PUBLION

Rights-Respecting Learning Analytics: Data Governance, Privacy, and Transparency for EdTech and Higher Education

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Abstract

Hybrid-Flexible (HyFlex) learning is increasingly treated as a durable mode of provision, yet many implementations still frame "flexibility" as a logistical feature rather than a pedagogical and psychosocial design problem. This can fragment belonging, produce uneven participation expectations, and raise cognitive load for students who must navigate shifting modalities, tools, and routines. This article proposes a wellbeing-first HyFlex design framework that integrates: (1) belonging and engagement research on identity-safe learning environments; (2) cognitive load theory and multimedia learning principles explaining overload risks in hybrid switching; and (3) blended learning models (Community of Inquiry, self-determination theory, and Universal Design for Learning) that operationalize teaching presence, autonomy-supportive structure, and accessible pathways. Using a design-science synthesis method, we develop a conceptual model, a course-level checklist with operational indicators, and an implementation roadmap with risk controls for equity, privacy, and instructor sustainability. The framework supports institutions in moving from ad hoc HyFlex delivery to accountable hybrid ecosystems that can scale without sacrificing care, rigor, or inclusion.

1. Introduction

Learning analytics refers to the collection, measurement, analysis, and reporting of data about learners and their contexts for the purpose of understanding and optimizing learning and the environments in which it occurs (Slade & Prinsloo, 2013). Over the last decade, learning analytics has moved from experimental dashboards to institution-wide infrastructures that connect learning management systems, student information systems, library systems, advising workflows, and third-party education technology (EdTech) services (Hillman, 2022). The diffusion has accelerated further with the mainstream adoption of AI-based tutoring and automated feedback, which depend on continuous streams of interaction data and often rely on predictive models to recommend interventions (Liu & Khalil, 2023; Paludi, 2024).

These developments promise measurable benefits: improved student retention, faster identification of learning difficulties, personalized study recommendations, and more efficient resource allocation (Reidenberg & Schaub, 2018). Yet the same infrastructures also concentrate power (Brown, 2019). When institutions and vendors can infer risk status, motivation, attendance patterns, or even mental well-being from digital traces, the boundary between support and surveillance becomes blurred. Students may not understand what is collected, how long it is stored, who can access it, or how algorithms shape high-stakes decisions such as advising holds and scholarship eligibility (Jones, 2019; Jones et al., 2020).

A rights-respecting approach treats these tensions as a governance problem rather than merely a technical one. Governance determines legitimate purposes, establishes oversight structures, defines accountability, and creates documentation that can be audited and contested (Hillman, 2022). Without governance, even well-intentioned analytics initiatives can produce harms: discriminatory risk scoring, chilling effects on participation, stigmatizing labels, function creep into disciplinary monitoring, and opaque vendor practices that lock institutions into data extraction (Heiser et al., 2023; Liu & Khalil, 2023).

The external environment has also changed. Many jurisdictions now apply comprehensive data protection rules to educational data processing, including requirements for lawful bases, data minimization, transparency, and rights to access and objection (Karunaratne, 2021; Paludi, 2023). Sector guidance emphasizes data governance in EdTech, including vendor transparency, security, and laws applicable to student privacy (Sun, 2023). Meanwhile, public debates about AI regulation and algorithmic accountability are reshaping expectations for explainability and the ability to contest automated decisions (Morales Tirado et al., 2024). Higher education therefore faces a dual challenge: to innovate responsibly while maintaining compliance and legitimacy.

Existing learning analytics ethics frameworks provide important principles, but institutions often struggle to translate them into operational controls, documentation, and decision workflows. Many initiatives still rely on informal approvals, ambiguous data ownership, and limited stakeholder consultation, especially when analytics is embedded in platform contracts and learning tool integrations. What is needed is an actionable bridge between high-level principles and day-to-day practice: a model that clarifies roles and evidence artifacts for transparency, consent and choice, equity, and accountability.

This article develops such a bridge. We ask three guiding questions: (1) Which rights and ethical principles are most consistently emphasized across learning analytics literature and EdTech governance guidance? (2) How can these principles be operationalized into governance controls and auditable artifacts across the analytics lifecycle? (3) What implementation roadmap can help institutions and vendors progressively mature their governance capabilities? To answer these questions, we combine a scoping review and policy synthesis with a design-science process that iteratively maps principles to controls and produces reusable templates.

Our contribution is practical and conceptual. Practically, we provide a governance model (Fig. 1), a principle-to-control mapping (Table 1), and a maturity roadmap (Table 2) that can be adopted as a baseline for institutional policy and vendor due diligence. Conceptually, we frame learning analytics governance as an alignment problem between educational mission, legal duties, and relational trust. The framework prioritizes transparency and contestability so that learning analytics can remain a support system rather than an invisible sorting mechanism.

