Understanding Learner Interaction Analytics through Data Visualization in Metaverse-Based Learning Environments

Akhil HOTHI[a*]
[a]*Centre for Educational Technology, IIT Bombay, India*
*akhilhothi@iitb.ac.in

Abstract: Metaverse-Based Learning Environments (MBLEs) generate rich, high-volume multimodal interaction data (e.g., gaze, gesture, speech, movement) that can reveal learner engagement patterns. Yet, instructors lack tools that can cluster and visualize these data in an actionable, real-time manner. This doctoral research aims to develop a data visualization framework that integrates unsupervised clustering of multimodal student interactions with adaptive, immersive dashboards to support pedagogical decision-making. The study proceeds in three phases: (1) establishing a validated operational framework for MBLEs, (2) designing and evaluating a clustering pipeline for multimodal learner data, and (3) prototyping immersive dashboards that reduce cognitive load and enhance instructional responsiveness. Preliminary outcomes include a Unity-based data capture prototype. This work advances immersive analytics, multimodal learning analytics, and Human–Computer Interaction by linking embodied learner behaviors to adaptive visual feedback.

Keywords: Learning analytics, Data visualization, Metaverse-Based Learning Environments, Immersive analytics, Human–Computer Interaction (HCI)

1. Introduction

The rapid adoption of extended reality (XR) technologies has enabled the creation of Metaverse-Based Learning Environments (MBLEs), offering embodied, multisensory, and interactive educational experiences. Within these environments, learners manipulate virtual objects, collaborate in spatial settings, and interact through gaze, gesture, voice, and movement. These activities produce high-dimensional, multimodal data streams with unprecedented potential for learning analytics (Ochoa & Worsley, 2016).

Despite this potential, current analytics systems for immersive learning remain limited in two ways:

1. Lack of utilization of rich interaction data: Most dashboards reduce complex behaviors to simple metrics, ignoring spatial and temporal patterns (Worsley & Blikstein, 2013).
2. Lack of adaptive visualization: Interfaces often fail to align with the 3D, embodied nature of MBLEs, leading to increased instructor cognitive load and reduced pedagogical responsiveness (Dwyer et al., 2018; Ochoa & Worsley, 2016).

This research addresses these challenges by developing and evaluating a data visualization framework that transforms raw multimodal MBLE interaction logs into adaptive, immersive dashboards. By integrating clustering-based pattern detection with Human–Computer Interaction principles, the study aims to enable timely, data-informed teaching interventions and learner self-regulation. Figure 1 shows a proposed data visualization workflow for Immersive Learning Analytics.

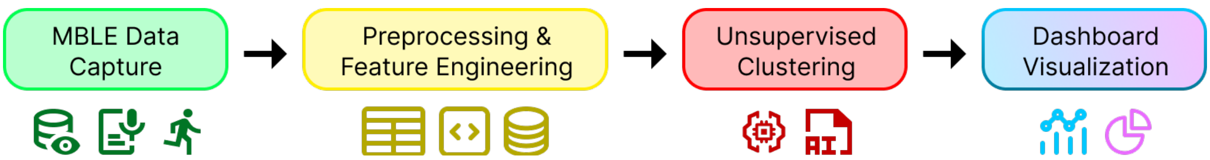

Figure 1. Proposed Data Visualization Workflow for Immersive Learning Analytics

2. Research Problem and Motivation

MBLEs can transform education through embodied and spatial learning, but their full potential is constrained by analytics systems designed for 2D, clickstream-based platforms (Mystakidis, 2022; Ochoa & Worsley, 2016). Rich interaction data such as gaze, gesture, spatial movement, remain underexploited in real-time pedagogical decision-making. Instructors face three major challenges which are shown in Table 1.

Table 1. Key Challenges in Leveraging Learning Analytics in MBLEs

Challenge	Description	Implication for Research
Ambiguity in MBLE definitions	No unified framework integrating technological, pedagogical, and social dimensions.	Develop validated operational definitions for consistent study and application.
Interpretation Bottleneck	High-volume, heterogeneous data without structured taxonomies.	Create clustering pipelines tailored to MBLE learning data.
Lack of adaptive visualization tools	Dashboards ignore 3D spatial context and embodied interaction.	Design immersive dashboards to align with instructor cognition and reduce cognitive load.

Addressing these challenges will improve real-time pedagogical responsiveness and learner self-regulation, bridging the gap between raw immersive interaction data and adaptive visual feedback (Dwyer et al., 2018; Ochoa & Worsley, 2016).

3. Research Gaps

While interest in immersive learning analytics is growing, current research studies still leave significant unanswered questions about how MBLEs should be defined, analyzed, and supported through visualization tools. A synthesis of prior work across XR, HCI, and educational technology reveals four key research gaps, as shown in Table 2, which shape the focus and contribution of this doctoral study.

