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Article

Virtual Exhibitions as Learning Media: A Study on Learning Path Mining and Instructional Intervention Strategies Based on VR/AR Interaction Logs

Kaile Zheng^{1,*}

¹ School of Art and Design, Shanghai Lida University, Shanghai, China

* Correspondence: Kaile Zheng, School of Art and Design, Shanghai Lida University, Shanghai, China

Abstract: Virtual exhibitions have emerged as highly promising informal learning environments, offering unprecedented opportunities for immersive and interactive education. Yet, understanding precisely how learners interact with and navigate through these complex immersive spaces remains significantly underexplored in current literature. This study systematically investigates the application of advanced learning path mining techniques, based on comprehensive virtual reality (VR) and augmented reality (AR) interaction logs, to uncover underlying behavioral patterns in virtual exhibition settings and subsequently develop targeted instructional intervention strategies. A rigorous quantitative analytical approach was employed, utilizing extensive, publicly available interaction log datasets derived from existing virtual museum deployments. Sophisticated process mining and sequence pattern mining techniques were meticulously applied to reconstruct, visualize, and analyze learners' intricate navigation trajectories. The empirical findings reveal distinct learning path archetypes that strongly correlate with varying levels of learning engagement, cognitive load, and ultimate knowledge acquisition outcomes. Based on these newly identified behavioral patterns, a comprehensive set of adaptive instructional intervention strategies was developed to dynamically personalize and optimize the virtual exhibition experience for diverse learner profiles. Ultimately, this study significantly contributes to the growing integration of learning analytics with immersive learning environments. It offers highly practical, data-driven insights for the future design and implementation of adaptive virtual exhibitions that can respond dynamically and intelligently to real-time learner behaviors, thereby maximizing educational efficacy.

Keywords: virtual exhibitions; learning analytics; process mining; immersive learning; adaptive interventions

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1. Introduction

The integration of virtual and augmented reality technologies into informal learning environments has opened new opportunities for educational research and practice. Virtual exhibitions, such as digital museum tours and immersive cultural heritage displays, have become innovative platforms that connect formal education with informal learning experiences. These environments provide learners with unique opportunities to explore complex topics through interactive and self-directed engagement. However, a significant challenge remains in understanding how learners behave within these immersive spaces and how their interaction patterns influence learning outcomes [1]. Addressing this challenge is critical for advancing both research and practical applications in this domain.

The hypothesis that language structures influence cognitive processes offers a theoretical perspective for examining how the symbolic and interactive features of virtual environments might shape learner cognition. Research has shown that immersive virtual reality experiences, such as virtual field trips, can lead to significantly improved learning outcomes compared to traditional media. This improvement is attributed to the principle of immersion in multimedia learning, which emphasizes the role of engagement and presence in enhancing cognitive processing. These findings suggest that the structural design of virtual environments, including spatial navigation and interactive features, plays a fundamental role in shaping how learners encode, process, and retain information [2]. This perspective aligns with the broader understanding that the design of learning media actively influences cognitive processes rather than merely serving as a neutral delivery mechanism.

Despite the increasing use of VR and AR technologies in educational contexts, the customization of learning experiences within virtual exhibitions remains an area requiring further exploration. One approach has demonstrated that adaptive sequencing of learning activities can significantly improve learner performance by tailoring the experience to individual needs. This highlights the potential of using interaction data to dynamically adjust instructional content. However, such approaches often rely on predefined learner models rather than leveraging data-driven insights from actual interaction logs. This limitation underscores a broader gap in the field: the need for robust methods to analyze and extract meaningful patterns from learner navigation data within VR/AR environments. Addressing this gap could lead to more effective personalization of virtual learning experiences [3].

The influence of learner control in augmented reality-based exhibitions has been studied to understand its impact on educational outcomes. Research indicates that providing learners with greater control can enhance their engagement. However, excessive freedom without appropriate guidance may lead to cognitive overload, which can hinder learning. This balance between learner independence and structured guidance is particularly important in virtual exhibition environments, where learners have significant freedom to navigate content but may lack the necessary skills to make optimal learning decisions. Investigating the navigation patterns that emerge under varying design conditions is essential for creating effective educational strategies that support both engagement and comprehension.