2. Research Method

This study employs a design-science research approach aimed at producing an actionable governance artifact for learning analytics (Lewis, 2015). The work proceeded in three stages: (1) scoping review of learning analytics ethics and governance literature, (2) comparative synthesis of external governance guidance relevant to education data processing, and (3) iterative design and validation of a governance framework with operational controls and evidence artifacts.

In Stage 1, we conducted a scoping review focusing on peer-reviewed articles and widely cited reports that address privacy, ethics, accountability, and governance in learning analytics (Schlunegger et al., 2024). Searches were conducted in Scopus and Google Scholar using combinations of terms such as learning analytics, ethics, privacy, data governance, transparency, and algorithmic accountability. Inclusion criteria emphasized (a) explicit discussion of normative principles or governance mechanisms, (b) relevance to higher education or comparable learning contexts, and (c) substantive proposals beyond purely technical model performance. The review prioritized seminal contributions and later syntheses that operationalize ethics into practice (Ruggiano & Perry, 2017).

In Stage 2, we synthesized external governance guidance, including comprehensive data protection rules and education-focused guidance on EdTech governance, AI principles, and learner rights. This stage utilized qualitative document analysis to ensure a systematic evaluation of policy texts (Morgan, 2022). We extracted recurring requirements and translated them into governance needs for learning analytics—such as purpose limitation, data minimization, documentation, and rights to contest decisions—using a directed approach to qualitative content analysis (Assarroudi et al., 2018).

In Stage 3, we mapped the combined set of principles to operational controls across an analytics lifecycle, encompassing data intake, processing and modeling, deployment and intervention, monitoring, and retirement (Bingham, 2023). We developed templates for documentation and accountability, including impact assessment, model cards, communication notices, access controls, and audit logs. To support adoption, we arranged controls into three maturity levels (Foundational, Developing, Advanced). Internal validation was conducted by checking traceability from each proposed control to multiple literature and guidance sources and by applying rigorous codebook development procedures to ensure the replicability of the thematic mapping (Roberts et al., 2019).

3. Result and Discussion

This section reports the synthesized principles and operational controls derived from the scoping review and policy synthesis. We present a governance model (Fig. 1), a principle-to-control mapping (Table 1), and a maturity roadmap (Table 2) for implementation.

3.1 Principles for Rights-Respecting Learning Analytics

Across learning analytics ethics literature and EdTech governance guidance, eight principles consistently recur and can be expressed in operational terms: (1) legitimate educational purpose and proportionality, (2) data minimization and quality, (3) transparency and intelligibility, (4) choice and meaningful control, (5) fairness and non-discrimination, (6) security and confidentiality, (7) contestability and due process, and (8)

accountability and auditability (Liu & Khalil, 2023; Slade & Prinsloo, 2013). These principles are mutually reinforcing. For example, fairness requires both high-quality data and the ability for students to contest harmful inferences; transparency is ineffective without accountability mechanisms that verify what is disclosed (Drachsler & Greller, 2016).

Purpose and proportionality are the starting point. Learning analytics should be justified by a clear educational mission such as supporting learning, improving course design, or providing timely advising. Vague objectives invite function creep, especially when institutional pressures for retention and performance metrics intensify, potentially compromising student autonomy (Jones et al., 2019). Governance should require a purpose statement that specifies intended benefits, acceptable interventions, and prohibited uses. Proportionality means that the intrusiveness of data collection and modeling should match the stakes and available alternatives (Rubel & Jones, 2014).

Transparency must be intelligible. Students rarely benefit from long privacy policies; instead, institutions should provide concise explanations of what data is used, what models infer, and what decisions may be affected, including clear descriptions of uncertainty (Jones, 2019). Transparency should also extend to staff: educators and advisors should understand the assumptions and limitations of risk scores so that analytics supports professional judgment rather than replacing it (Zhan et al., 2024).

Choice and meaningful control remain complex in higher education, where some data processing is required for core services. A rights-respecting approach avoids treating consent as a checkbox. Where consent is inappropriate or non-meaningful, institutions should provide opt-out choices for non-essential analytics, offer alternative learning pathways when tools require extensive tracking, and ensure that refusal does not trigger punitive consequences. These controls help align analytics with respect for learner autonomy and the role of institutions as information fiduciaries (Jones et al., 2019).

