11th International Conference of the Immersive Learning Research Network
Practitioner Proceedings iLRN2025

DOI: https://doi.org/10.56198/3gw1jn66

AI-Powered Learning Dashboard with Multimodal Metrics for Embodied Performance in XR Training Simulation

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Abstract. The growing adoption of XR-based simulations in educational settings has highlighted the need for intelligent systems to monitor, predict, and visualize learners' experiences in real-time. This paper presents the design and implementation of a Real-Time Intelligent Monitoring System (RTIMS) for XR Learning that predicts learners' Quality of Experience (QoE) by analyzing cognitive, affective, and behavior data collected during XR-based simulation learning. The system leverages 14 sets of multi-dimensional data from HoloLens 2, including head and hand positions and pupil size measurements captured via NEON eye-tracking glasses. Using the RTIMS, cognitive (e.g., attention, task load), affective (e.g., self-efficacy, learning satisfaction), and behavioral (e.g., task accuracy, completion time) domain data were gathered through controlled experiments and used to train deep learning models. The RTIMS predicted QoE scores and generated a Learning Effectiveness Index (LEI), visualized in a real-time dashboard, enabling continuous monitoring and predictive insights into learners' learning quality progress. This research lays the groundwork for advancing XR-based learning by enhancing learner monitoring through QoE prediction, improving instructional adaptability, and fostering high quality learning experiences.

Keywords: Real-Time Intelligent Monitoring System, Quality of XR-Based Learning, Learning Effectiveness Prediction.

1 Introduction

The integration of Extended Reality (XR) technologies into educational settings has provided immersive and engaging learning experiences [1]. However, the dynamic nature of XR-based learning environments poses challenges in effectively monitoring and analyzing learning experiences in real-time. Traditional monitoring methods often fail to capture the multidimensional aspects of XR-based learning, such as cognitive, affective, and behavioral learning experiences. To address this research gap, we developed a Real-Time Intelligent Monitoring System (RTIMS) for XR-Based Learning, which collects, analyzes, and visualizes learners' cognitive, affective, and behavioral data to predict their Quality of Experience (QoE) by calculating a Learning Effectiveness Index (LEI) [2]. RTIMS was designed to empower educators with actionable insights for adaptive learning and to enhance the overall effectiveness of XR-based learning.

2 System Design and Architecture

2.1 Data Framework

We aim to integrate Bloom's taxonomy into the dashboard to comprehensively address the three major domains of learning: cognitive, affective, and psychomotor. Bloom's taxonomy provides a robust theoretical framework for structuring instructional design and strategies, enabling a deeper understanding of how learners engage with training. The dashboard will not only track engagement levels but also measure embodied performance by leveraging multimodal data and predictive models to evaluate learning effectiveness. By aligning metrics with Bloom's taxonomy, the dashboard can present consistent, actionable insights into learners' cognitive processes

(e.g., problem-solving and critical thinking), affective responses (e.g., motivation and self-efficacy), and psychomotor skills (e.g., task accuracy and completion time). This integration will ensure that the dashboard serves as a holistic tool for monitoring and enhancing training outcomes.

2.2 System Architecture

The system consists of three core components: data collection, data processing, and data visualization. Data acquisition integrates HoloLens 2 (Microsoft, Redmond, WA, USA) and NEON eye-tracking glasses (Pupil Labs, Berlin, Germany) to capture 14 behavioral features, including head and hand positions and pupil size. The data is transmitted to a centralized server where preprocessing and in-depth prediction of learning quality is performed. The results, including QoE metrics and the LEI, are visualized through an intuitive real-time dashboard.

Data Collection. Spatial and physiological metrics data were collected using HoloLens 2 and NEON eye-tracking glasses. Three domains of data were obtained during the controlled experimental sessions: cognitive indicators (e.g., attention and task load), affective indicators (e.g., self-efficacy and learning satisfaction), and behavioral indicators (e.g., task accuracy and completion time) [3]. The collected data spans multiple dimensions to provide a holistic view of learner performance. In this study, data is collected when a participant wears the HoloLens 2 and NEON eye-tracking glasses while performing assigned XR learning tasks (Figure 1). Figure 2 shows a virtual safety training module in the XR based construction site, where the XR simulation content is given to the participants for the learning tasks. In this simulation, learners were tasked with identifying potential hazards and practicing equipping a virtual mannequin with appropriate safety gear, allowing them to understand the correct usage of safety equipment in various construction site scenarios.