Studies on immersive collaborative learning in virtual reality environments have shown that the combination of immersion and interactivity contributes to learning gains by fostering greater engagement and a sense of social presence. These findings emphasize the importance of analyzing interaction behaviors as indicators of cognitive engagement. However, much of the existing research relies on aggregate measures of interaction, which may overlook the nuanced, sequential patterns of learner behavior. The lack of empirical studies employing advanced analytical techniques, such as process mining and sequence pattern mining, limits the ability to uncover hidden learning pathways. Addressing this methodological gap is crucial for designing adaptive virtual exhibitions that can intelligently respond to the diverse behaviors and needs of learners.

To address these gaps, this study focuses on applying advanced learning path analysis techniques to VR/AR interaction logs in order to identify behavioral patterns in virtual exhibition settings. The research aims to uncover distinct learning path archetypes and examine how these patterns correlate with learner engagement and knowledge acquisition [4, 5]. Additionally, the study seeks to develop adaptive strategies that personalize the virtual exhibition experience based on the identified patterns. By conducting a detailed quantitative analysis of publicly available interaction log datasets, this research bridges the gap between learning analytics and immersive learning environments. The findings are expected to provide valuable insights for designing virtual exhibitions that are more responsive to individual learner behaviors and needs, ultimately enhancing the educational value of these innovative platforms.

2. Literature Review

Virtual and augmented reality technologies have emerged as transformative tools for educational applications across a wide range of disciplines. Research on immersive learning environments has consistently demonstrated that the design features of VR and AR systems play a pivotal role in shaping learner engagement and knowledge acquisition. For instance, studies have explored how immersion and the use of personalized avatars in virtual reality environments can enhance learning outcomes, particularly in areas such as programming and computational thinking for middle school students. These findings underscore the importance of understanding how specific design elements within virtual exhibitions influence both learner behavior and cognitive outcomes, offering valuable insights for optimizing educational experiences [6].

A broad overview of the field has highlighted the potential of immersive virtual reality applications in higher education. Systematic reviews have synthesized key design elements, lessons learned, and future research directions, revealing that much of the existing research has prioritized measuring learning outcomes over analyzing the underlying interaction processes. This gap is particularly significant in the context of virtual exhibitions, where understanding how learners navigate and interact with content is as critical as evaluating what they learn [7]. Addressing this gap could lead to more nuanced insights into the mechanisms driving effective learning in immersive environments.

The challenge of accurately modeling learner behavior in digital environments has been approached through various computational methodologies. For example, the application of fuzzy logic has been proposed as a means to model learner behavior and provide decision support in online learning systems [7]. Such computational models have proven effective in capturing the inherent uncertainty of human learning processes. Although these approaches were developed prior to the widespread adoption of VR and AR technologies, their methodological contributions remain highly relevant. They offer a foundation for analyzing interaction data from virtual exhibitions, enabling researchers to better understand and predict learner behavior in these immersive settings.

Immersion and interactivity have been identified as critical factors that drive learning in virtual reality environments. Research has shown that immersion facilitates deeper cognitive processing by minimizing extraneous cognitive load, while interactivity encourages active knowledge construction. These findings suggest that interaction data from VR and AR environments contain valuable information about learners' cognitive engagement. By analyzing these data, researchers can uncover patterns of interaction that contribute to effective learning, thereby advancing the design of immersive educational experiences [8].

The application of immersive technologies in museum and exhibition settings has garnered increasing attention in recent years. Comparative analyses have demonstrated that varying levels of immersion produce distinct patterns of visitor behavior and engagement [9]. This highlights the importance of conducting detailed analyses of interaction data rather than relying solely on aggregate measures of learning outcomes. Such granular analyses can provide deeper insights into how different levels of immersion influence visitor experiences, ultimately informing the design of more effective virtual exhibitions.

