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RESEARCH PAPER

Towards Human-Centered VR in STEM Education: A Framework for Student–Teacher Challenges through Learning Analytics and Personalized Learning

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Abstract. This paper proposes a conceptual theoretical framework that integrates Virtual Reality (VR) with Learning Analytics (LA), Personalized Learning (PL), and a Student Behavior Model aligned with the Brazilian HCI Grand Challenges, particularly GC1 (new theoretical and methodological approaches) and GC5 (human–data interaction), to advance adaptive and personalized education in STEM. While VR offers immersive and engaging learning opportunities, most current systems lack the adaptability and learner-centered design needed to address individual differences and support teacher decision-making. Our framework introduces four interconnected models: (1) a simplified LA model, (2) a PL model designed to personalize instruction through learner profiles and adaptive recommendations, (3) a structured User Model, further enhanced by a three-mode questionnaire system capturing learner pace, prior knowledge, and instructional feedback, and (4) a Student Behavior Model addressing cognitive, social, and emotional dimensions of engagement within VR simulations. Together, these models conceptually interact to provide a holistic, learner-centered framework that links data, personalization, user profiling, and behavioral insights for adaptive VR-based education. The framework is developed through a conceptual mapping with the Design-Based Research (DBR) phases, verifying its components with established educational theories and iterative design principles of the DBR. To further verify the framework, we conducted a reverse engineering exercise by aligning it with a Unity-based educational VR game. This mapping demonstrates the framework's applicability in real-world learning environments, showing how the framework insights can be embedded into gamified VR-based educational settings. This work contributes a theoretically grounded foundation for future research on immersive VR learning environments, offering pathways toward scalable, adaptive, and inclusive educational practices.

Keywords: Virtual Reality, Learning Analytics, Personalized Learning, Design-Based Research, Reverse Engineering.

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1 Introduction

Education is a fundamental pillar of society, playing a crucial role in shaping individuals' knowledge, skills, and attitudes. Traditional educational approaches often rely solely on textbooks, lectures, and static visual aids, which can limit students' engagement and experiential learning opportunities [Zaman *et al.*, 2024]. To address these limitations, educators are increasingly exploring Extended Reality (XR) technologies such as Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR) that support more interactive and experiential forms of learning. Among these immersive technologies, VR refers to a computer-generated artificial environment where users can perceive and interact with their surroundings [Chan *et al.*, 2022].

One of the key benefits of VR in education is its ability to increase student motivation and foster deeper understanding, particularly in STEM subjects [Radianti *et al.*, 2020]. As VR technology continues to evolve and become more accessible, it is poised to play a growing role in modern educational approaches, offering more personalized and engaging learning experiences. This innovative technology is reshaping conventional teaching methods, turning education into a more dynamic and impactful process. Such advancements demonstrate how VR can make complex topics more approachable and stimulating for learners [Mazzuco *et al.*, 2022]. The VR immersive capabilities enable dynamic simulations, real-time experimentation, and spatial visualizations that can improve students' comprehension and engagement [Budi *et al.*, 2021]. However, despite these benefits, existing VR-based educational platforms often fall short in delivering adaptive, personalized, and responsive learning experiences, particularly in terms of accommodating individual learner needs and fostering effective student–teacher interaction [Marougkas *et al.*, 2021; Huang *et al.*, 2022].

We previously identified that students and teachers face specific challenges in immersive environments, as mentioned in Ahsan *et al.* [2025], including limited adaptability to diverse learning needs, weak feedback loops between teachers and students, technological complexity, students' enhancement, lack of personalization, and teachers' training with VR environments, etc. These limitations necessitate a reevaluation of how VR technologies are integrated into the

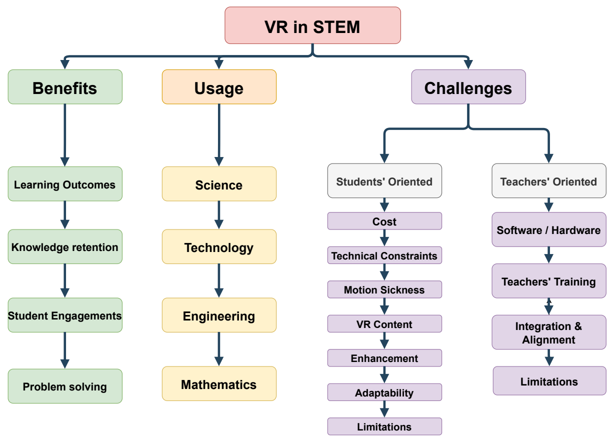

Figure 1. Challenges faced by Teachers and Students in VR-based education Ahsan *et al*. [2025].

learning process, particularly in environments where human-centered data interaction and personalized instruction are crucial [Stephanidis *et al*., 2019; Viberg *et al*., 2020]. To address these gaps, this study proposes a theoretical framework that integrates Learning Analytics (LA) and Personalized Learning (PL) into VR environments (detailed in Section 4), following the four key phases of Design-Based Research (DBR) as described by Reeves [2006]. The framework is both theoretically grounded and conceptually verifiable at this stage and would be adaptable for practical implementation in a real classroom environment as our future tasks.

This paper is an extended and significantly enhanced version of our earlier work Ahsan *et al*. [2025] presented at "ACM International Conference on Interactive Media Experiences (IMX) 2025", with additional framework design, theoretical modeling, and discussion. This paper's research contributions include a conceptually verifiable framework, actionable design principles for educational technology development, and a roadmap for future empirical testing in resource-diverse settings.

1.1 Goal of the Study

The goal of this study is to integrate LA and PL technologies into VR environments, thereby proposing a theoretically grounded framework for immersive, adaptive, and learner-centered education. Building on the demonstrated technical feasibility of multi-user VR simulations [Viol *et al*., 2025], the framework specifically responds to the challenges identified by Ahsan *et al*. [2025], including insufficient student–teacher interaction, limited adaptability of VR environments to diverse learner needs, and weak feedback mechanisms. By capturing and analyzing student behavior during VR interactions, the framework seeks to enhance personalization, strengthen teacher agency, and improve engagement, retention, and overall learning outcomes.

1.2 Challenges and Objectives

Despite the growing adoption of VR in STEM education, several key challenges persist as shown in **Figure 1**. These constraints hinder the full pedagogical potential of VR-based systems in learning environments. This framework is conceptually grounded in theory and motivated by the work of Viol *et al*. [2025] as well, which demonstrated the technical feasibility of multi-user VR environments where learners share and interact within the same immersive space. Their architecture validates VR as a reliable platform for collaborative learning by ensuring synchronization, shared presence, and interaction fidelity across users. While their work emphasizes technical robustness, the present study advances this foundation by proposing a theoretical framework that integrates LA and PL into such environments.

Thus, where Viol *et al*. [2025] establish the technical validity of VR-based multi-user systems, our contribution lies in extending this architecture toward a pedagogically grounded, human-centered design that prioritizes adaptivity, personalization, and enhanced teacher–student interaction. Our framework offers significant benefits for both students and teachers. For students, the framework enables: (1) personalized learning pathways adapted to individual pace, prior knowledge, and interests; (2) real-time feedback during immersive simulations; and (3) enhanced engagement through behaviorally adaptive VR experiences. For teachers, the framework provides: (1) actionable insights through LA dashboards to inform instructional decisions; (2) improved visibility into student motivations, cognitive load, and collaboration patterns; and (3) structured tools (three-mode questionnaires) to co-design adaptive learning strategies with students. Together, these benefits support more effective, human-centered, and data-informed educational practice."

To address the above challenges and enhance student learning outcomes in an improved learning environment by integrating LA with PL strategies, the current study sets out the following objectives:

- To propose a comprehensive three-phase adaptive learning theoretical framework that integrates LA and PL with VR technologies for modern educational settings.
- To offer a user model to support teachers and students in data-informed lesson planning and instructional design, helping them customize their teaching strategies.
- To introduce a three-mode questionnaire system through LA dashboards that enhances student–teacher interaction and supports data-driven personalization.
- To provide design principles and practical guidelines for implementing adaptive, scalable, and inclusive educational technologies.
- To identify student behavior during VR simulations to better understand and personalize each student's progress and improve their learning through a student behavior model.

1.3 Alignment with HCI Grand Challenges

In an international context, the literature has shown some major challenges in the field of HCI. With the collaborative efforts of 32 HCI experts involved in the Human-Computer Interaction International (HCII), seven major challenges have been defined within the HCI domain in 2019 [Stephanidis *et al*., 2019]. Regarding the challenges, *Human Environment-Interactions* (enumerated as 2) and *Learning and Creativity* (enumerated as 6) are directly related to spatial computing in context of students learning environment as described in this article. At a National level, this framework also aligns with the Grand Challenge *new theoretical and methodological* *approaches* (GC1) and Grand Challenge *human–data interaction* (GC5) of the Brazilian HCI research agenda (2025–2035) [Pereira *et al.*, 2024], which emphasize theoretical innovation and human-data engagement in interactive systems which are related in the research of this article with-in educational context. The proposed framework responds to GC1 by offering a theoretical and methodological contribution to the design of educational systems that integrate VR, PL, and LA into VR settings. Then, the framework addresses GC5 through the use of structured questionnaires which empowers learners and educators to interact meaningfully with data enhancing personalization, reflection, and instructional planning.

