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

DOI: https://doi.org/10.56198/bph5bj27

Exploring Data-Driven Approaches to Visualize Learners' Engagement Profile in Immersive Gameful Experiences

Zilong Pan[1], Robson Araujo-Junior[2], Thi Tran[1], Alec Bodzin[1] and Thomas Hammond[1]

[1] Lehigh University, Bethlehem, Pennsylvania, USA
[2] Kutztown University, Kutztown, Pennsylvania, USA
zip322@lehigh.edu

Abstract. This paper presents a design approach to process, visualize, and analyze use of behavioral log data collected from the Watershed Explorers: Industrial History immersive virtual reality (VR) environment. We managed 1,142 quantitative behavioral log records generated by 18 players interacting within the environment. Time-stamped log data was extracted via REDCap and organized chronologically based on action types associated with different VR learning experience features. The raw quantitative log data was further processed into four activity categories—engagement with videos, images, glossaries, and narration—allowing for a macro-level visualization of the time spent on each activity type by all players. We demonstrate how individual players' behavioral engagement profiles can be visualized to replicate their gameplay trajectories across different elements (Narration, Photo, Video, and Glossary). These insights pave the way for future design implications, particularly in curating personalized immersive VR experiences. Implications and design considerations for future research, including aligning engagement profiles with survey data and diversifying the types of behavioral engagement log data to enrich player engagement profiles, are also discussed.

Keywords: VR, Learning Analytics, Behavioral Patterns, Engagement Profiles, Data Visualization.

1 Introduction

In the context of virtual reality (VR) immersive learning experiences such as gameful explorations, learning games, and virtual field trip, players engage with content through a variety of actions such as pointing, tapping, and selecting. Although players interact with the same environment, their engagement patterns can differ significantly based on factors such as the sequence of their actions, the time spent interacting with various game features, and the frequency of specific actions [1]. These variances highlight the complexity and individuality of user interaction within VR learning experiences.

To better understand how players interact with the content designed in VR learning experiences, commonly applied methods include surveys and interviews. However, these methods can be subjective and prone to memory lapses. To objectively analyze user behaviors across the entire immersive experience, an alternative approach is to use behavioral log data. This type of data precisely records all action players take in the environment, including the sequence, duration, and frequencies of those actions. The process of collecting, processing, analyzing, and utilizing user-generated data is known as learning analytics (LA) [2]. By leveraging LA techniques, designers can capture and analyze detailed behavioral log data as players engage with a VR headset or with a desktop VR environment. This approach enables an accurate depiction of player interactions with the content, revealing their trajectory within the environment and offering insights into their behavioral engagement.

More specifically, as players engage freely with VR content, each generates unique behavioral engagement patterns, reflecting their distinct paths of interaction. These behavioral patterns can be used to construct user gameplay engagement profiles, which provide a granular view of how individual players engage with the game [3]. Examining these profiles offers valuable insights into user experiences, such as identifying the design or game features players interact with most frequently or detecting underutilized features that may require design improvements. Moreover, as log data is collected in real-time manner, it allows designers to uncover in-situ engagement patterns by analyzing the dynamics of gameplay actions over time.

Constructing user profiles from VR experience log data enables designers to optimize game experiences and tailor them to diverse player types, improving satisfaction and retention [4]. For designers, these profiles provide a robust foundation for studying user interactions, learning outcomes, and the effectiveness of specific game mechanics, contributing to evidence-based improvements in VR systems. Additionally, understanding user profiles facilitates accessibility enhancements, ensures better alignment with target audiences, and informs iterative design processes.

Given the complexity, diversity, and volume of user-generated log data, it becomes crucial to design and develop effective methods for processing, interpreting, and visualizing this information. Data visualization, the graphical representation of data using visual elements such as charts and graphs, serves as a powerful tool for making sense of complex datasets [5]. Visualization techniques can transform intricate user log data into vivid and intuitive formats, enabling designers to quickly identify key patterns within user engagement profiles and derive actionable insights for design and development improvements.

This proposal aims to present a design approach for visualizing and analyzing user profiles in VR learning experiences. These user profiles, derived from detailed behavioral log data, encapsulate the unique engagement patterns, preferences, and interaction pathways of individual players. The proposed approach seeks to offer a mechanism that can be adapted by VR learning developers across various disciplines. By leveraging visualization techniques, this research intends to transform complex user engagement data into intuitive representations, enabling a more efficient interpretation of user profiles. This, in turn, will facilitate iterative improvements in gameful design for learning, provide tailored experiences for diverse player types, and advance the field of immersive learning interfaces through a data-driven design approach.