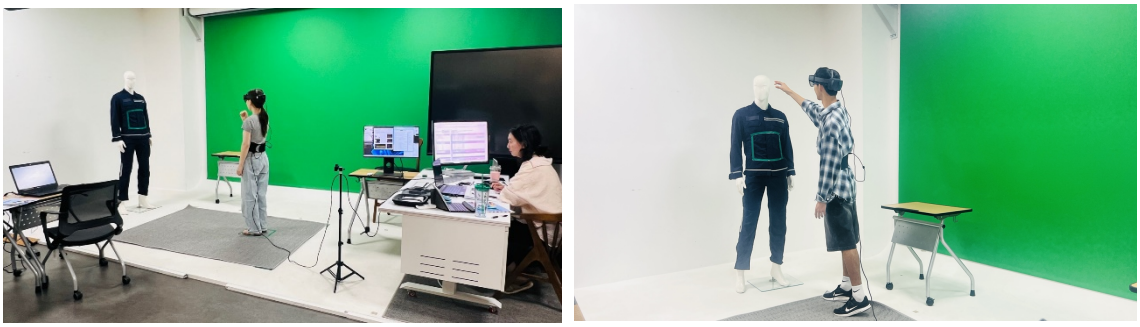

Fig. 1. Experimental Setup for Data Collection Using HoloLens 2 and NEON Eye-Tracking Glasses.

Fig. 2. XR Simulation for Construction Safety Training.

Data Processing. The data processing pipeline includes synchronization of multi-modal data streams, noise reduction, and feature extraction. The collected behavioral data (e.g., head and hand positions) and physiological data (e.g., pupil size) were normalized and processed for real-time analysis. Deep learning models leverage these features to predict QoE and combine cognitive, affective, and behavioral metrics into the LEI. Therefore, these models were utilized to detect patterns in the collected data and predict learners' QoE. These predictions were

updated continuously, enabling real-time insights into the learning experiences. The LEI is a single interpretable score that provides educators with an overview of learners' effectiveness during XR-based training sessions.

Data Visualization. The real-time dashboard presents an interactive interface designed to visualize and interpret key data insights. The dashboard contains data visualizations that include QoE metrics, LEI trends, and individual pattern analyses (e.g., head and hand movement patterns). The dashboard interface was designed to support educators in monitoring learner performance, facilitating timely interventions where necessary. Key visualization elements include:

- LEI and Domain Metrics: Visualizations of cognitive, affective, and behavioral domain results, allowing educators to understand learners' overall performance and specific area strengths.
- Behavioral and Physiological Data Trends: Real-time plots of head and hand positions, gaze movements, and pupil size changes provide insights into learners' engagement and task performance over time.
- Heatmaps and Task Interactions: Heatmaps for attention and interaction density illustrate focus areas and highlight key interaction patterns across XR tasks.
- Multi-View Session Playback: Single-user and multi-user views allow detailed observation of learners' task execution with synchronized data visualizations.
- QoE Metric Analysis: A breakdown of metrics such as attention, task load, self-efficacy, learning satisfaction, task accuracy, and completion time, visualized over time and integrated into a composite QoE score.
- Comprehensive Feedback and Analysis Summary: Automated insights and summaries provide actionable feedback based on learners' performance and overall QoE trends.