Table 2. Summary of Research Gaps in MBLE Learning Analytics

Gap Type	Current State	Limitation	Research Opportunity
Conceptual	“Metaverse” variably defined across XR, HCI, and education (Mystakidis, 2022)	Lack of unified framework integrating technological, pedagogical, and social dimensions	Develop an operational MBLE definition via literature synthesis + expert consensus (Delphi study).
Methodology	Clustering in LA applied mainly to clickstream/quiz data	Minimal work on embodied, spatial, multimodal logs	Adapt clustering methods to immersive data (Davies & Bouldin, 1979).
Design	Dashboards primarily 2D and static	Limited adaptation to spatial contexts	Create immersive dashboards with adaptive feedback mechanisms

Empirical	Few evaluations in real-world teaching contexts.	Limited evidence of cognitive or pedagogical impact.	Test dashboards on usability, cognitive load, and responsiveness.

4. Research Questions

Guided by the identified gaps, this research formulates three overarching research questions with specific sub-questions. Together, they span the conceptual framing of MBLEs, the methodological development of clustering pipelines for multimodal data, and the design and evaluation of adaptive immersive dashboards.

RQ1. How can MBLEs be operationally defined across technological, pedagogical, and social dimensions?

- *RQ1.1:* What are the core technological features (e.g., embodiment, synchronicity, persistence) that define MBLEs?
- *RQ1.2:* How do pedagogical models (constructivist, experiential) shape interactions in MBLEs?
- *RQ1.3:* How can constructs like co-presence and agency be measured within immersive learning platforms to identify their impact when compared to other online and physical technology-enhanced learning (TEL) environments?

RQ2. How can unsupervised machine learning methods be used to cluster multimodal learner interaction data in MBLEs?

- *RQ2.1:* What data types (e.g., gaze, gesture, speech, spatial movement) are most salient for clustering learner behaviors?
- *RQ2.2:* What combination of feature engineering and clustering algorithms (e.g., DBSCAN) provides optimal interpretability and accuracy?

RQ3. How can the resulting clusters be visualized in adaptive immersive dashboards to support real-time teaching and self-regulated learning?

- *RQ3.1:* What design principles support cognitive alignment between immersive dashboards and instructor decision-making?
- *RQ3.2:* How do immersive analytics dashboards compare to traditional 2D interfaces in supporting awareness, reflection, and pedagogical action?

5. Methodology

A Design-Based Research (DBR) approach will be followed in three iterative phases, integrating literature synthesis, expert consultation, multimodal data clustering, and immersive dashboard design/evaluation (Ochoa & Worsley, 2016). A three-phase research plan is shown in Table 3.

Table 3. Three-Phase Research Plan

Phase	Activities	Outputs	Evaluation
1. Conceptual Framework	Scoping review; Delphi study with experts	Validated MBLE framework	Delphi consensus metrics
2. Data Collection & Clustering	Pilot Unity MBLE activity; capture gaze, gesture, speech, movement; feature engineering; clustering (DBSCAN)	Behavior taxonomies	Silhouette score, Davies–Bouldin index, ratings

3. Dashboard Design & Evaluation	Identify baseline 2D dashboard to compare the adaptive 3D dashboard through usability study	Comparative usability/impact metrics	NASA-TLX, SUS, detection accuracy, Wilcoxon test

6. Expected Contributions

The anticipated outcomes of this research extend beyond technical implementations to include theoretical, methodological, and design-oriented contributions. These contributions aim to advance scholarly understanding of immersive learning analytics while offering practical tools and guidelines for instructors and developers. Table 4 summarizes the planned contributions and their significance.

Table 4. Research Contributions and Their Significance

Contribution	Scholarly Significance	Practical Significance
Operational MBLE Framework	Integrates technological, pedagogical, social dimensions	Guides platform design and standardization
Multimodal Clustering Pipeline	Adapts unsupervised ML to immersive data	Enables interpretable behavioral insights
Design Guidelines for Data Visualization	Extends HCI theory to immersive LA	Enhances informed decisions in MBLEs
Dashboard Impact Evaluation	Evidence of immersive analytics effectiveness	Informs adoption in real classrooms

7. Future Work

The next phase begins with completing the Delphi study to finalize a validated operational framework for MBLEs (Phase 1). Building on this, a full multimodal clustering pipeline will be implemented, incorporating statistical validation and expert evaluations for interpretability and accuracy (Phase 2). Next, two dashboard prototypes will be developed: a baseline 2D web interface and an adaptive 3D immersive dashboard within the Unity-based learning environment (Phase 3). A controlled study with instructors will then assess cognitive load, usability, event detection accuracy, and response time. Findings will refine dashboard guidelines and be shared via publications, open-source code, and practical recommendations for immersive analytics in education.

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