The remainder of this paper is structured as follows. Section 2 describes the literature review and related work. Then, Section 3 discusses the Theoretical Research Design used alongside the methodology, and Section 4 contains the proposed framework. Section 5 presents the Theoretical Feasibility & Conceptual Verification of this framework, Section 6 includes the discussions based on the validation, Section 7 discusses the limitations and threats to validity, while Section 8 presents the ethical and methodological considerations. Finally, Section 9 provides the concluding remarks and final considerations.

2 Literature Review

2.1 Virtual Reality in STEM Education

The integration of VR in educational settings offers significant benefits for both students and teachers in education by creating immersive and interactive learning environments as mentioned by Zekeik *et al.* [2025]. For students, VR increases motivation, engagement, and understanding of complex concepts, while also supporting the development of critical thinking and collaboration skills. Teachers benefit from enhanced tools for delivering content, enabling more effective demonstrations and collaboration with diverse learning needs for students. These immersive environments allow students to interact with complex concepts in ways that traditional methods cannot achieve [Gutiérrez Constante *et al.*, 2024]. The advancement in this technology have opened new possibilities for teaching and learning in educational settings where humans interact with computer-generated simulations using VR, AR and MR [Alnagrat *et al.*, 2022]. In the realm of STEM education, the use of VR enables students to dive into complex scientific ideas and perform virtual experiments that might be too risky or impractical in real life [Makransky and Petersen, 2021].

Several works discuss the benefits and possibilities of using VR in learning [de Azevedo Pedrosa and Zappala-Guimarães, 2019; Jesus *et al.*, 2024; da Silva, 2023; de Lima *et al.*, 2025]. In *biological sciences*, VR has been applied to visualize the 3D structural models for functions such as macromolecules e.g,. proteins, RNA, and DNA to enhance student learning through molecular graphics [Turhan and Gümüş, 2022; de Moraes Pinheiro *et al.*, 2023; dos Santos *et al.*, 2023]. Many works also highlight the use of VR for *Physics education* [Nakamoto *et al.*, 2005; Silva and De Sousa, 2013; dos Santos Oliveira *et al.*, 2024; Tito and Moraes, 2022]. According to Sari *et al.* [2023], VR also holds significant potential as a teaching tool in chemistry, opening pathways for future research. With just a basic smartphone and appropriate software, learners can now explore complex chemical processes in VR, overcoming the financial, geographic, and physical constraints of traditional laboratories and their expensive equipment [Fombona-Pascual *et al.*, 2022].

As shown in Ardito *et al.* [2014], VR can also empower students to act as content creators within integrated STEM learning environments. Moreover, VR offers a practical means of exploring complex STEM concepts through *technological applications* [Laseinde and Dada, 2024]. Virtual laboratory environments further support student learning by integrating application tools within mobile learning platforms and web-based e-learning systems [de coopération et de développement économiques, 2016]. VR technology has been increasingly integrated into the field of *engineering*. For instance, ViRILE, a VR-based software designed for undergraduate chemical engineering students, simulates the configuration and operation of polymerization plants [Schofield, 2012]. In *mining and civil engineering*, VR is applied to improve occupational health and safety practices [Strzałkowski *et al.*, 2024]. Similarly, Wang *et al.* [2022] highlight the use of VR in civil engineering education through multi-perception teaching, where multiple senses such as vision, hearing, and touch are engaged to enhance learning efficiency. In *electrical engineering*, the integration of AR with e-worksheets in courses on electrical machines has been shown to positively and significantly influence students' attitudes, with learners expressing a highly favorable perception of this approach [Yanto *et al.*, 2024].

Research by Ardito *et al.* [2014] designed robots to support students in learning and practicing mathematical concepts in an integrated manner, offering progressively challenging tasks. Robotics was shown to help students connect and apply mathematical skills in meaningful ways. In *mathematics education*, game-based learning is primarily employed to simplify abstract concepts rather than highly complex ones [Shi *et al.*, 2022]. Tools such as VR and GeoGebra create 3D drawing environments that strengthen students' spatial understanding [Su *et al.*, 2022]. Furthermore, the combination of VR and gamification has been found to improve mathematical performance by making learning more engaging and enjoyable [Alzoubi and Ahmed, 2024].

VR has demonstrated substantial potential across STEM domains. Most existing approaches primarily focus on content visualization and interactive simulation, while comparatively fewer studies address adaptive personalization or teacher-centered instructional support. Latin American research has particularly highlighted the critical importance of teacher agency, affective engagement, and scalable design in resource-diverse contexts [Silva and De Sousa, 2013; Tito and Moraes, 2022; dos Santos Oliveira *et al.*, 2024], insights that directly informed our framework's emphasis on structured teacher models, and behavioral indicators capturing emotional dimensions. Similarly, Jesus *et al.* [2024] and da Silva [2023] discussed the necessity of personalization mechanisms that accommodate diverse prior knowledge levels insights that reflect our three-mode questionnaire system design. These limitations and regional perspectives collectively motivate the need for frameworks that combine VR with LA and PL to create truly adaptive and learner-centered educational systems, as proposed in this study.

2.2 Learning Analytics in Education

LA involves the collection, measurement, analysis, and reporting of data about learners and their interactions to understand and optimize learning and the environments in which it occurs [Siemens and Gasevic, 2012]. LA has the ability to boost learners' and teachers' knowledge to make informed decision to take great benefits from their efforts [Scheffel *et al.*, 2014]. Many applications of LA are used to predict the performance of learners as well as to diagnose their annoying problems which affect students' learning process [Karthikeyan and Kavipriya, 2017]. In context of educational settings, this could be considered as:

1. Tracking where a learner spends more time in a VR environment.
2. Analyzing response times of a student or error rates during a VR simulation.
3. Generating reports that show learning progress, engagement levels, or knowledge gaps of each individual.

The major goal of LA is to establish a personalized and student-friendly learning environment that helps learners achieve their learning objectives. Hence, LA focuses on the application of algorithmic approaches and techniques to treat issues affecting student learning and organization of learning material [Kavitha and Raj, 2017].

Most conventional LA systems are primarily designed for non-immersive educational environments and therefore rely heavily on relatively simple interaction metrics, including clicks, quiz scores, login frequency, and task completion records [Viberg *et al.*, 2018]. Such approaches often fail to capture the rich multimodal behavioral, spatial, physiological, and contextual interaction data generated within immersive VR learning environments [Blikstein and Worsley, 2016; Tao *et al.*, 2025]. The integration of LA within immersive VR introduces unique technical challenges, including the complexity of synchronizing and interpreting multimodal data streams such as gaze tracking, spatial movement, physiological responses, and interaction logs that require specialized capture, integration, and analysis techniques [Clay *et al.*, 2019; Suhaimi *et al.*, 2022]. Moreover, existing LA models often prioritize automated processes and may insufficiently incorporate teacher agency, which can limit pedagogical responsiveness and the contextual appropriateness of analytics in educational settings [van Leeuwen *et al.*, 2022].

Consequently, there remains a significant need for frameworks capable of translating multimodal VR-generated learner data into actionable instructional strategies that support both learners and educators in immersive STEM education contexts. This paper presents a theoretical framework that incorporates LA and PL techniques into VR environments to enhance student-teacher interaction for an improved learning environment.

2.3 Personalized Learning in Education

PL is referred as when the learning experience is tailored to each student's needs, skills, pace, and interests, this way teaching students in a way that works specifically for them. PL depends on the preference and interests that promote engagement and academic achievement of the individual student [Alenezi, 2023]. PL is used to provide a customized experience based on student profiles in order to support VR more effectively by considering students' needs, preferences, interests, skills, capabilities, learning styles, prior knowledge of the subject, and even special needs [Marougkas *et al.*, 2021]. In context of VR environment it could be considered as:

1. Adapting the difficulty level of a virtual lab simulation in real-time, such as by adjusting the difficulty level for a science subject experiment according to the student pace and how well he performed in last experiment.
2. Guiding a student through different virtual learning paths based on their previous interactions.
3. Providing immersive feedback or hints to a student when they are struggling with a task in a VR scenario.

To improve student learning outcomes, higher education institutions have used PL methodologies in recent years to enhance student learning outcomes. Yuyun and Suherdi [2023] conducted a systematic review of 40 studies, identifying key components such as adaptive content delivery and learner autonomy as pivotal for enhancing students' engagement and their academic performance. Similarly, Zhong [2022] analyzed 41 articles, highlighting that structuring learning content and the sequence of materials based on individual readiness significantly improves students' learning outcomes.