3.2 Governance Controls Across the Analytics Lifecycle

Principles become enforceable when embedded into lifecycle controls. Figure 1 presents a governance model that links principles to decisions at each lifecycle stage: intake (data and vendor selection), design (feature engineering and modeling), deployment (interventions and communications), monitoring (drift, bias, and impact), and retirement (data deletion and contract exit). This systematic approach reflects the necessity of addressing privacy and data protection issues throughout the entire development cycle to increase trustworthiness (Liu & Khalil, 2023).

At intake, governance should require a data inventory and a vendor due diligence process. A data inventory identifies data categories (clickstream, assessment, biometric, location), sensitivity, retention periods, and sharing. Due diligence for third-party tools should include contractual clauses for data ownership, sub-processors, breach notification, and restrictions on secondary use. Institutions should insist on vendor transparency about data flows and analytics logic, especially as universities often lack full control over data collected by third parties (Hillman, 2022).
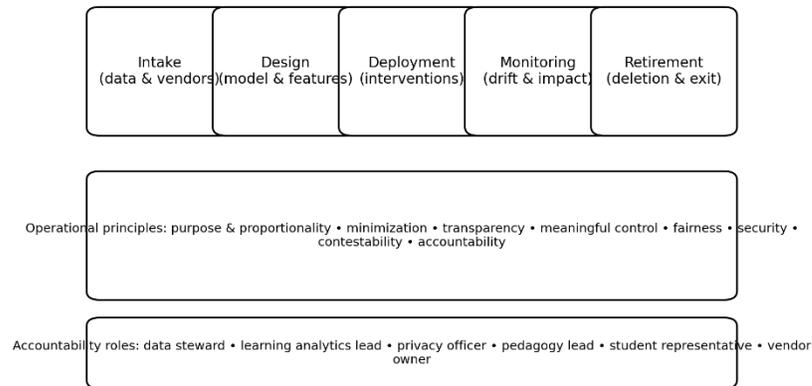
Figure 1. Rights-respecting learning analytics governance model across the analytics lifecycle.

At design, responsible analytics demands documentation and testing. Feature selection should be justified by relevance to the purpose and screened for proxy discrimination. For predictive models, institutions should document model type, training data scope, evaluation metrics by subgroup, and intended decision role. Model documentation can be implemented through model cards and decision records that capture why a model was adopted and what safeguards accompany it, ensuring that accountability is built directly into the technology (Reidenberg & Schaub, 2018).

At deployment, governance must define permissible interventions and avoid stigmatizing labels. Early-alert systems often categorize students as "at risk"; such labels can shape expectations and interactions. A safer approach uses graduated signals with uncertainty indicators and requires that interventions be supportive, optional where possible, and accompanied by human review for high-stakes actions. Communication should clearly explain that analytics is probabilistic, not deterministic, and should provide contact points for questions and appeals (Jones, 2019).

At monitoring, institutions should treat learning analytics as an ongoing socio-technical system. Monitoring includes technical drift (changes in data distributions), fairness drift (changes in subgroup performance), and impact assessment. Audit logs and periodic reviews can ensure that dashboards and models remain aligned with their stated purposes. Retirement procedures should specify data deletion timelines and vendor exit strategies to prevent lock-in and ensure sustainable data use (Ncube & Ngulube, 2024).

**Table 1.** Principles mapped to governance controls and evidence artifacts.

Principle	Governance control (institution + vendor)	Evidence artifact (auditable)
Purpose & proportionality	Purpose statement; prohibited uses; intervention policy; stakeholder review	Use-case charter; intervention register; consultation notes
Minimization & quality	Data inventory; minimization rules; data quality checks; retention limits	Data map; retention schedule; data quality log
Transparency & intelligibility	Layered notices; staff guidance; model communication plan	Student notice; staff playbook; communication checklist
Meaningful control	Opt-out for non-essential analytics; alternatives; role-based access	Choice record; access matrix; exception log
Fairness & non-discrimination	Subgroup evaluation; proxy-feature screening; bias mitigation; human review thresholds	Fairness test report; model card; decision threshold policy
Security & confidentiality	Security baseline; encryption; breach response; vendor security attestations	Security controls matrix; incident response plan; audit report
Contestability & due process	Student access; correction workflow; appeal path; no fully automated adverse decisions	Rights request workflow; appeal records; rationale notes

Source: Processed by the researcher, 2026

3.3 Transparency, Contestability, and Student Rights in Practice

Transparency and contestability are often discussed as abstract ideals, yet they can be implemented through concrete artifacts and workflows. A rights-respecting analytics program should provide students with layered notices, access to their own data, and pathways to challenge harmful inferences. This is critical because students often feel "tracked at all times" and lack awareness of how their data is used (Jones et al., 2020).

