A Systematic Review of Learning Analytics in Immersive Virtual Reality: Trends, Challenges, and Implications

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Abstract
Immersive virtual reality (immersive VR) has emerged as a transformative platform in education, offering unique opportunities to leverage multimodal data for learning analytics (LA). This paper examines the application of multimodal learning analytics (MMLA) within immersive VR environments, analysing 11 peer-reviewed studies published between 2013 and 2024. Immersive VR's affordances, such as real-time interaction tracking, eye-tracking, and physiological sensors, enable detailed insights into learners' behavioural, affective, and cognitive dimensions. However, these capabilities also present challenges, including the integration and interpretation of complex multimodal data, privacy concerns. By focusing exclusively on immersive VR, this study identifies key gaps in the current literature and outlines future directions for advancing MMLA in immersive educational contexts. These findings highlight immersive VR's potential to support personalised and collaborative learning while addressing its unique challenges.

Keywords
learning analytics, immersive virtual reality, systematic review

1. Introduction

Learning analytics (LA), defined as the measurement, collection, analysis, and reporting of data about learners and their contexts (Siemens & Long, 2011), has increasingly informed instructional design and student support interventions in diverse educational settings. Traditionally, LA has been applied in online learning environments to detect at-risk students, provide personalised feedback, and enhance pedagogical practices (Foster & Siddle, 2020; Mai et al., 2022; Topali et al., 2023). These applications highlight LA's potential to improve decision-making and learning outcomes through data-driven insights.

With the rise of immersive virtual reality (VR) technologies, learning environments have become more dynamic and interactive, enabling richer multimodal data collection and heightened learner engagement. Immersive VR integrates behavioural, affective, and cognitive dimensions through technologies such as eye tracking, physiological sensors, and real-time interaction tracking (Shadiev & Li, 2023; Halbig & Latoschik, 2021). These affordances present unique opportunities for multimodal learning analytics (MMLA), which extends traditional LA by incorporating diverse data streams to provide a comprehensive understanding of learners' experiences. Unlike desktop or mobile VR, immersive VR offers a higher degree of immersion, enabling researchers to explore complex learning processes, such as cognitive load, metacognition, and collaborative problem solving, with greater granularity (Hwang & Chien, 2022).

However, immersive VR also introduces significant challenges. The integration and interpretation of multimodal data are technically complex, requiring innovative computational approaches and interdisciplinary collaboration (Iop et al., 2022; Nair et al., 2023). Privacy concerns are particularly pronounced in VR environments, as rich sensory data, such as head and hand motion, can uniquely identify individual users, raising ethical and security issues (Carter & Egliston, 2023; Nair et al., 2023).

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Additionally, the lack of robust theoretical frameworks for guiding research and practice limits the potential of immersive VR in educational settings (Sakr & Abdullah, 2024).

Despite these challenges, immersive VR holds significant promise for educational innovation. The recent expansion of VR technologies, coupled with decreasing hardware costs (Goswami, 2023), has made immersive learning more accessible to educators and students. Emerging frameworks, such as the metaverse, further underscore the transformative potential of immersive VR in creating interactive, collaborative, and personalised learning experiences (Dwivedi et al., 2022; Hwang & Chien, 2022). As the field advances, it becomes increasingly important to understand the specific affordances and barriers associated with immersive VR to maximize its impact on multimodal learning analytics.

This paper focuses exclusively on immersive VR, analysing 11 empirical studies published between 2013 and 2024 to identify its unique affordances, challenges, and opportunities for MMLA. By highlighting the specific role of immersive VR in education, this study aims to provide targeted insights and recommendations for leveraging its potential in multimodal analytics and advancing future research in immersive learning contexts.

2. Methods

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021) to ensure methodological rigor and transparency. This paper focuses specifically on immersive VR. Specifically, we sought to address the following research questions:

1. What are the primary research purposes of LA studies in immersive VR environments?
2. What types of data and analysis techniques are used in immersive VR for LA?
3. What challenges are documented in applying LA to immersive VR environments?

2.1. Search and selection of studies

We conducted a comprehensive search across five databases—ACM Digital Library, Scopus, Web of Science, the Journal of Learning Analytics, and ERIC—due to their broad coverage of educational technology and LA research. The search terms combined "learning analytics" with keywords reflecting various VLE technologies, such as "virtual reality", "3D learning environment", "mixed reality", "VR", and "metaverse". To align with the focus of this paper, we specifically analysed studies dealing with immersive VR environments.

The initial search yielded 839 records. After removing duplicates, 536 unique publications remained for title and abstract screening. Studies were excluded if they did not focus on immersive VR or the use of LA in these environments. A full-text review of 108 articles was conducted against the following inclusion criteria:

1. The study investigated LA in an immersive VR environment (e.g., head-mounted displays).
2. It presented empirical data (e.g., learner interaction logs, multimodal data).
3. It addressed learning processes, outcomes, or behaviours specific to immersive VR settings.