Studies also emphasize that VR can enhance students' engagement and support PL [Radianti *et al.*, 2020], [Rutten and Brouwer-Truijen, 2025]. To broaden the scope of perspectives represented in this review and to address concerns about citation bias, we also integrate work led by women and underrepresented groups across XR, LA, and PL. In the area of immersive technologies, studies such as Latin American contributions including Bellido García *et al.* [2022] and Silva [2022] highlight regional advances and contextual challenges in deploying AR/VR in educational practice. Complementing this, foundational work in LA led by Ferguson [2019] emphasizes ethical, socio-technical, and pedagogical considerations necessary for responsible data-driven decision making. In PL and AI-supported adaptation, influential contributions by Luckin *et al.* [2016] and Conati and Kardan [2013] deepen understanding of intelligent student modelling, human-AI collaboration, and transparent adaptive support.

PL cannot achieve its full potential in isolation. LA provides the data infrastructure to identify learner patterns, predict challenges, and measure progress capabilities that PL requires to move beyond static profiles toward real-time adaptation [Long and Siemens, 2011]. VR provides the immersive context where embodied, spatial, and experiential learning occurs, and that enables PL to extend beyond traditional content delivery into adaptive interactive scenarios which engage cognitive, affective, and behavioral dimensions together [Makransky and Petersen, 2021; Radianti *et al.*, 2020]. Teachers provide the pedagogical expertise to interpret analytics, validate automated recommendations, and make instructional decisions that algorithms alone cannot replicate, ensuring that personalization remains educationally sound, ethically responsible, and contextually appropriate [Luckin *et al.*, 2022]. Consequently, there remains a strong need for integrated frameworks that this paper fulfills, capable of combining immersive VR interaction, multimodal learning analytics, personalized learning mechanisms, and teacher-supported instructional decision-making within immersive educational environments.

2.4 Frameworks for the design of immersive learning environments

A related study proposed a framework for designing adaptive and gamified VR learning environments using fully immersive Head Mounted Displays, emphasizing personalization based on students' cognitive states, behavioral patterns, and gameplay balance [Marougkas *et al.*, 2021]. While this work contributes an important step toward adaptive and engaging VR-based education, its primary focus lies in gamification and adaptive design. In contrast, our framework advances the field by integrating LA and PL into VR contexts, supported by a structured User Model and a Student Behavior Model.

The work from Srimadhaven *et al.* [2020] also demonstrates the potential of combining VR with gamified learning to improve students' motivation and cognitive skills, particularly in programming courses. By embedding Python problem-solving activities into VR-based maze games, the study leverages LA techniques such as clustering and reinforcement learning to assess performance and identify slow learners. While this approach provides valuable insights into cognitive skills and engagement, its scope remains limited to domain-specific applications and does not address personalization beyond gamification mechanics. In contrast, our framework advances it by integrating a broader set of models that together support both teachers and students across diverse STEM domains in VR settings.

The LAVA model by Chatti *et al.* [2020] introduces a human-centered LA approach by integrating visual analytics into the indicator design process. By keeping "human in the loop," LAVA enhances transparency, usability, and user acceptance of LA tools, as demonstrated through its implementation in the OpenLAP platform and evaluation using the Technology Acceptance Model (TAM). While LAVA focuses on improving indicator customization and user engagement in conventional learning settings, it does not address personalization or behavioral modeling in immersive VR environments. Our framework extends this line of work by integrating LA, PL, and multidimensional behavioral indicators tailored specifically for VR-based learning experiences.

The PERLA framework introduced by Chatti and Muslim [2019] represents an important contribution at the intersection of LA and PL, offering a systematic approach for designing effective indicators that support personalized and lifelong learning. PERLA emphasizes requirements such as multimodal data integration, learner-centered analytics, context modeling, and privacy-aware LA, providing a theoretical foundation for analytics-enhanced personalized learning environments. While our work builds upon similar goals of blending LA and PL, it diverges in two critical ways. First, our framework situates personalization and analytics within immersive VR contexts, thereby addressing the unique challenges of adaptability, engagement, and feedback in multi-user simulations. Second, beyond indicator design, we propose two additional models: a structured *User Model* that incorporates both teacher and student profiles through collaborative and automatic data input, and a *Student Behavior Model* that captures cognitive, social, and emotional dimensions of engagement during VR-based learning. Furthermore, our approach is conceptually related to the phases of a DBR methodology defined by Reeves [2006], enabling iterative conceptual refinement and alignment with learning theories. In this way, our framework complements and extends PERLA by embedding LA and PL into VR-enhanced environments while simultaneously providing mechanisms for teacher support and human–data interaction.

Troussas *et al.* [2019] defines a multi-module model that highlights the role of big data and LA in predicting learners' cognitive states, improving curricula, and enabling personalized pathways in digital education. Their architecture offers useful modular components, including behavior prediction and target material identification, which are essential in large-scale e-learning environments. However, the framework primarily focuses on analytics-driven personalization in conventional or online learning platforms, without considering the unique challenges of immersive VR learning environments.

Various LA techniques have been employed in the literature to enhance student learning outcomes in VR-based education. These approaches have also been utilized to improve student–teacher interactions by providing real-time feedback and personalized support [Viberg *et al.*, 2020]. Authors emphasize that LA integrated within immersive environments allows instructors to monitor performance and adapt instruction dynamically [Huang *et al.*, 2022]. A major challenge is figuring out how to use these technologies effectively from designing content to delivering the learning experience [Stephanidis *et al.*, 2019]. Particularly, we are designing a framework that integrates PL and LA with VR technologies. We also offer a user model (Student and Teacher) as a new theoretical approach and target to achieve better student–teacher interaction to enhance student learning outcomes and improve the learning environment in educational settings. To better highlight the conceptual and methodological contribution of the proposed framework, **Table 1** synthesizes a comparison between existing models discussed in the literature. The table contrasts their primary strengths, limitations, and design characteristics with the proposed framework. This comparative analysis demonstrates how our framework advances beyond prior work by integrating immersive VR interactions with LA, PL, user modeling, and multidimensional behavioral indicators, supported by DBR-informed conceptual development.

3 Theoretical Research Design and Methodology

In order to develop a robust and pedagogically grounded framework, this study employs a conceptual mapping approach based on DBR principles, as detailed in the following subsections.

3.1 Rationale for DBR

DBR is a widely recognized research methodology for investigating complex, real-world learning environments through the design and iterative refinements of educational interventions. Originally it was introduced by Brown [1992]. It was further

Table 1. Comparison of related works with the proposed framework.

Paper	Strengths	Limitations	Comparison with the Proposed Framework
Marougkas *et al.* [2021]	Adaptive and gamified VR design with consideration of cognitive states.	Focused primarily on gamification; lacks integrated LA and PL mechanisms, as well as explicit teacher and student behavior models.	The proposed framework extends beyond gamification by integrating LA, PL, a User Model, and a Student Behavior Model to support broader personalization and teacher–student interaction in immersive learning environments.
Srimadhaven *et al.* [2020]	Integrates LA within a VR gamification context and supports motivation and cognitive-skill development.	Domain-specific and primarily performance-based personalization; limited modeling of affective and social dimensions.	The proposed framework generalizes personalization across STEM domains and integrates multidimensional cognitive, social, and emotional indicators with teacher-supported adaptation.
Chatti and Muslim [2019]	Provides strong integration between LA and PL through indicator-based personalization.	Not designed for immersive VR environments and lacks modeling of spatial interaction and real-time VR-based feedback.	The proposed framework embeds LA and PL within VR environments and extends them with User and Student Behavior Models to support multimodal data collection, adaptive interaction, and real-time feedback.
Troussas *et al.* [2019]	Provides scalable learning analytics and cognitive prediction for e-learning environments.	Primarily focused on conventional e-learning platforms and does not address embodied VR interaction, spatial behavior, or teacher modeling.	The proposed framework extends analytics into immersive VR by incorporating interaction, attention, collaboration, and cognitive indicators within a teacher-supported adaptation loop.
Chatti *et al.* [2020]	Supports multimodal learning analytics visualization and real-time dashboard-based analysis.	Does not explicitly address VR-based learning, personalized instruction, or student behavior modeling.	While LAVA emphasizes real-time visualization of learning data, the proposed framework integrates VR, LA, PL, and behavior modeling to support data-informed personalization and teacher decision-making in immersive environments.
Proposed Framework	Integrates VR, LA, PL, User Model, and Student Behavior Model within a DBR-informed conceptual framework.	Currently conceptual; empirical evaluation is planned for future research.	Provides an integrated framework for immersion-aware personalization, combining multidimensional learner indicators with teacher-supported adaptation across cognitive, social, emotional, and behavioral dimensions.

formalized by Collins [1992] and Reeves [2006] as shown in **Figure 2**.