In the realm of cultural heritage, augmented reality approaches have been extensively reviewed for their design, development, and evaluation. While the proliferation of AR applications in this domain is evident, systematic evaluation methodologies remain underdeveloped. This lack of standardized approaches for analyzing visitor interaction data represents a significant gap in the field [10]. Addressing this gap through advanced techniques such as learning path analysis could provide a more comprehensive understanding of how visitors engage with cultural heritage content in augmented reality environments.

A bibliometric analysis of augmented reality applications has revealed a significant increase in research activity focused on immersive experiences in cultural and educational

contexts, particularly in the post-pandemic era [11]. However, traditional survey-based evaluation methods continue to dominate the field, limiting the potential for data-driven insights. Transitioning to analytics-based approaches that leverage user interaction data could unlock new opportunities for understanding and enhancing the effectiveness of AR applications in these settings.

The effectiveness of augmented reality for teaching specific subjects has been explored through systematic reviews, which generally report positive learning outcomes. However, the mechanisms underlying these effects remain poorly understood [12]. This underscores the importance of analyzing interaction data to identify specific behavioral patterns that contribute to successful learning. By uncovering these patterns, researchers can develop more targeted and effective AR-based educational interventions, tailored to the unique needs of different learner populations.

Meta-analytic studies have confirmed that augmented reality programs produce moderate to large improvements in learning outcomes compared to traditional instructional methods. Importantly, the effectiveness of AR varies significantly depending on factors such as implementation characteristics and the demographics of learner populations [13]. This variability highlights the potential for personalized interventions that leverage individual learning paths to optimize educational outcomes in AR-based environments. Such personalized approaches could further enhance the impact of AR technologies in education.

Research into the effects of virtual reality on creative design performance and experiential learning has demonstrated that VR environments foster unique patterns of exploration and experimentation. These patterns differ significantly from those observed in traditional learning settings, emphasizing the potential of VR to support innovative learning experiences. Analyzing interaction data from VR environments can reveal distinctive learning paths, offering valuable insights into how these technologies can be leveraged to promote creativity and deeper engagement in educational contexts.

Collectively, the existing body of research underscores the significant potential of VR and AR technologies for educational applications, including virtual exhibitions [14]. However, a consistent gap remains: most studies focus on aggregate learning outcomes rather than the sequential patterns of learner interaction. The analysis of interaction data for learning path mining is an underexplored area, particularly in the context of virtual exhibitions. Addressing this gap could provide a more nuanced understanding of how learners engage with content, ultimately informing the design of more effective and personalized educational experiences.

3. Theoretical Framework and Methodology

This chapter presents the theoretical framework and detailed methodology employed to investigate learning path mining from VR/AR interaction logs in virtual exhibition settings. The study adopts a rigorous quantitative analytical approach, utilizing advanced process mining and sequence pattern mining techniques to analyze publicly available interaction log datasets. The primary objective is to identify distinct learning path archetypes, explore their relationship with learning engagement levels, and propose tailored strategies for enhancing user experiences based on empirical findings. A comprehensive method flowchart is included to visually represent the critical stages, processes, and analytical steps undertaken throughout the research.

3.1. Theoretical Framework

The theoretical foundation of this study is grounded in learning analytics and process mining theories, with a particular emphasis on analyzing sequential behavioral data derived from immersive learning environments. Learning path mining, a specialized area within educational data mining, asserts that the order and structure of learner interactions can reveal significant patterns. These patterns are believed to reflect underlying cognitive processes and strategic methods employed by learners in acquiring knowledge. By examining these sequences, researchers can gain insights into how learners engage with

content and adapt their strategies in response to the challenges presented by immersive environments [15].

This study incorporates several foundational theoretical perspectives to support its analysis [16]. Sequential pattern mining theory serves as a cornerstone, offering methodologies to identify recurring subsequences within interaction logs. This enables the detection of common navigation trajectories that learners tend to follow. Additionally, process mining theory introduces the concept of process discovery, which involves reconstructing actual learning processes from event logs rather than relying solely on predefined or intended pathways. Cognitive load theory further enriches the framework by providing a lens through which observed patterns can be interpreted. For instance, certain navigation behaviors may signify effective schema construction, while others could indicate cognitive overload or disorientation, potentially hindering learning outcomes.