From the broader pool of studies on VLEs, 11 studies met these specific criteria and were included in this analysis. Figure 1 illustrates the identification, screening, and inclusion process in detail.

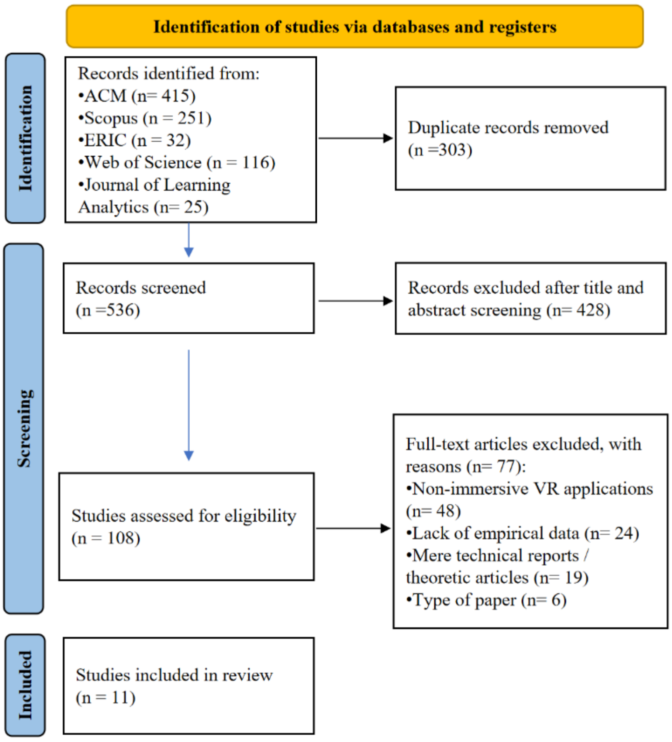

Figure 1: Literature searching and screening process.

2.2. Data extraction and coding

Two authors collaboratively developed a coding scheme tailored to address the research questions. The coding framework was adapted from the broader systematic review but refined to focus on the unique characteristics of immersive VR. To ensure consistency, an initial subset of the 11 studies was independently coded by both researchers, achieving a Cohen's kappa of 0.85, indicating strong inter-rater reliability. Any discrepancies were resolved through discussion to refine the coding scheme.

The final coding framework included categories such as research purposes, theoretical frameworks, data types (e.g., eye-tracking data, physiological signals, interaction logs), analysis techniques, and documented challenges (e.g., privacy concerns, technical complexity). The synthesized data were used to identify key patterns, trends, and gaps in the literature on LA in immersive VR.

3. Results and discussion

The reviewed studies included 6 journal articles and 5 conference papers, reflecting a balanced contribution from both types of publications. Conference papers (45.5%) were primarily presented at prominent venues such as the International Learning Analytics and Knowledge Conference (LAK), known for advancing the understanding of learning analytics, and the IEEE International Conference on Serious Games and Applications for Health, which emphasizes innovative applications of game-based learning. Journal articles were published in diverse outlets, including Applied Sciences (Switzerland) and the Journal of Computer Assisted Learning (JCAL), showcasing the interdisciplinary and practical applications of LA research in immersive VR.

The studies span publication years 2016 to 2024, with the majority published after 2020, aligning with the increased focus on virtual and immersive learning during the pandemic. The peak in publications occurred in 2022, accounting for 18% of the reviewed studies, indicating a surge in research interest during this period. This was followed by consistent output in 2023 and 2024, reflecting sustained academic and practical interest in integrating immersive VR into education. This trend highlights the increasing adoption of immersive technologies for educational purposes and suggests that the momentum for exploring LA in VR environments is likely to continue. A summary of the reviewed studies is provided in Table 1. The full dataset, including full title, sources, analysis techniques and challenges, is available on Zenodo (Tao, 2025) at https://doi.org/10.5281/zenodo.14808884.