DBR is a method from the learning sciences that uses learning theories to explore how students learn. It looks at how different parts of the learning environment such as teachers, students, and classroom settings, work together to support learning Brown [1992]; Cobb *et al.* [2003]; Peffer and Renken [2016]. DBR is ideal for educational technology research because it enables researchers to design and evolve interventions while continuously reflecting on and improving the theoretical foundation [McKenney and Reeves, 2013]. DBR is a systematic but flexible methodology that aims to improve educational practices through an iterative process of analysis, design, development, and implementation in real-world settings as shown in **Figure 2**. In this research, we adopt DBR to conceptually develop, theoretically refine, and verify our proposed learning framework that merges VR with LA and

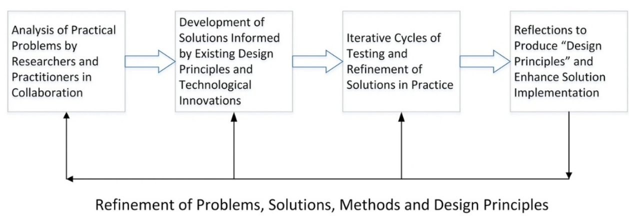

Figure 2. Design research approaches in educational technology research. Source: Reeves [2006].

PL.

3.2 Components of DBR

3.2.1 Phase 1: Analysis of Practical Problems

The purpose of the first phase of the DBR process was to analyze the problem, addressing the research objective of identifying the challenges in VR-based STEM education. Our prior review Ahsan *et al.* [2025] highlighted issues such as the lack of content adaptation for different learners, weak feedback loops, limited teacher control in VR environments, and low adaptability to individual student needs. This analysis revealed the need for a demanding framework where we integrate LA and PL to overcome these gaps and support more effective teacher–student interaction in VR context.

3.2.2 Phase 2: Development of Solutions

The second phase of the DBR process focused on designing an intervention to address the identified challenges. We proposed a three-phase framework consisting of: *Modeling Step*, Technological Step, and Resulting Step, which are discussed in the next section.

3.2.3 Phase 3: Iterative Design Cycles

This phase focuses on iterative refinement of the proposed framework. The user model and questionnaire modes (pace/interest, upcoming topic awareness, overall course strategies) are refined conceptually based on feedback from existing literature and alignment with learning theories. Although empirical testing has not yet been conducted, the iterative cycles at this stage involve theoretical adjustments and philosophical verification to ensure feasibility in VR-based settings. Based on theoretical reflection motivated by a technologically grounded framework from Viol *et al.* [2025], aligned with our previous paper Ahsan *et al.* [2025], and integration of components (e.g., user modeling, behavior modeling, richer feedback loops, and advanced technological elements with LA,PL), the framework represents a promising conceptual foundation.

3.2.4 Phase 4: Design Principles as Output

The final phase of the DBR cycle involves reflection to extract design principles from the proposed framework. These principles include: (1) The integration of LA and PL into VR environments fosters personalized and adaptive learning, (2) Structured teacher and student models enhance instructional planning and real-time adaptation, (3) Iterative refinement guided by 3-mode feedback questionnaires improves both learner engagement and teacher agency, and (4) Student behavior models during VR simulations help teachers to better understand learning progress and behavioral tendencies, enabling more effective feedback and instructional decisions.

DBR is thus selected due to its ability to support early-stage theoretical modeling without requiring full-scale empirical testing and to produce generalizable design principles for future implementations in a real classroom environment. **Table 2** represents the components of DBR aligned with the goals of this research. However, this paper does not represent a fully empirical DBR cycle. Rather, it focuses on the conceptual and theoretical development, ensuring its internal coherence before empirical implementation.

Table 2. DBR components aligned with this study based on the four phases. Source: Reeves [2006]

DBR Component	Role in This Study
Analysis of Practical Problems	Student adaptability, learning enhancement, and teacher feedback gaps.
Development of Solutions	Three-phase framework comprising modeling, technological, and resulting components.
Iterative Design Cycles	Refinement of the User Model and the three-mode questionnaire.
Design Principles as Output	Framework and guidelines for implementing adaptive VR–PL–LA systems in future studies.

4 Proposed Framework

This section introduces the proposed conceptual framework presented in **Figure 3**, which integrates LA, PL, user, and the Behavior Models within immersive VR environments. In this paper, we primarily address the Modeling step of the framework, while the Technological and Resulting phases are outlined as future work with empirical validations through experiments with students and teachers.

The system architecture illustrated in **Figure 4** shows the overall data flow among teachers, students, the LA dashboards, and PL mechanisms. *Step.1* represents the interaction between students and teachers through the LMS, including the three-mode questionnaire that supports profile initialization and instructional planning. *Step.2* corresponds to the LA dashboard layer, where analytics reports are generated to support personalized lesson planning based on the learner data obtained in the previous stage. *Step.3* captures user behavior during immersive VR interaction, including cognitive, motivational, and performance indicators collected through system logs and multimodal sensors. The proposed framework is structured into three complementary phases (1) Modeling, (2) Technological, and (3) Resulting, which are described in detail below.

4.1 Modeling step

In the modeling step, we define user model (Student's and Teacher's), LA model, PL model, and the student behavior model. This paper focuses on this step which shows the conceptualization of the modeling step without having any empirical validation at this stage.

4.1.1 User Model

In this step, both teacher and student models are developed together.

Teacher Model: The *Teacher Model* includes educational data, curriculum, teaching methods, and instructional strategies. The Teacher Model contains the educational material needed to design the specific subject knowledge that defines the educational goals for a particular curriculum [Marougkas *et al.*, 2021]. This Model serves as a key component that informs both the LA and PL dimensions of the framework. It incorporates parameters such as the curriculum (learning objectives, scope, and sequencing of content), instructional strategies (e.g., problem-based learning, collaborative

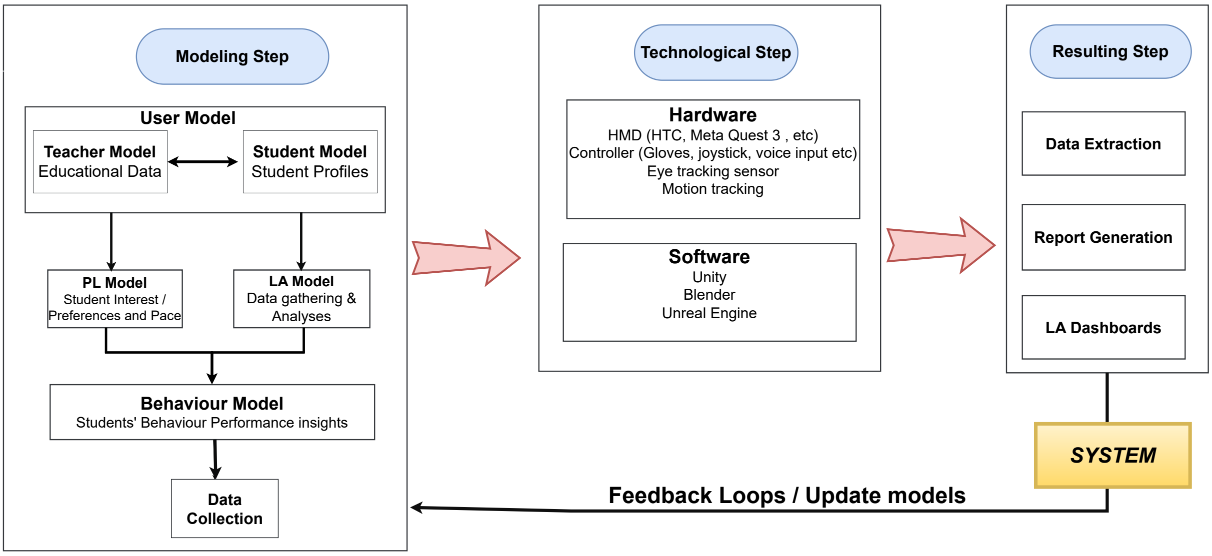

Figure 3. Proposed Theoretical Framework with the integration of LA and PL into VR settings.

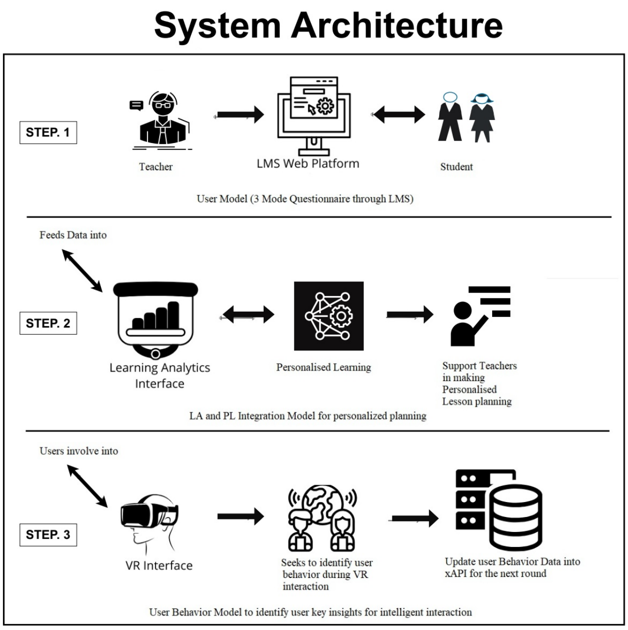

Figure 4. Proposed system architecture, divided into 3 steps.

tasks, or guided exploration), educational data (records of student progress, assessment results, and prior performance), and teaching methodologies (traditional, blended, or VR-enhanced practices). These attributes define the teacher's pedagogical profile, providing input for the LA and PL models and supporting the interpretation of learner behaviors within the VR-based Behavior Model.