2 Methods

2.1 Immersive Experience

The VR immersive learning experience is called Watershed Explorers: Industrial History (WE:IH). It is a gameful exploration designed for non-formal educational contexts [6]. In this learning experience, players take on the role of an employe hired by the Delaware & Lehigh National Historical Corridor National Canal Museum (D&L) to kayak down the Lehigh River and identify locations suitable for boosting tourism in the watershed (see Fig. 1). Players explore seven sites along the river, guided by four virtual avatars, to learn about environmental challenges and the industrial history of the watershed. During the experience, players engaged with seven 360º high-resolution photospheres containing interactive elements, such as video clips, historical images, informational glossary, image gallery, and narrational texts highlighting the environmental or historical significance of the area (see Fig. 2). Players interact with these media artifacts and answer location-specific questions before progressing. After visiting all locations, players return to the D&L museum to propose their recommendation for one of the explored sites to receive enhancements aimed at promoting tourism.

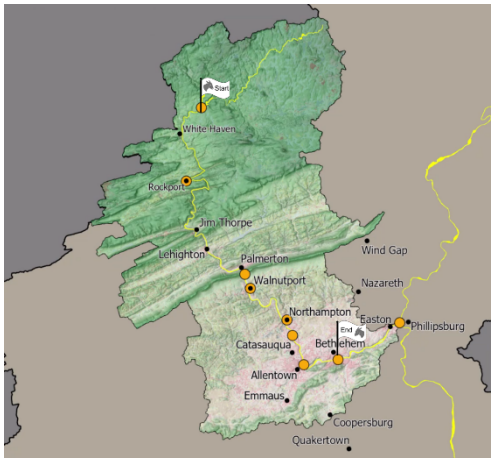

Fig. 1. Map of the kayaking route and nearby cities.

Fig. 2. An example of narration guided by virtual avatar.

2.2 Participants

A total of 18 participants engaged with the final prototype version of WE:IH at a summer expo at our institution. The researchers obtained approval from the Institutional Review Board (IRB) for Human Subjects Research, and user consent was obtained before they began the VR experiences. Among the 18 participants: 8 identified as male, 8 as female, and 2 did not provide gender information, with ages ranging from 16-80 years old (M = 38.5, SD = 22.4) completed the entire experience. The participants reported their racial and ethnic identities as follows: 10 as White, 4 as Asian, 1 as Black, and 3 did not disclose their racial or ethnic backgrounds.

2.3 Data Processing and Analysis

Participants' behavioral log data while engaging with seven different photospheres in WE:IH were collected using REDCap (Research Electronic Data Capture), a secure, web-based platform for data manipulation. We designed the experience in Unity and created a coding scheme to capture each type of player action within the experience with a corresponding timestamp. We exported the raw data (n = 1141) and processed them using python in chronological order, based on the time point at which each action was conducted. As indicated in Table 1, the Player ID column represents each individual participating player, while the Action ID indicates each unique action performed by all players. The Action Type column describes the purpose of the actions. For example, the action type labeled "Continue on Narration" indicates players used the raycast to interact with the "continue" button in the photosphere to proceed with the narration. The Timestamp column captures the exact time each action was performed, accurate to the second. Finally, the Photosphere column identifies the specific photosphere with which the player was interacting during that action.

Table 1. Example of the behavioral log data collected.

Player ID	Action ID	Action Type	Timestamp	Photosphere
1	1	Continue on narration	2:21:13 PM	Francis E. Walter
1	2	Continue on narration	2:21:20 PM	Francis E. Walter
1	3	Exit narration	2:21:33 PM	Francis E. Walter
1	6	Open the video	2:21:48 PM	Francis E. Walter
1	7	Exit the video	2:21:59 PM	Francis E. Walter
1	8	Open the photo	2:22:01 PM	Francis E. Walter
1	9	Exit the photo	2:22:06 PM	Francis E. Walter
1	10	Continue on narration	2:22:32 PM	Rockport
1	11	Continue on narration	2:22:35 PM	Rockport

As indicated in Table 1, after compiling the time information, we were able to extract aggregated data, such as the average time all players spent on each photosphere for further analysis. For instance, the distribution of time

spent on different actions (Narration, Photo, Video, and Glossary) by users in WE:IH (see Fig. 3). Despite all players having access to the same environment, their engagement patterns differ significantly. For instance, some players, such as player 3 and player 21, dedicated substantial time to the Glossary, while others, like player 2 and player 12, focused more on Narration. The duration spent on actions such as viewing Photos and Videos also varied, indicating diverse interaction preferences and approaches to engaging with the available resources. This variability underscores the importance of understanding different players' behavioral engagement patterns and preferences in WE:IH in informing future design and development.