Table 1
Summary Table of Reviewed Studies

Article	Research Purposes	Data Types
Aldana-Burgos et al. (2022)	[A1], [A2]	Behavioural data (Interaction logs, task performance)
Antoniou et al. (2020)	[A2], [A7]	Physiological data (Biosensors: HR, EDA, EEG), Behavioural data (Interaction logs)
Baena-Perez et al. (2024)	[A1], [A2], [A6], [A7]	Behavioural data (Interaction logs, user activity tracking)
Baker et al. (2016)	[A1], [A2], [A3], [A6]	Behavioural data (Interaction logs, behaviour feature extraction)
Birt et al. (2019)	[A1], [A2], [A6]	Spatial Data (Head movement, hand tracking, positional tracking), Interaction Data (VR-specific) (Motion tracking, object manipulation), Video Data (Recorded interactions)
Chen et al. (2021)	[A1], [A2], [A7]	Behavioural data (Task completion metrics), Self-reported Data (Questionnaires, self-assessments), Video Data (Screen recordings)
Diederich et al. (2021)	[A1], [A2], [A4]	Interaction Data (VR-specific) (Motion tracking, hand gestures), Behavioural Data (Interaction logs in multi-platform simulation)
Heinemann et al. (2023)	[A1], [A2]	Eye-tracking Data (Gaze fixation, pupil dilation), Interaction Data (VR-specific) (Controller movement tracking)
Ng et al. (2022)	[A2], [A4]	Eye-tracking Data (Gaze fixation, pupil dilation), Self-reported Data (Questionnaires)
Stefan et al. (2016)	[A2]	Behavioural Data (Log data)
Vatral et al. (2022)	[A2], [A4]	Speech Data (Audio recordings), Video Data (Recorded interactions), Eye-tracking Data (Gaze fixation), Interaction Data (VR-specific) (Motion tracking)

3.1. Research purposes

The studies investigated a range of research purposes that illustrate the evolving applications of LA in immersive VR environments. These purposes included [A1] Enhancing learning outcomes, [A2] Evaluating learning behaviours, [A3] Predicting performance, [A4] Increasing reflection and awareness, [A5] Improving assessment and feedback, [A6] Enhancing social interaction, and [A7] Understanding affective states. Early studies (2016–2019) predominantly focused on [A1] Enhancing learning outcomes and [A2] Evaluating learning behaviours, leveraging the immersive nature of VR to create engaging and interactive learning environments. For example, Baker et al. (2016) analysed behavioural data (interaction logs, task performance) to assess students' autonomous learning behaviours in science inquiry tasks. From 2020 onwards, the scope of research expanded. Birt et al. (2019) explored [A6] Enhancing social interaction and used multimodal learning analytics to predict performance ([A3]) and improve assessment and feedback ([A5]) in mixed-reality health education. Studies also began investigating [A7] Understanding affective states, as Antoniou et al. (2020) and Baena-Perez et al. (2024) incorporated biosensor data (physiological data: HR, EEG) to evaluate emotional responses in VR settings. Additionally, Diederich et al. (2021) focused on [A4] Increasing reflection and awareness by using VR simulations and interaction tracking to analyse learners' self-regulated behaviours. Ng et al. (2022) combined self-reported data and eye-tracking to evaluate how students reflect on their learning processes ([A4]). This shift reflects the growing interest in addressing social, emotional, and self-regulatory aspects of learning alongside traditional performance-oriented goals, demonstrating the potential of immersive VR for capturing behavioural, cognitive, and affective dimensions of learning analytics.

3.2. Data types and data analysis techniques

3.2.1. Data types

The studies utilized diverse data types to investigate learning processes in immersive VR environments. Behavioural data (e.g., interaction logs, user activity tracking, and task performance metrics) was the most common, appearing in 7 studies: Aldana-Burgos et al. (2022), Antoniou et al. (2020), Baena-Perez et al. (2024), Baker et al. (2016), Chen et al. (2021), Diederich et al. (2021), and Stefan et al. (2016). These datasets captured user engagement patterns and learning behaviours in VR environments. Physiological data, such as biosensors (HR, EEG, electrodermal activity), was analysed in 1 study: Antoniou et al. (2020), which focused on evaluating affective states and emotional responses in immersive learning contexts. Spatial data (e.g., head movement, hand tracking, positional tracking) was utilized in 1 study: Birt et al. (2019), helping assess learners' spatial reasoning and movement within virtual environments. Eye-tracking data appeared in 3 studies (27.3%), including Heinemann et al. (2023), Ng et al. (2022), and Vatral et al. (2022). These studies analysed gaze fixation and pupil dilation to understand attention distribution and interaction patterns. Self-reported data, such as questionnaires and self-assessments, was used in 2 studies: Chen et al. (2021) and Ng et al. (2022), providing insights into learners' subjective experiences and reflections on their learning processes. Video data, used in 2 studies: Birt et al. (2019) and Vatral et al. (2022), helped analyse recorded interactions for qualitative and multimodal assessment of team performance and learning behaviours. Speech data, collected in 1 study: Vatral et al. (2022), was utilized to examine audio recordings for sentiment analysis and conversational dynamics within group learning activities. VR-specific interaction data, distinct from traditional LMS logs, includes motion tracking, hand gestures, and object manipulation. This data type was analysed in 3 studies: Birt et al. (2019), Diederich et al. (2021), and Heinemann et al. (2023) to assess how learners engage dynamically with virtual environments.