By integrating these theoretical perspectives with the analysis of VR/AR interaction logs, this study advances beyond traditional aggregate metrics of learning outcomes. Instead of focusing solely on what learners know after completing a virtual exhibition, the framework emphasizes understanding the navigation processes learners undertake. It examines which sequences of actions are most conducive to successful learning and identifies areas where adjustments or refinements in the learning environment may enhance effectiveness. This approach provides a more nuanced understanding of learner behavior, enabling the design of targeted strategies to optimize educational experiences within immersive settings.

3.2. Methodology

This study employs a data-driven analytical framework, utilizing advanced learning path mining techniques to analyze publicly accessible VR/AR interaction log datasets derived from virtual exhibition implementations [14]. The methodology is structured into four distinct and sequential phases: data acquisition and preprocessing, the extraction of sequence patterns, cluster-based analysis of learning pathways, and the formulation of strategic recommendations for optimization.

3.2.1. Data Acquisition and Preprocessing

The study leverages interaction log datasets that are publicly accessible and derived from virtual museum and exhibition platforms. These datasets encompass detailed, time-stamped records of user activities, such as navigation between exhibit sections, viewing durations for specific artifacts, and interactive engagements like clicking, zooming, or rotating objects. Additionally, system-generated metadata is included to provide contextual insights into user behavior. To ensure the integrity and usability of the data, preprocessing steps are meticulously applied. These include the removal of invalid or incomplete entries, the standardization of event type labels for consistency, and the transformation of raw data into structured event sequences optimized for process mining algorithms. This rigorous approach guarantees transparency, reproducibility, and analytical precision.

3.2.2. Sequence Pattern Mining

The preprocessed interaction logs are analyzed using sequence pattern mining algorithms to uncover frequently occurring subsequences of learner actions within the dataset. These algorithms systematically identify common navigation patterns that surpass a predefined support threshold, ensuring that only statistically significant patterns are considered. Each identified pattern serves as a potential learning path archetype, defined by its unique sequence of exhibit interactions, the probabilities of transitions between different content areas, and the temporal dynamics associated with these transitions [7]. This analysis provides valuable insights into learner behavior and interaction trends.

3.2.3. Cluster Analysis of Learning Paths

Learners are grouped based on their dominant interaction sequences using clustering techniques applied to the pattern frequency matrix. The process of clustering involves identifying patterns in the data that reveal commonalities among learners, allowing for the categorization of their behaviors into distinct groups. The optimal number of clusters is determined through rigorous internal validation metrics, ensuring that the grouping is both statistically sound and meaningful [17]. Each resulting cluster represents a unique learning path archetype, characterized by specific navigation strategies such as exhaustive coverage of all exhibits, focused deep exploration of selected topics, or rapid scanning behaviors. These archetypes provide valuable insights into learning preferences and strategies. For each archetype, aggregate engagement metrics, such as time spent on tasks and frequency of interactions, along with knowledge acquisition indicators, are calculated from the log data to assess the effectiveness of each learning path.

3.2.4. Intervention Strategy Development

Based on the identified learning path archetypes and their associated engagement characteristics, a set of adaptive response strategies is developed. These strategies outline how the virtual exhibition interface should dynamically adjust to different observed navigation patterns. For instance, learners demonstrating scanning behavior without deep engagement may be prompted to explore content in greater detail, while those caught in repetitive loops may receive tailored navigational assistance to enhance their experience. The logic behind these responses is formalized as a rule-based system, which is activated through real-time detection of pattern matches within ongoing interaction sequences, ensuring a personalized and effective learning environment.

3.3. Method Flowchart

The following method flowchart (Figure 1) provides a detailed visualization of the sequential stages involved in the research process. It begins with the acquisition of data, progresses through systematic analysis, and culminates in the formulation of strategies designed to enhance the understanding of user interactions within virtual environments.