Student Model: The Student Model builds a comprehensive learner profile to support and enhance the personalization process [Marougkas *et al.*, 2021]. Without such a model, personalized learning cannot be achieved [Ismail *et al.*, 2023]. This profile captures key parameters, including learning style, goals, behavior, performance, preferences and interests, and prior knowledge, which together reflect both cognitive states and behavioral tendencies [Amzil *et al.*, 2023]. Learner profiling may rely on automatic approaches, where traits are inferred from interactions, system logs, or sensor data [Ismail *et al.*, 2023; Chen and Li, 2010], or on collaborative approaches, where information is provided directly by the learner through surveys, forms, or interviews [Abbey *et al.*, 2013]. These mechanisms ensure that the Student Model provides accurate, multi-dimensional data to inform the LA, PL, and Behavior Models within the VR-based framework.

Student and Teachers interaction can be observed by any dashboard. Different LA dashboards and indicators were proposed to support several crucial PL processes, such as motivation, awareness, and self-reflection feedback [Verbert *et al.*, 2014]. The proposed user model diagram is depicted in **Figure 5**. The teacher and student models contribute to the adaptive learning process by enabling the system to personalize the content delivery and suggesting helpful activities based on what the teacher plans and what the student needs or prefers by using any dashboard and a feedback generated by Questionnaires. We propose a questionnaire-based approach to improve student-teacher interaction and get the key insights from students' perspectives that will help teachers to design strategies for better learning environments. The three-mode questionnaire system is proposed following User-Centered Design principles and learner-profiling with the goal to elicit learner background, readiness, and instructional preferences as part of the User Model. The sample of these modes is shown in **Table 3**.The detailed material regarding the proposed questionnaire is available [1]. This questionnaire can be done using LA dashboards as suggested in this research or can be via gamified application through VR to better engage the students in the activity and enhance their interaction with teachers. The questionnaire are based on 3 modes as described below.

Mode 1. This includes questions about student Pace, Interest, previous knowledge and skills to better understand the background of each learner to achieve their academic goals more appropriately.

[1] `https://github.com/xr4good/LA-PL-VR_Model`. Accessed on 20 July 2026

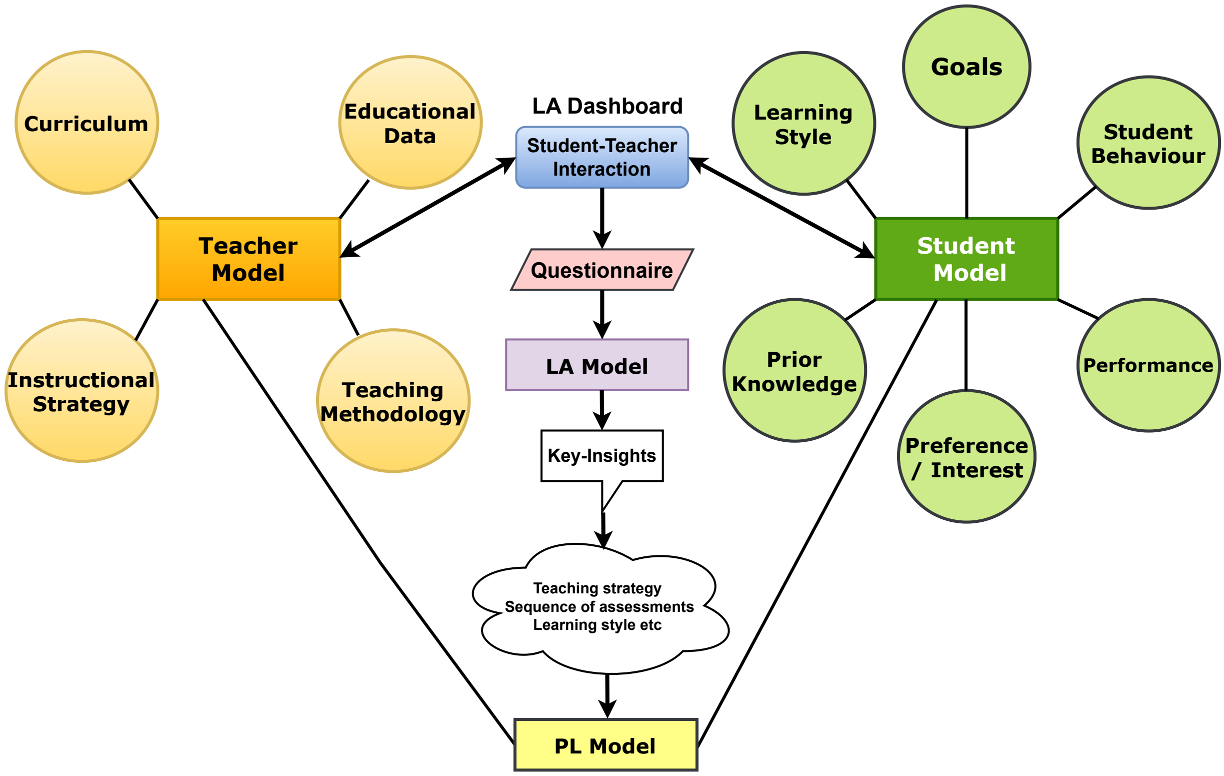

Figure 5. Proposed User Model to enhance student-teacher interaction.

Table 3. Questionnaire sample designed to enhance student–teacher interaction.

Mode	Focus	Sample Questions
Mode 1	Student Background (Pace, Interest, Knowledge, Skills)	• Skills related to this course? • Interest in the subject? • Preferred learning pace/style?
Mode 2	Upcoming Topic Overview	• Familiarity with the concepts? • Support needed before the topic? • Preferred activities for learning?
Mode 3	Course Goals and Learning Preferences	• Preferred teaching method? • Assessment schedule? • Strategies for difficult topics?

Mode 2. This should be designed to provide the information on the objectives and content of the upcoming topic that the teacher wants to present so that students will have an idea of the upcoming topics, tasks, etc.

Mode 3. This can be organized to give details to the students about the over all course Goals and strategies to be taken in the time period from Teachers. The sample of these three mode questions are shown in **Table 3**.

The LA will generate the reports and the feedback from students will be observed such as which teaching strategy they prefer, how the sequence of assessment can be organized, what is their learning styles, what is their capabilities for a unique topic, etc. These efforts put up by teachers suggesting that instructional quality, shaped by teacher self-efficacy, significantly influences student outcomes [Burić and Kim, 2020]. The PL techniques further can be utilized to refine student learning outcomes and improve their learning skills accordingly with the pace, interest in user friendly environment with improved student-teacher interaction.

4.1.2 LA Model

The LA model has significantly advanced over the years, integrating various frameworks to better support data-informed educational practices. It focuses on understanding how students learn within individual subjects, while also tracking their progress throughout entire training programs [Siemens, 2013]. By using advanced LA tools, we can better support students and improve their performance and study results, which helps make learning and education more effective [Van Barneveld *et al.*, 2012]. LA is an iterative process normally carried in six phases such as Data Collection, Data Storage and Processing, Analyses, Visualization, and Action [Chatti *et al.*, 2020].

Different LA techniques have been used in the literature such as non-statistics, questionnaire or survey , information visualization, data mining , machine learning and statistics, etc [Ranjeeth *et al.*, 2020]. Many LA models have been defined in the literature which are summarized in **Table 4** [Sciarrone and Temperini, 2019]. These models are designed to collect and analyze data on students' behavior, performance, and engagement within digital or physical learning environments. The main goal is to transform the generated raw data into meaningful insights that helps to improve teaching and learning outcomes and enhance students learning outcomes. LA provides real-time feedback to teachers about student progress and challenges, allowing them to adjust instruction accordingly [Papamitsiou and Economides, 2014]. Building on prior LA frameworks such as the 7-step cycle [Siemens and Baker, 2012], LAVA model [Chatti *et al.*, 2020], and the PLAF model [Susnjak, 2022], we propose a simplified three-phase LA process as shown in **Figure 6**. This abstraction reduces complexity while retaining the essential cycle of data-driven educational improvement.

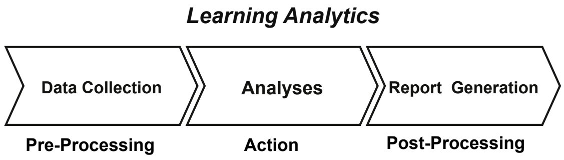

Figure 6. The proposed three-phased simplified LA process steps.