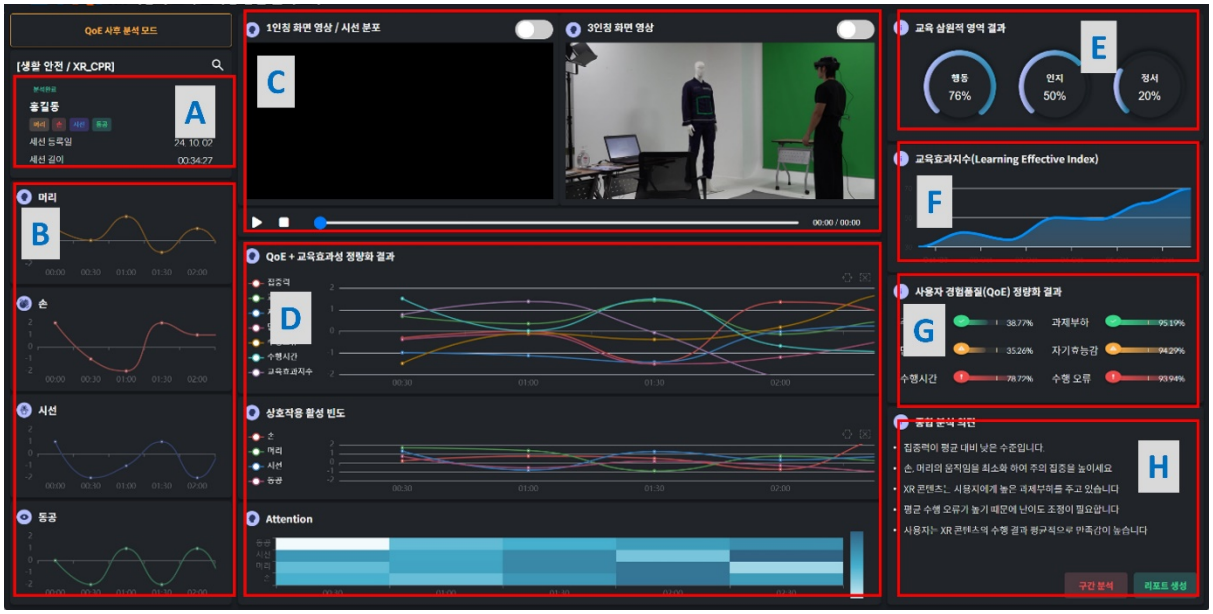

Fig. 3. Dashboard Design for Real-Time Monitoring in XR Learning Simulations.

Fig. 3 presents the design and functionality of the dashboard, highlighting its capacity to deliver real-time, comprehensive analyses of XR learning sessions. A displays user-specific information, such as session details and timestamps. B visualizes multimodal metrics, including head movement, hand positions, eye-gaze direction, and pupil size, enabling detailed tracking of user interactions. C offers playback functionality for first-person and third-person views, facilitating a direct comparison between the captured metrics and the actual performance during training. All metrics are synchronized with the corresponding training events for enhanced contextual understanding.

D provides a timeline-based visualization of QoE (Quality of Experience) metrics, allowing the observation of fluctuations over time to assess user performance throughout the training session. E quantifies scores across behavioral, cognitive, and affective domains, reflecting a pedagogical perspective. These scores are derived by combining various QoE metrics, offering insights into the user's engagement and learning progression within the training simulation. This pedagogical evaluation is further elaborated in H, which provides an overall assessment of the learner's progress. F and G present operational definitions of learning progression within the dashboard,

utilizing metrics to indicate trends and outcomes in training performance. Together, these elements exemplify the dashboard's ability to integrate multimodal data and pedagogical insights, supporting a holistic evaluation of XR-based learning effectiveness.

3 Implementation and Evaluation

3.1 Implementation

RTIMS has been fully developed, integrating data acquisition devices with a centralized processing and visualization platform. Deep learning models were trained in collected data to predict QoE and calculate the LEI. The dashboard was implemented using modern Web development frameworks, ensuring responsiveness and usability.

3.2 Evaluation

Future work will evaluate the validity of the system's performance through rigorous experiments in diverse XR-based learning scenarios. The evaluation will compare predicted QoE scores from learners. Usability testing of the dashboard will also be conducted to ensure its effectiveness in real-world educational settings.

3.3 Results and Discussion

Preliminary data analyses suggest the system effectively captures and analyzes multi-dimensional learning experience data in real-time. Planned evaluations aim to validate the QoE models' predictive accuracy and the LEI dashboard's usability. Potential improvements, such as integrating additional features or refining prediction algorithms, will be explored based on the findings to further improve the accuracy and functionality of RTIMS.

4 Implication and Future Work

This research lays the foundation for intelligent monitoring systems in XR-based learning environments. By enabling real-time insights into learners' QoE in XR-based learning, the system has the potential to revolutionize adaptive learning and instructional design. Future work will focus on evaluating the validity of the system performance, expanding the dataset to include diverse learning contexts, enhancing predictive models, and integrating real-time intervention mechanisms to personalize learning experiences further.

5 Conclusion

The development of the RTIMS for XR-Based Learning marks a significant advancement in educational technology. By leveraging deep learning and multi-modal data analysis, the system provides actionable insights into learners' experiences, enabling adaptive learning strategies and improved instructional outcomes [4]. This work paves the way for more effective and engaging XR-based educational environments, with future efforts aimed at system validation and scalability.

Acknowledgements

This work was supported by Institute of Information and communications Technology Planning and Evaluation (IITP) grant funded by the Korea government (MSIT) (No.2022-0-00137, XR User Interaction Evaluation and Employing Its Technology)

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