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Preliminary Exploration of Learning Analytics in Virtual Reality: A Space-Themed Approach

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Abstract: In this study, we present an end-to-end implementation of learning analytics for a virtual reality (VR) learning environment. The proposed solution includes a VR environment featuring a virtual International Space Station, an Experience API (xAPI) schema based on Actor–Verb–Object triples, a Learning Record Store (LRS), and a dashboard. The current dashboard presents summary metrics, task completion, accuracy, and the distribution of logged action verbs, providing an initial view of learner participation, task progression, and spatial exploration in the VR environment. To demonstrate feasibility, we conducted a workshop with 28 elementary school students using a scaffolded learning activity, during which 1,052 behavioral statements were collected. This preliminary work also revealed several technical challenges, including (1) device-sharing constraints, (2) verb–object semantic ambiguity, and (3) multi-level data granularity. Future studies will extend the analytical depth of the dashboard and explore sequence-based approaches for better understanding learners' behavior in VR environments.

Keywords: Virtual reality, learning analytics, xAPI

1. Introduction

The adoption of Virtual Reality (VR) in education represents a major shift toward immersive, student-centered learning. In fields such as space science, VR enables learners to explore environments such as the nodes of the International Space Station (ISS) (see Figure 1) or observe rocket launch simulations that are difficult to reproduce through conventional classroom instruction. While this trend gives learners greater agency, it also creates a "data gap." Traditional assessments are often unable to capture the autonomous process of discovery taking place inside the headset.

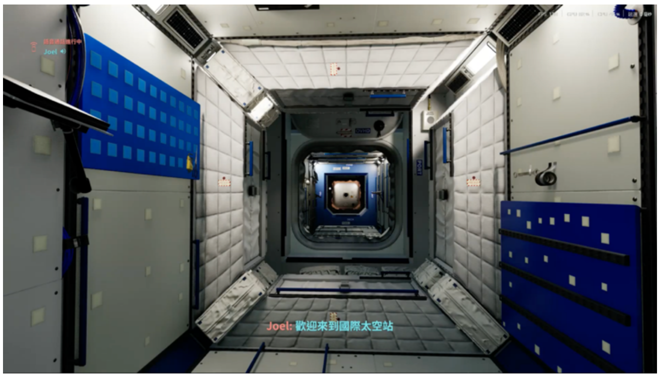

Figure 1. The Virtual International Space Station (ISS) Exploration Environment

At present, the majority of VR interaction data constitutes "dark data," meaning that it is difficult to interpret and often unstable because of practical issues such as system crashes or hardware reboots (Lampropoulos & Evangelidis, 2025). To realize the benefits of learning analytics (Siemens, 2013), this study presents an end-to-end solution that applies the Experience API (xAPI) to address this challenge, similar to prior studies (Görzen, Heinemann, & Schroeder, 2024; Secretan, Wild, & Guest, 2019). By structuring raw events into a standardized format, the proposed xAPI-based pipeline transforms unstructured VR logs into analyzable data and addresses the engineering challenge of maintaining persistent learner identity across changing classroom settings. This paper presents a preliminary, practice-oriented end-to-end VR learning analytics pipeline, demonstrates its deployment in an elementary school workshop, and discusses the practical challenges and pedagogical implications identified from this implementation.

2. Architecture

The system adopts a modular architecture to bridge the gap between immersive VR experiences and learning analytics. The pipeline, shown in Figure 2, consists of a Unity-based VR client, a Learning Record Store (LRS), and a dashboard, all connected through a Flask-based middleware. Interaction events within the VR environment, such as a student entering a collider or interacting with an ISS console, are serialized as xAPI statements and transmitted to the LRS in near real time. In this way, the system captures learner movement, object interaction, and task-related responses in a standardized format. These measures were selected to capture key behavioral dimensions of VR learning, including where learners go, what they interact with, and how they progress through the activity. This design helps convert interaction logs into interpretable indicators for monitoring participation, exploration, and task progression.

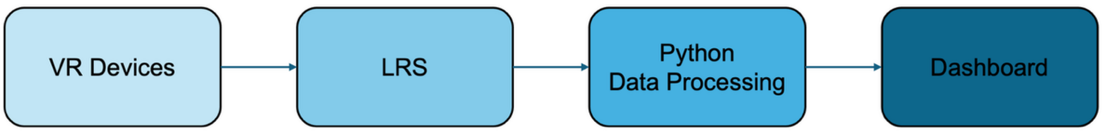

Figure 2. The proposed end-to-end VR Learning analytics pipeline

Over a three-day workshop with 28 student participants, the system captured 1,052 behavioral statements. The current dashboard (see Figure 3) focuses on descriptive metrics, including task completion, accuracy, and verb distribution. Here, verb distribution refers to the frequency distribution of logged xAPI action verbs, such as *enter, check, cut in, pick up*, and *submitted answer*. These verbs describe learner interactions with the VR environment rather than spoken commands. The high frequency of the verb *Enter* suggests that learners were actively moving across different modules in the VR environment. These records also provide a basis for reconstructing individual navigation paths in future work. Although the current dashboard is mainly descriptive, the logs already reveal interpretable patterns of learner participation, spatial exploration, and task progression.

Figure 3. Grafana Dashboard.

3. Technical Design and Challenges

To address the difficulty of turning raw VR interaction logs into interpretable records, the current implementation combines a Python-based middleware for event transformation and transmission with Grafana for dashboard-based monitoring. The first challenge was **device-sharing constraints**. Because the activity was scaffolded section by section, with the instructor providing guidance before each VR segment, time-based comparisons were not the primary analytical focus in this deployment. Because the number of available VR devices was limited, students worked in pairs and rotated headsets after each section. As a result, the system had to handle multiple users on a single device. In the initial implementation, this rotation was managed manually by the instructors, which led to phantom student effects and technical reboots.

The second challenge was **verb–object semantic ambiguity**. By applying the standardized xAPI format, we were able to convert complicated interactions into a readable log. In this project, verbs such as *enter, check, cut in, pick up, stop*, and *submitted answer* were defined to represent key learner interactions. For example, rather than logging only a coordinate change, the system records a verb “*Enter”* whenever a student triggers a collider associated with a specific module, such as Node2 or the Spaceship. By naming each module a unique xAPI “object,” the system records which areas were visited, transforming raw movement into a semantic sequence of events.

The third challenge was **multi-level data granularity**. Addressing this challenge will require the dashboard to support views not only for a single activity, but also for previous and parallel activities. This requires a hierarchical perspective that supports interpretation at the activity, cohort, and cross-material levels. Using the existing data structure, we will implement additional tracking features, including a cumulative progress bar for the entire cohort. Because the current data structure preserves timestamps and ordered events, it also provides a basis for future sequence-based analysis, such as Lag Sequential Analysis (LSA).

4. Conclusion

This study shows that for VR to function as an effective classroom tool, the software must be designed to be “log-ready” from the outset. Structuring instructional activities with an xAPI schema enables researchers to make learner interactions in VR more transparent and analyzable. Although the current implementation mainly supports descriptive monitoring, it demonstrates the feasibility of an end-to-end VR learning analytics pipeline and highlights important challenges for future refinement.

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