1. **Pre-Processing:** This phase corresponds to the data capture, integration, and preparation stages found in existing models [Siemens and Baker, 2012; Chatti *et al.*, 2012]. It involves collecting learner interaction data from VR environments, questionnaires, and digital traces, followed by cleaning, formatting, and structuring to ensure quality and reliability. Similar to the data pre-processing phase in the PLAF model [Susnjak, 2022], this step establishes the foundation for meaningful analysis.
2. **Action:** The Action phase reflects the core analytics and intervention cycle. Here, data is analyzed using statistical, visualization, or machine learning methods to identify patterns of student engagement, risks, and opportunities. This phase aligns with the analysis–visualization–action loop described in the LAVA model [Chatti *et al.*, 2020]. In our framework, this stage also supports personalized feedback and adaptive learning strategies, enabling teachers to adjust instruction in real time.
3. **Post-Processing:** This phase emphasizes evaluation and reflection on the outcomes of interventions. It is comparable to the refining step in the Oblinger model [Campbell *et al.*, 2007] and the validation stage in Dynamic LA models [De Freitas *et al.*, 2015]. Post-Processing ensures that insights are reintegrated into the learning cycle, guiding continuous improvement of both teaching practices and the conceptual framework.

4.1.3 PL Model

In the teaching and learning process, PL refers to how individual students' learning needs can be addressed [Cheung *et al.*, 2023].

Many research have defined different PL techniques in the literature to tailor educational experiences to meet the unique needs, preferences, and abilities of individual learners. These models often rely on LA to collect and analyze data about how students interact with learning materials [Papamitsiou and Economides, 2014]. Integrating LA into PL Systems offers significant benefits by turning student data into practical findings. As Siemens [2013] describe, LA acts as the engine that powers the personalization of content and feedback. Similarly, Ifenthaler *et al.* [2019] emphasize the importance of using real-time data and feedback loops to enhance students' learning outcomes. Most PL approaches focus on students' previous knowledge and needs and aim to provide content accordingly [Shemshack *et al.*, 2021]. The most common aim of a PL design was to improve students' performance [Bernacki *et al.*, 2021].

For better and easier understanding, we represent a PL flow diagram in 6 phases, as shown in **Figure 7**. Many metrics related to students have been improved by using different PL strategies such as digital citizenship, learner engagement, seamless learning, lifelong and life-wide learning, learning-oriented assessment, and desire paths [Keppell, 2014]. The flow of this general diagram of PL is described as follows:

1. **Capture:** The data is collected from students and teachers in this step. The data will be performance data, metrics, feedback, and contextual learning environment information. Ifenthaler *et al.* [2019] explain that capturing real-time learning data is essential for constructing a student model that supports a personalized and adaptive learning environment.
2. **Reports:** After capturing student data, LA tools generate dashboards and visual reports that track student progress, engagement, and behavior patterns. These metrics help teachers to identify learning gaps and support personalized interventions. These reports are accessible to teachers and sometimes to learners themselves as well. Verbert *et al.* [2014] discussed the importance of dashboards in LA for informing both students and teachers regarding learning progress.
3. **Predict:** Based on the data collected from students' learning activities and reports, predictive models are used to guess how students might perform in the future. These models can help find out if a student might fail a course, stop studying, have a problem during learning, or understand the subject well. This helps teachers take early action to support students who may be struggling [Baker and Inventado, 2016]. Campbell *et al.* [2007] introduced predictive analytics in education to predict student success and guide interventions.
4. **Act:** In the Act step, the system uses the data to offer content/tasks such as videos, readings, and quizzes that are customized to each student's needs. The purpose of this step is to make sure the content matches each learner's academic level and preferences that helps them to learn better. How personalized content based on students' need can improve their performances are also studied by Marougkas *et al.* [2021].
5. **Feedback:** Before the learning content is delivered, the system uses feedback from teachers and students, such as in surveys, interviews, or pre-assessments, etc., to understand what learners need. The main purpose of this Pre-Learning Feedback is to help the system to prepare and adjust content in advance, based on learner preferences, learning styles, or previous difficulties. The importance of using feedback loops to improve learning personalization have an important role [Ifenthaler *et al.*, 2019]. Siemens [2013] emphasized how feedback and analytics can be used to improve learning environments.
6. **Refine:** As the student interacts with the system, real-time data from their performance (like quiz scores, time on tasks, etc.) is used to refine the learning path in this final step. The system adapts immediately, changing or

Table 4. Learning analytics models from previous studies.

S. No.	Name	Reference	Steps	Citations
1	Oblinger Model	Campbell *et al.* [2007]	Capture, Reporting, Predicting, Acting, Refining	1105
2	LA Cycle	Clow [2012]	Learner, Data, Metrics, Intervention	712
3	4-Dimensional LA	Chatti *et al.* [2012]	What (data), Who (user), Why (performance), How (method)	1187
4	7-Step LA	Siemens and Baker [2012]	Collection, Storage, Data Cleaning, Integration, Analysis, Representation and Visualization, Action	1802
5	Dynamic LA	De Freitas *et al.* [2015]	Strategy development, infrastructure creation, learner-centered service, dynamic context, adaptive user behavior model, ethics, crowdsourced hypotheses, review/validation	215
6	LAVA Model	Chatti *et al.* [2020]	Learning activities, data collection, analysis, visualization, perception, exploration, and action (who and how explored)	23
7	PLAF Model	Susnjak [2022]	Data preprocessing, predictive analytics, prescriptive analytics	5

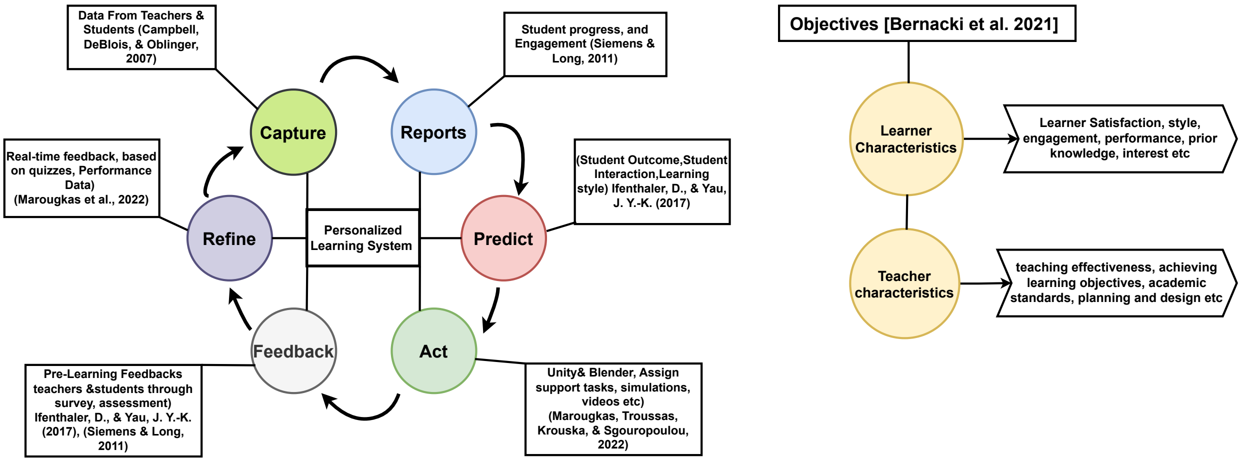

Figure 7. Proposed PL data flow diagram.

adjusting content based on how the student is doing in real time. Marougkas *et al.* [2021] showed how adaptive content delivery based on current performance leads to better results.

4.1.4 Student Behavior Model

In addition to LA and PL, we propose a *Student Behavior Model* to capture the multidimensional aspects of learner engagement in immersive VR-based education. As demonstrated by Viol *et al.* [2025], multi-user VR simulations are technically feasible and provide a strong foundation for educational applications where learners share and interact within the same immersive space. Motivated by this technical validation, our contribution shifts toward the pedagogical and theoretical domain, where we propose a Student Behavior Model as part of our proposed theoretical framework. The purpose of this model is to identify and capture key behavioral parameters that emerge during immersive VR learning simulations, enabling a deeper understanding of how learners interact, collaborate, and adapt within these environments. The proposed model is structured into three interconnected phases as shown in **Figure 8**:

1. **Cognitive Behavior:** This dimension captures aspects such as motivation, adaptability, and self-regulation, which are essential to sustaining learning in personalized and adaptive systems. Prior studies highlight that student modeling and personalized recommendation systems benefit from including cognitive features to align instruction with individual learner needs [Wu *et al.*, 2024].
2. **Social Interaction:** This phase emphasizes engagement and collaboration with peers and instructors in multi-user VR settings. Social and interactive behaviors have been successfully modeled in e-learning environments to detect how learners engage with systems and peers, demonstrating that behavior modeling is crucial for fostering collaborative and effective learning [Paquette and Baker, 2019].
3. **Emotional and Motivational State:** This dimension addresses attention, emotional responses, and cognitive load management, which directly affect persistence and performance. Intelligent e-learning systems increasingly incorporate behavioral modeling to detect learner challenges in real-time and to dynamically adapt instruction, ensuring sustained motivation and improved learning