3.2.2. Data analysis techniques

The reviewed studies employed a range of statistical, machine learning (ML), and qualitative methods to analyse learning processes in immersive VR environments. Statistical methods were the most prevalent, used in 7 studies (Aldana-Burgos et al., 2022; Antoniou et al., 2020; Baker et al., 2016; Chen et al., 2021; Diederich et al., 2021; Heinemann et al., 2023; Ng et al., 2022). These techniques included linear/logistic regression, correlation analysis, ANOVA, and time series analysis, primarily to identify patterns and relationships between learning behaviours and outcomes. For instance, Aldana-Burgos et al. (2022) used regression analysis to evaluate learning outcomes, while Diederich et al. (2021) applied time series plots to analyse user interactions in a multi-platform VR simulation. Machine learning (ML) techniques were utilized in 6 studies (Antoniou et al., 2020; Baena-Perez et al., 2024; Birt et al., 2019; Chen et al., 2021; Heinemann et al., 2023; Vatral et al., 2022), particularly clustering and predictive modelling. Clustering (Chen et al., 2021; Vatral et al., 2022) was commonly applied to identify behavioural patterns in collaborative learning and speech analysis, whereas predictive modelling (Birt et al., 2019) was used to analyse multimodal data and forecast learner performance. Additionally, Baena-Perez et al. (2024) leveraged data mining and interaction heatmaps to assess learning behaviour within VR-based collaborative activities. Qualitative analysis was used in 2 studies (Birt et al., 2019; Vatral et al., 2022) to complement quantitative findings. Observational video analysis helped researchers assess group interactions and engagement in collaborative VR environments.

Notably, none of the studies employed deep learning techniques, which presents a research gap in applying advanced neural network-based approaches to analyse complex multimodal data in immersive VR settings. The reliance on statistical and traditional ML methods suggests that while current approaches provide meaningful insights, they may not fully capture the richness of multimodal, time-series data inherent in VR learning environments. Future studies could explore deep learning frameworks to enhance interpretability and predictive modelling.

3.3. Challenges

The reviewed studies identified several challenges in applying LA to immersive VR environments, spanning technical, methodological, ethical, and resource-related concerns. Technical barriers were a recurring issue, particularly in integrating multimodal data sources with VR platforms. Birt et al. (2019) and Diederich et al. (2021) reported difficulties in synchronizing real-time VR interaction data with other learning analytics inputs, such as eye-tracking and video recordings. Methodological challenges included data interpretation and generalizability. For example, Antoniou et al. (2020) highlighted the complexity of analysing physiological data like EEG and electrodermal activity in real-time, raising concerns about measurement accuracy and noise reduction. Additionally, Chen et al. (2021) reported difficulties in aligning self-reported measures with behavioural analytics, indicating the challenge of integrating subjective and objective learning metrics. Resource constraints were frequently cited, particularly regarding the high cost of VR hardware, the need for specialized training, and data processing limitations. Aldana-Burgos et al. (2022) and Baena-Perez et al. (2024) noted economic and infrastructure challenges, which may restrict the scalability of LA-based VR applications in educational settings. Ethical concerns, particularly regarding privacy and data security, were also discussed. Vatral et al. (2022) and Ng et al. (2022) raised issues related to collecting and analysing sensitive learner data, such as biometric and eye-tracking data, emphasizing the need for robust data protection mechanisms.

To address these challenges, researchers proposed several solutions. Birt et al. (2019) and Antoniou et al. (2020) suggested modular architectures and edge computing to improve data processing efficiency and reduce real-time analysis latency. Additionally, explainable AI (XAI) techniques were recommended to enhance model transparency and support educators in interpreting learning analytics results. Lastly, Luckin et al. (2022) emphasized the importance of teacher training and user-friendly interfaces to facilitate the adoption of learning analytics in VR classrooms.

4. Conclusion

This review examined the use of LA in immersive VR environments from 2016 to 2024, highlighting trends, challenges, and opportunities. The findings emphasize the potential of MMLA to capture social, emotional, and collaborative dimensions of learning using diverse data types like interaction logs, eye-tracking, and physiological measures. Machine learning techniques have been widely applied, though the lack of deep learning indicates an area for future exploration. Challenges include technical integration, resource constraints, and ethical concerns, particularly regarding data privacy. This review is limited by its focus on peer-reviewed works and studies with explicit data analysis techniques, potentially excluding innovative approaches.

Future research should address these gaps by expanding study inclusion and exploring under-researched areas such as equity, ethical considerations, metacognition, and collaborative problem solving. Additionally, the application of advanced methodologies, including deep learning and real-time analytics, could unlock richer insights into complex multimodal data. Interdisciplinary frameworks and scalable, teacher-friendly tools will be essential to bridge the gap between research and practice, ensuring that LA in immersive VR effectively enhances educational outcomes and learner experiences.

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Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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