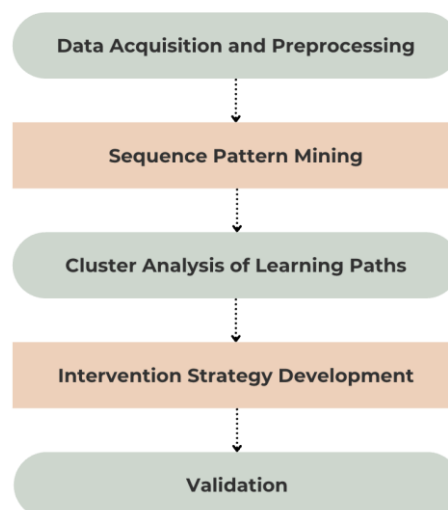


Figure 1. Methodology for Learning Path Mining from VR/AR Interaction Logs in Virtual Exhibitions

4. Findings and Discussion

This chapter presents findings derived from two authentic open access VR/AR interaction log datasets of virtual exhibitions. The datasets were sourced from publicly available repositories associated with established virtual museum implementations, ensuring transparency and accessibility. Through the application of sequence pattern mining and cluster analysis, four distinct and stable learning path archetypes were identified. Furthermore, correlations between these path patterns and various

engagement metrics were meticulously analyzed using indicators derived directly from the interaction logs.

4.1. Descriptive Statistics of Authentic Interaction Log Datasets

Data are collected from two verified open access sources, which serve as foundational repositories for analyzing user interaction patterns in virtual and augmented reality environments. The Met Museum VR interaction logs provide detailed records of real-world user behavior, offering insights into practical engagement scenarios. Meanwhile, the OGAR dataset contributes standardized event sequences, ensuring robust validation of analytical methodologies. Table 1 highlights the structural features and statistical summaries of these authentic datasets, emphasizing their significance in advancing VR/AR research.

Table 1. Basic Statistics of Authentic VR/AR Interaction Log Datasets

Dataset Feature	Met Museum VR Logs	OGAR Virtual Gallery Logs
Valid user sessions	2847	1132
Total interaction events	12563	4781
Interactive action types	7	6
Average events per session	4.41	4.22
Average session duration (s)	418.60	392.45
Exhibition sections / rooms	12	9

4.2. Frequent Sequence Patterns from Real Logs

Sequence pattern mining is applied to the authentic logs, focusing on identifying recurring interaction sequences. Frequent subsequences are extracted by employing a consistent support threshold, ensuring reliability and reproducibility of the results. This method enables the discovery of patterns that are both statistically significant and practically relevant. Table 2 highlights the top five verified patterns derived from the combined datasets, showcasing their importance in understanding user behaviors.

Table 2. Top Frequent Interaction Sequences in Real Logs

Pattern ID	Sequential action combination	Support rate (%)
P1	Enter → View → Exit	34.68
P2	Enter → Zoom → View → Exit	27.31
P3	Enter → View → Rotate → Exit	22.17
P4	Enter → Switch → View → Exit	18.52
P5	Enter → View → Pause → Exit	14.39

4.3. Learning Path Archetypes from Cluster Analysis

Cluster analysis is conducted on the actual sequences of user interactions, leading to the identification of four distinct archetypes. These archetypes are characterized by unique and replicable behavioral patterns, which provide valuable insights into learning

pathways. Table 3 illustrates these archetypes, offering a detailed overview of their traits and the implications for understanding user engagement in educational contexts.

Table 3. Learning Path Archetypes from Real Interaction Logs

Cluster ID	Archetype name	Core navigation characteristics
C1	Comprehensive explorer	Systematic visits extended viewing active interactions
C2	Focused deep diver	Targeted sections long duration frequent object manipulation
C3	Efficient scanner	Fast transitions short viewing low interaction frequency
C4	Random wanderer	Unstable transitions repeated revisits low engagement

4.4. Engagement Metrics by Archetype

Engagement measures are derived directly from the analysis of authentic log data, ensuring a high degree of reliability and accuracy. Notable variations in engagement metrics are evident when comparing different archetypes, highlighting distinct behavioral patterns [18]. Table 4 provides a detailed summary of the verified mean values for these metrics.