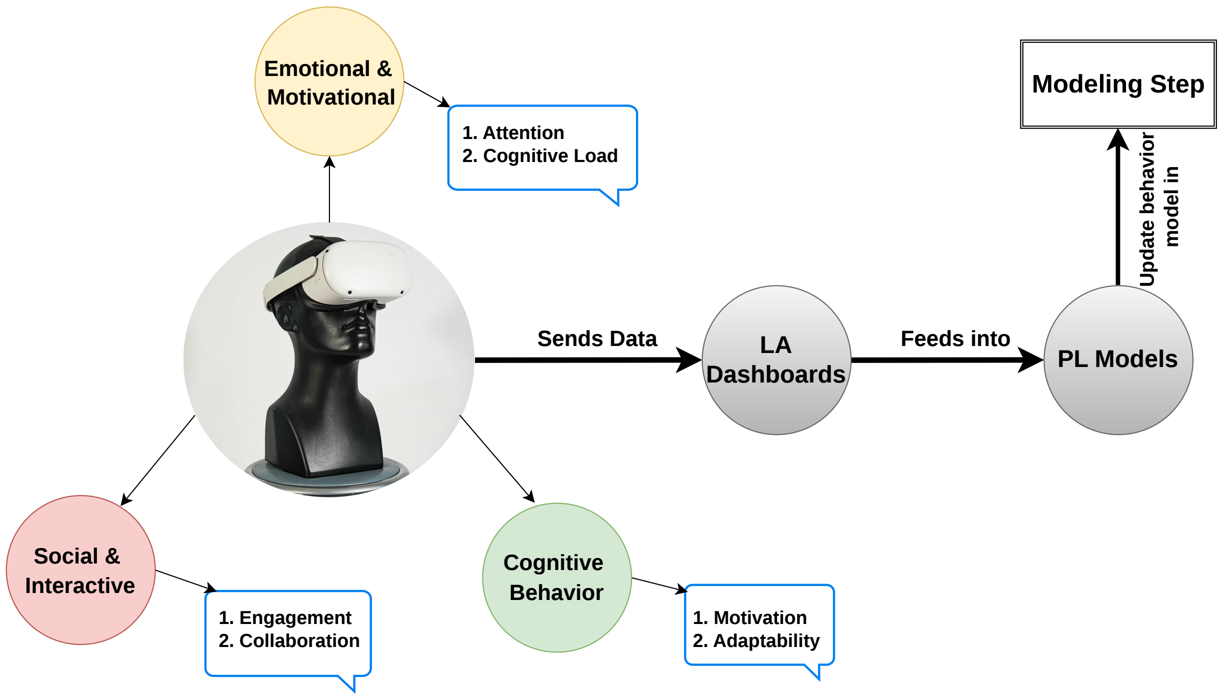

Figure 8. Proposed Student Behavior Model.

outcomes [Abhirami and Devi, 2022].

Importantly, the Student Behavior Model is also grounded in Behaviorist learning theory, which posits that learning outcomes are shaped by observable behaviors in response to stimuli, rewards, and corrective feedback [Skinner, 2019]. Within our framework, this principle is reflected through feedback loops and adaptive interventions that provide reinforcement for desirable learning behaviors (e.g., collaboration, persistence) while offering corrective support for disengagement. To effectively operationalize the proposed Student Behavior Model, it is necessary to identify how behavioral parameters can be detected in immersive VR environments. The advancement of VR technologies, including wearable sensors and integrated analytics systems, allows researchers and educators to capture observable aspects of learner behavior. By leveraging multimodal data streams such as eye movements, physiological responses, speech, and interaction logs, the framework ensures a comprehensive understanding of cognitive, social, and emotional dimensions of learning.

The following subheadings outline the three dimensions of behavior and their technological enablers, which are also depicted in **Figure 9**:

Cognitive Behavior (Motivation, Adaptability):

1. *Eye-tracking sensors:* Monitor attention shifts and focus duration, enabling real-time identification of learner engagement [Clay *et al.*, 2019].
2. *Headset usage data:* Capture behavioral data obtained through the use of VR and AR headsets, which provides information for user profiling in a virtual scenario [Tricomi *et al.*, 2023].
3. *Adaptive VR software logs:* Record learner responses to adaptive prompts, reflecting adaptability to new instructional content [Johnson *et al.*, 2016].

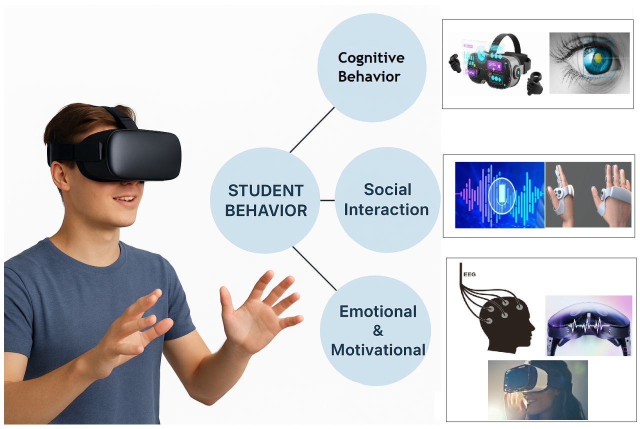

Figure 9. Behavior Recognition parameters.

Social Interaction (Engagement, Collaboration):

1. *Voice/speech recognition (VR headsets with microphones):* Track participation in collaborative discussions, enabling detection of communication and peer engagement [Schroeder, 2018].
2. *Positional tracking (motion sensors, hand controllers, full-body trackers):* Identify gesture-based interactions and co-presence in VR learning tasks [Slater and Sanchez-Vives, 2016].
3. *Interaction logs (shared VR objects, task completion):* The use of interaction logs promotes social interaction by providing insights into peer collaboration [Theoktisto and Fairén, 2005] and task-oriented exercise etc. [Chen and Chen, 2023].

Emotional & Motivational State (Attention):

1. *Physiological sensors (heart rate monitors, skin conductance):* Assess stress, emotional arousal, and cognitive load [Suhaimi *et al.*, 2022].

2. *Facial expression recognition (integrated VR cameras or external webcams):* Detect affective states such as frustration or enjoyment during learning [Zhang *et al.*, 2023].
3. *EEG-Based Brain-Computer Interfaces (BCI):* Devices such as Emotiv Insight or Muse Headbands capture brainwave activity to measure attention, cognitive workload, and levels of mental engagement in real time [Thwe *et al.*, 2024].

By integrating cognitive, social, and emotional dimensions with behaviorist principles, the proposed Student Behavior Model extends beyond technical feasibility and adds a behavioral lens to enrich LA and PL within immersive VR contexts. This approach bridges the gap between technological possibility and pedagogical value, ensuring that VR-based learning environments are not only functional but also adaptive, learner-centered, and responsive to diverse behavioral profiles.

4.2 Technological step

This step involves both software and hardware to create an immersive virtual learning experience. Students actively engage with educational content through interactive simulations. Software like Unity or Blender is used to build the virtual environment, allowing users to interact with 3D objects and scenarios. For a more immersive experience, HMDs like the Oculus or other VR devices, along with controllers, are used to navigate and engage with the virtual environment, providing users with a realistic, interactive learning experience.

4.3 Resulting Step

After users interact with virtual elements in the environment, the data is collected in this step. This data will be then extracted, cleaned, and organized into structured formats. A centralized any database will be used to store the collected information, ensuring it is ready for subsequent analysis to evaluate user behavior, learning outcomes, and system performance etc.

5 Theoretical Feasibility & Conceptual Verification

In this section, we demonstrate the theoretical feasibility and conceptual verification of the framework through alignment with DBR phases in Section 5.1, it's alignment with established theories in Section 5.2, mapping framework with identified Brazilian HCI challenges in Section 5.3, and reverse-engineering with a VR game in Section 5.4. Empirical validation with students and teachers will be conducted in future work.

5.1 Conceptual Alignment with DBR Phases

As outlined in Section 3, this framework follows the four DBR phases. Below, we demonstrate theoretical verification for each phase:

1. *Analysis of Practical Problems:* Drawing from our prior research on VR in STEM education, significant challenges were identified, such as a lack of personalized learning, insufficient student–teacher interaction, and difficulty adapting teaching strategies to learner profiles, etc.
2. *Development of Solutions:* In response, a three-phase framework was developed in this research, including Modeling, Technological, and Resulting components. It integrates LA, PL, and a structured User Model with a three-mode questionnaire system for personalized teaching and feedback mechanisms.
3. *Iterative Design and Refinement:* The framework has undergone several rounds of conceptual refinement through literature review, theoretical alignment, and scenario-based verification, ensuring its internal coherence and pedagogical relevance.
4. *Reflection to Produce Design Principles:* The final design serves as a generalizable model for adaptive learning in VR environments as well as for low-budget institutions without the facility of VR hardware. It supports scalable instructional design grounded in personalization, learner profiling, and ethical data feedback loops.