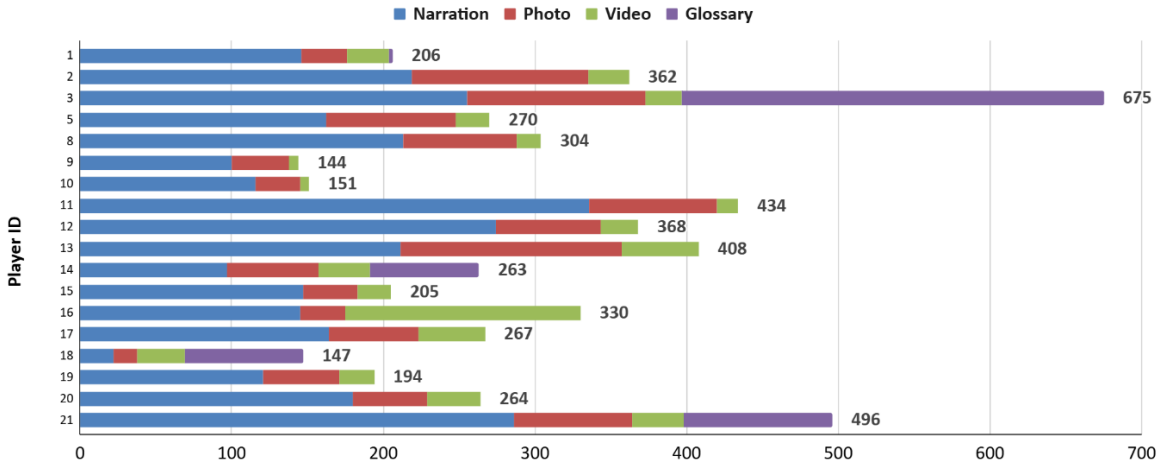

Fig.3. Aggregated time spent on each action type for all players.

However, although the aggregated time spent visualization provides a macro perspective on engagement, it is limited in capturing how individuals progress through different actions. A more nuanced approach is needed to visualize the sequential patterns of how individual players interact with various activities within the immersive VR environment. The processed behavioral logs enable both designers and researchers to visualize each individual's personalized gameplay trajectory or interaction profile.

Therefore, Figures 4 and 5 were created to provide an example for demonstrating how individual players' sequential patterns could be traced and visualized for gaining a better understanding of their chronological engagement profile. These two visualizations represent the sequential patterns of two users engaging with the WE:IH environment, highlighting their distinct approaches to interacting with various features such as Narration, Video, Photo, and Glossary. In the first graph (see Fig. 4), the user exhibits a balanced interaction, with shorter yet frequent shifts between narration, video, and photo, indicating a more exploratory behavior with rapid transitions between activities. Notably, this user did not engage with the glossary feature. In contrast, the second graph (see Fig. 5) reveals a more structured interaction pattern, characterized by periods of narration interspersed with occasional engagement in videos, photos, and the glossary. This user demonstrates longer attention spans on specific activities, such as narration and glossary, suggesting a more focused and deliberate approach to using the environment.

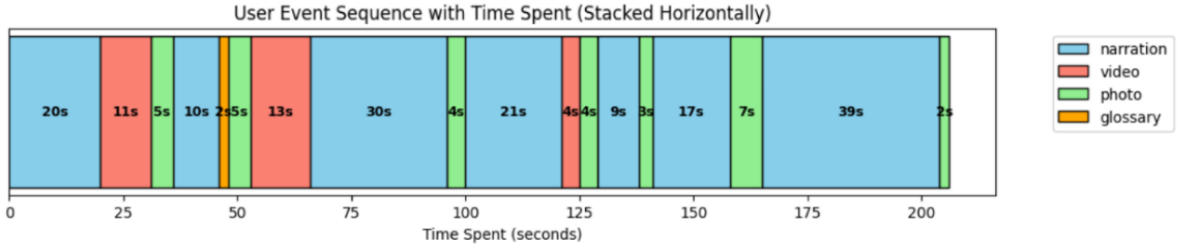

Fig.4. Behavioral engagement profile for Player 1.

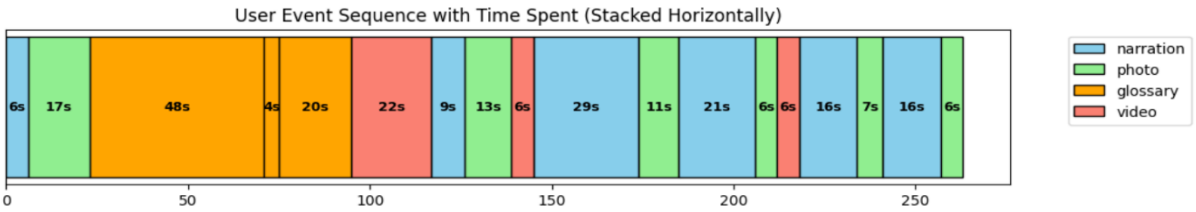

Fig.5. Behavioral engagement profile for Player 14.