Contestability matters because learning analytics can make errors and because data can misrepresent complex learning realities. Missing device access, caring responsibilities, or disability accommodations may distort engagement traces. Students should be able to annotate contextual factors and request corrections where feasible. For predictive risk models, institutions can provide simplified explanations of risk signals. The goal is meaningful due process rather than full algorithm disclosure (Paludi, 2024).
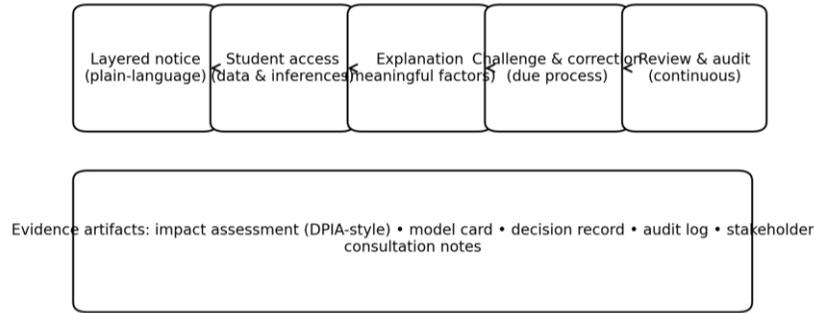
Figure 2. Transparency and contestability workflow for learning analytics decisions.

To institutionalize these rights, governance should specify decision thresholds that require human review and prohibit purely automated adverse decisions. Even for supportive outreach, students should be informed about the data that triggered the concern. This reduces the sense of surveillance and enables dialogue, acknowledging that students are often willing to trade privacy for pedagogical benefits if trust is established (Soffer & Cohen, 2024). Importantly, staff should be trained to use analytics ethically, documenting discretionary decisions to maintain accountability (Reidenberg & Schaub, 2018).

Vendor transparency is a critical dependency. Institutions should require transparency reports disclosing data categories, retention, security, and use of data for model training. Where tools use generative AI, vendors should disclose training sources and safeguards. Contracting and procurement are therefore governance levers that help institutions fulfill their responsibility to protect student intellectual privacy (Jones et al., 2020).

3.4 Implementation Roadmap and Maturity Model

Adoption barriers are often practical: limited staffing and fragmented tool ecosystems. Table 2 provides a maturity roadmap to help institutions prioritize actions. The Foundational level focuses on minimum viable governance, while the Advanced level supports continuous auditing and participatory governance with student representation. Such a roadmap is essential for balancing technological innovation with robust privacy protections (Azra & Zeeshan, 2025).

Progression should be incremental. Institutions can start by applying the full governance cycle to one high-impact use case. Successful pilots create reusable templates and demonstrate that governance is an enabler of innovation, not a blocker. This approach aligns with the need for evidence-based solutions that increase the overall usefulness of learning analytics (Liu & Khalil, 2023).

Finally, governance must be aligned with institutional values and public trust. A rights-respecting approach strengthens the university's role by demonstrating that educational benefits can be pursued without sacrificing student autonomy and dignity. This alignment is vital as institutions navigate the complex ethical challenges inherent in educational data mining (Jones et al., 2019; Slade & Prinsloo, 2013).

Table 2. Maturity roadmap for rights-respecting learning analytics governance.

Capability area	Foundational	Developing	Advanced
Purpose & oversight	Use-case charter; accountable owner	Portfolio review; student representation	Independent ethics/audit panel
Transparency & rights	Layered notice; contact point	Access + correction workflow; staff training	Public transparency report; regular rights audits
Model governance	Basic documentation; human review thresholds	Subgroup fairness testing; model card	Continuous monitoring; external evaluation

Source: Processed by the researcher, 2026

4. Conclusion

This article proposed a rights-respecting governance framework for learning analytics that translates ethical and legal principles into actionable controls, documentation artifacts, and an adoption roadmap. By organizing governance across the analytics lifecycle and emphasizing transparency and contestability, the framework supports institutions and vendors in implementing analytics as a support system rather than a surveillance apparatus.

The framework is intentionally pragmatic. It provides a principle-to-control mapping and a maturity model that can be used for institutional policy, procurement due diligence, and program evaluation. Future work should empirically evaluate the framework in diverse institutional contexts, including resource-constrained universities and cross-border EdTech arrangements, and should develop measurement tools for learner trust and perceived legitimacy of analytics interventions. Ultimately, learning analytics will be sustainable only if it remains legitimate in the eyes of learners and the public. Rights-respecting governance provides a path to that legitimacy by embedding accountability, intelligibility, and due process into the everyday routines of data-intensive education.

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