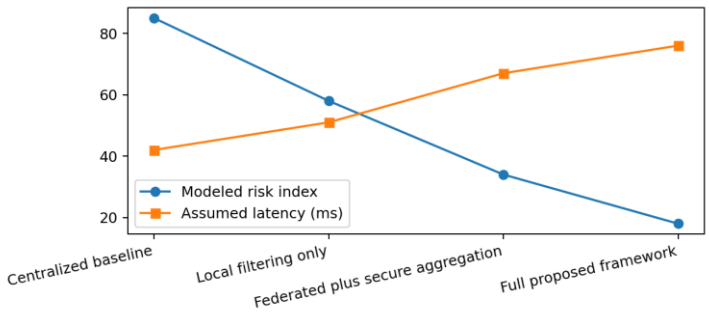

Figure 2. Illustrative trade-off between modeled privacy risk and assumed interaction latency across architectural configurations.

4.1 Privacy and retention

Under the assumptions in Table 1, the full architecture lowers the modeled risk index from 85 to 18 and retains 8% of the baseline data volume. These numbers illustrate the expected direction of a data-minimizing architecture but do not establish actual privacy protection. Formal protection depends on the differential privacy budget, secure aggregation threat model, access policy correctness, and residual inference from live collaboration streams.

4.2 Interaction cost

Assumed latency increases from 42 ms to 76 ms as additional filtering, protected aggregation, and authorization checks are introduced. The increase should not be interpreted as a measured cryptographic overhead; actual latency must be decomposed by capture, processing, network, server, and rendering stages. Federated training can occur asynchronously and need not be on the live rendering path.

4.3 Utility and adversarial testing

The scenario assumes a modest decline in normalized model utility from 0.82 to 0.77. A deployment study should compare recognition accuracy, learning gain, and collaboration quality using identical tasks and statistically powered samples. Inference risk must be evaluated through specified attacks, including membership inference, identity linkage, and scene reconstruction, with attacker knowledge and base rates reported.

4.4 Sensitivity and validity

The scenario is sensitive to device capability, network conditions, class size, consent rates, clipping thresholds, and privacy budget selection. A rigorous sensitivity study should vary these parameters, plot confidence intervals, and report failures. The current tables cannot justify claims of statistical significance, superior educational outcomes, or regulatory compliance.

5. Conclusion

This manuscript proposes a privacy-preserving XR architecture for immersive education and collaborative virtual environments. It combines local feature minimization, purpose-specific consent, policy-enforced ephemeral collaboration, federated optimization, secure aggregation, differential privacy, and accountable retention. Its mathematical formulation explicitly separates utility optimization from mandatory privacy constraints. Illustrative scenario calculations demonstrate how data exposure, inference risk, latency, and model utility can be compared transparently, but they do not constitute experimental evidence. Future research should implement the architecture, validate end-to-end privacy accounting, test adversarial inference, and conduct controlled learning studies across diverse devices and learners. The central design lesson is that meaningful privacy requires coordinated technical and governance controls throughout the XR data lifecycle.

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