These visualizations effectively demonstrate how sequential patterns capture user behaviors in a VR environment, offering valuable insights into their behavioral engagement profiles. By analyzing these patterns, we can uncover not only the duration of interactions but also the flow of engagement across various features. This type of analysis serves as a powerful tool for understanding user interactions in immersive environments, providing critical data for evaluating and refining immersive learning designs.

3 Discussion and Implications

This iLEAD paper extends prior practices on learning analytics to the realm of immersive VR learning environments. By introducing a data-driven approach to immersive learning experiences, this paper demonstrates the feasibility of collecting and analyzing behavioral log data from VR headsets and visualizing engagement profiles for different players. One contribution of this paper is the exploration of sequential patterns in user engagement behavior, such as how participants interact with specific design features and activities, the time they spend on each, and the sequence in which tasks are completed. For example, those who engage in iterative pattern and refinement (i.e., returning to the same task multiple times) are likely benefiting from deliberate practice guided by feedback and reflection. On the other hand, players who engage in rapid experimentation with various tasks in the environment may demonstrate an adaptive inquiry profile, which might benefit from dynamic challenge adjustments and embedded hints that support adaptive learning.

Moreover, these insights can be enhanced by integrating demographic and survey data to provide a more comprehensive view of user engagement. For example, combining demographic data, such as age and prior experience, can reveal how different user groups interact with an immersive VR learning experience. This was particularly important since approximately 25% of the users were 60-80 years old and over 90% were first-time headset users. Such data highlights opportunities to design experiences that cater to both novice users and older adults, ensuring inclusivity and accessibility for lifelong learning.

Furthermore, incorporating additional embedded survey data collection in an immersive VR learning experience further enriches the analysis by capturing user-specific characteristics, such as prior game experience and digital literacy. These factors can be aligned with engagement data to uncover associations that inform design improvements. Moreover, understanding differences in play patterns across diverse player characteristics allows for the development of tailored onboarding processes (e.g., tutorials and modeling immersive interactions) to enhance the overall user experience.

Future design efforts for research should consider diversifying data collection to include metrics such as head tracking or spatial movements. These additions will not only enrich player profiles but also provide deeper insights into how users interact with VR environments, ultimately informing the development of more personalized and effective VR experiences. However, as data collection expands, ethical considerations such as user privacy, informed consent, and data security must be addressed. By combining behavioral analytics, demographic information, and diverse data types, future practices could further inform the design and development of engaging and inclusive immersive VR environments that are tailored to meet the needs of a wide and diverse range of users.

Acknowledgements

We thank Nathan Lerro who developed the REDCap API for this project.

References

1. Christopoulos, A., Pellas, N., Laakso, M. J.: A learning analytics theoretical framework for STEM education virtual reality applications. Education Sciences 10(11), (2020).

2. Lang, C., Siemens, G., Wise, A., Gasevic, D. (eds.): Handbook of Learning Analytics. SOLAR, Society for Learning Analytics and Research, New York (2017).
3. Pengnate, S., Riggins, F. J., Zhang, L.: Understanding users' engagement and responses in 3D virtual reality: The influence of presence on user value. Interacting with Computers 32(2), 103–117 (2020).
4. Tricomi, P. P., Nenna, F., Pajola, L., Conti, M., Gamberini, L.: You can't hide behind your headset: User profiling in augmented and virtual reality. IEEE Access 11, 9859–9875 (2023). https://doi.org/10.1109/ACCESS.2023.3240071
5. Börner, K., Bueckle, A., Ginda, M.: Data visualization literacy: Definitions, conceptual frameworks, exercises, and assessments. Proceedings of the National Academy of Sciences 116(6), 1857–1864 (2019).
6. Bodzin, A., Araujo-Junior, R., Hammond, T., Pan, Z., Anastasio, D., Burd, J., Jhaveri, K., Le, Q.: Designing for headset VR from a longer desktop VR learning experience: Watershed Explorers: Industrial History. In: MacDowell, P., Moon, J., Wilson, D., Pedrosa, D., Beck, D., Bourguet, M.L., Dengel, A., Ghannam, R., Miller, A., Peña-Rios, A., Richter, J. (eds.) Immersive Learning Research Network. Practitioner Proceedings of 10th International Conference, iLRN 2024, pp. 52–55. Immersive Learning Research Network, Glasgow (2024). https://doi.org/10.56198/5M1RHFWF0