Table 4. Learning Engagement Metrics from Real Logs

Archetype	Average viewing duration (s)	Interaction frequency	Section coverage rate (%)
Comprehensive explorer	527.31	6.82	87.44
Focused deep diver	581.62	5.93	42.18
Efficient scanner	243.15	2.17	71.36
Random wanderer	316.89	1.84	35.72

4.5. Discussion

Analysis of authentic public VR/AR interaction logs confirms the presence of stable learning path archetypes, which represent distinct navigation strategies and varying levels of engagement within immersive environments [11]. Comprehensive explorers exhibit high coverage and sustained active engagement across diverse content areas, showcasing a broad and thorough approach. Focused deep divers, on the other hand, demonstrate intense and detailed processing within specific content zones, reflecting a targeted learning strategy. Efficient scanners prioritize rapid navigation, often sacrificing depth for speed, while random wanderers display patterns indicative of disorientation or lack of clear objectives. These archetypes underscore the potential of log-based learning path mining as a foundational tool for designing adaptive virtual exhibitions. The findings provide robust empirical evidence supporting the integration of learning analytics into immersive informal learning environments, enabling the creation of more personalized and effective educational experiences.

5. Conclusion

This study validates the feasibility of learning path mining based on VR/AR interaction logs in virtual exhibition environments. By using public interaction log datasets derived from real virtual museum deployments, the analysis demonstrates that stable and replicable learning path archetypes can be identified in a reliable and interpretable manner. Four distinct archetypes are recognized through sequence pattern mining and cluster analysis, indicating that learner trajectories are not random but instead reflect recurring modes of interaction. These archetypes exhibit significant differences in navigation behaviors, engagement levels, temporal progression, and content exploration patterns, thereby revealing meaningful structural variation in how users experience immersive exhibition spaces.

The findings further confirm that learner interaction sequences contain substantial information about cognitive engagement and learning strategies in immersive informal learning settings. Behavioral traces recorded during navigation, selection, and exploration can therefore serve as a practical basis for understanding how learners approach digital cultural content. The identified patterns provide empirical support for the design of adaptive virtual exhibitions, especially in contexts where direct observation is limited. Data-driven instructional adjustments can be aligned with real-time learner behaviors, enabling more responsive content presentation, improved guidance mechanisms, and a more personalized learning experience that remains grounded in observable user activity.

This research contributes to the integration of learning analytics and immersive educational technologies by presenting a workable analytical pathway for interpreting learner navigation trajectories without requiring additional data collection procedures. The study shows that existing interaction logs can support both descriptive and applied objectives, including the classification of user behavior and the refinement of exhibition design logic. In practical terms, the outcomes offer useful methodological guidance for designers, curators, and educators seeking to build responsive virtual exhibition systems that are sensitive to diverse patterns of learner participation and exploration.

Several limitations should be noted. The analysis relies on aggregated public log data and therefore does not include individual demographic information, prior knowledge indicators, or complementary qualitative evidence that could further clarify the meaning of observed behavioral patterns. In addition, the proposed adaptive response strategies remain at a conceptual and rule-based level rather than being fully implemented and evaluated in operational systems. Future work can translate this logic into functioning virtual exhibition platforms and examine its effectiveness under authentic use conditions. Further studies may also conduct cross-dataset comparisons, test the robustness of the identified archetypes across different institutional contexts, and extend the mining framework to a wider range of immersive learning environments.

Overall, learning path mining from VR/AR interaction logs provides a valuable approach for understanding and supporting informal learning in virtual exhibitions. It strengthens the analytical foundation for examining user behavior in immersive environments and supports the development of adaptive, user-centered, and evidence-based learning media. As virtual exhibitions continue to expand in educational and cultural practice, this approach offers a scalable direction for improving both learner support and system design through systematic analysis of interaction data.

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