5.2 Alignment with Established Theories

The framework components are conceptually aligned against established educational theories and HCI paradigms:

1. The *Modeling Phase* of our framework aligns with constructivist learning theory, which emphasizes learner-centered environments, prior knowledge integration, and active engagement in building understanding rather than passive knowledge transmission [Piaget, 1952; Vygotsky, 1978].
2. The use of *LA and PL* supports adaptive learning theory, where instructional strategies and resources are dynamically adjusted based on learners' profiles, pace, and performance [Corno *et al.*, 1986; Walkington, 2013].
3. The inclusion of a *3-mode questionnaire* feedback loop supports user agency, transparency, and human-in-the-loop decision-making [Shneiderman, 2020], thus treating learners as active co-designers in their educational path.

5.3 Mapping Framework to Identified Challenges

As identified in our prior review on VR in STEM education [Ahsan *et al.*, 2025], students and teachers face specific challenges in immersive environments, including limited adaptability to diverse learning needs, Weak feedback loops between teachers and students, student enhancement, technological complexity, and lack of personalization, etc. The key design components were explicitly mapped to the practical challenges previously identified in STEM-based VR research, as summarized in **Table 5** that shows how each component of the proposed framework addresses these documented challenges, thereby reinforcing its relevance and practical grounding.

This research also aligns with long-term goals defined in the Brazilian HCI research agenda (2025–2035) [Pereira *et al.*, 2024]:

1. *GC1: Advancing theoretical and methodological models in education through VR:* By offering a theory-driven framework that integrates VR, LA, and PL. This work

Table 5. Challenges identified in prior STEM-focused VR research and how the proposed framework addresses them.

Challenge Identified in Prior STEM Research	**Proposed Framework Component Addressing the Challenge**
Lack of personalized pathways for diverse learners	Student Profiling through the PL Model; adaptive learning content based on User Model data.
Absence of real-time feedback and engagement mechanisms	Three-Mode Questionnaire System; LA Dashboard enabling dynamic learner input.
Limited instructional control within immersive platforms	Teacher Model integrating curriculum control with adaptive planning interfaces.
Minimal visibility into student motivations and preferences	Mode 1 (pace and interests) and Mode 3 (strategy feedback); Learning Analytics reports.
Technological inaccessibility of VR-only solutions	Dual-delivery design (VR and screen-based); inclusive deployment in resource-constrained contexts.

contributes to methodological innovation in digital education.

2. *GC5: Designing effective human–data interactions using LA and feedback systems:* The framework enables meaningful interactions with learning data via three-mode questionnaire, LA dashboards and feedback loops, enhancing instructional decision-making and learner engagement

5.4 Reverse-Engineering Mapping with VR Educational Game

The proposed framework is also verified conceptually with the use of an educational VR game [2] designed to teach Geographical concepts to children through an engaging treasure-hunt activity as shown in **Figure 10**.

Figure 10. In-game view of the VR educational game showing the interactive map and compass.

The game was developed in Unity and integrated with Moodle using the *SeriousGameComponents* package, which provides reusable components for generic learning management system integration, enabling the inclusion of content by the teachers and the collection of interaction data. The learning journey begins indoors from **Figure 11**, where students interact with slides, audio, and quizzes added by the tutor as shown in **Figure 14** to acquire foundational knowledge. Once prepared, they move into the outdoor virtual environment, where the central challenge is to explore a landscape using a compass and map to locate hidden treasures. Players orient themselves, mark coordinates, and attempt to uncover treasures by digging at the correct positions as illustrated in **Figure 13**. Each attempt is tracked with timers and scores, where incorrect digs or quiz errors increase difficulty or reduce available time. The task is completed when the player successfully opens the discovered treasure chest with a key, signifying mastery of the activity that can be seen in **Figure 15**. These mechanics engage learners in active, interactive tasks that promote spatial reasoning and applied location and spatial orientation skills in an immersive and gamified way. This game is used as a reverse engineering exercise to verify the proposed framework.

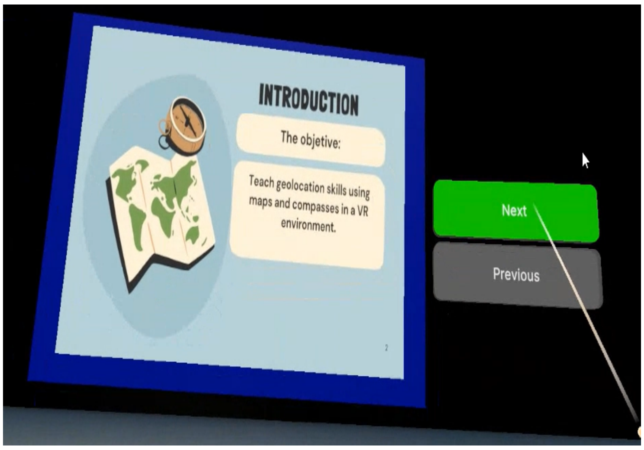

Figure 11. Image of the "Slider Component" that is feed by Moodle API. Source: from authors (2026).

5.4.1 *Method of reverse engineering*

The reverse-engineering exercise conducted with the Unity-based Compass VR game serves as a conceptual illustration of the framework's applicability rather than functioning as empirical validation. The reverse-engineering process used in this study follows established software reverse-engineering principles, particularly system decomposition and abstraction techniques [Chikofsky and Cross, 1990], which guide the identification of system functions, operational behaviors, and their alignment with higher-level conceptual models. We

[2] `https://github.com/xr4good/Compass-VR`. Accessed on 20 July 2026

inspected the game design, available telemetry, and teacher authoring interfaces and performed a structured mapping exercise. For each game element we: (1) identified the raw data produced (events, counters, timestamps), (2) proposed derived analytics indicators, (3) proposed personalization rules, and (4) identified student-behavior parameters that connect with the game (cognitive, social, emotional). The result is a tranche of operational mappings and example decision rules that show how the game can be used to conceptually verify and relate to the proposed objectives of the framework.

5.4.2 User Model (concrete instantiation)

We populated teacher and student profile fields directly from the game and LMS integration:

- Teacher profile: Geography teacher; grade: 4–5; curriculum topics: cardinal points, maps, compass; pedagogical strategy: treasure-hunt problem solving.
- Student profile: Age 9–10; grade 4–5; prior knowledge: limited on map/compass; motivation/interest: high for games; goal: complete the task within the allotted time.

Implication: The Moodle integration supplies identity, course membership, and quiz history; the game supplies session-level progress to enrich the user model. The three-mode questionnaire can be used to capture explicit attributes (pace, preference, prior knowledge) that add to the information collected automatically.

5.4.3 LA model (data $\rightarrow$ indicators $\rightarrow$ reports)

We mapped game telemetry to the three LA phases (pre-processing, action, post-processing):

Pre-processing (data collection & cleaning):

- Raw events: `session_start`, `dig_attempt` (See **Figure 12**), `dig_success/fail`, `dig_coordinates`, `compass_use`, `map_open`, `quiz_attempt`, `timestamp`, `audio_slide_views`.
- Derived fields: `time_to_first_dig` (See **Figure 13**), `total_digs`, average distance to target (per dig), `quiz_score`, map vs. compass usage ratio, wandering time (time moving without interacting).

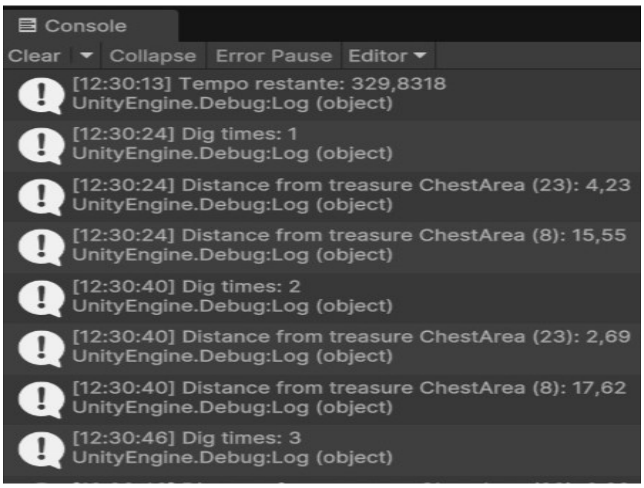

Figure 12. Console logs showing the first dig interactions.

Action (analysis & intervention):

Figure 13. Screenshot from the game, with the user digging with the shovel on the ground.

- Analytics: descriptive statistics, simple clustering of learners by performance (fast/accurate vs. slow/error-prone), anomaly detection (very high dig counts), lightweight predictive rules (e.g., if average distance to target $>$ X and total digs $>$ Y $\rightarrow$ likely map comprehension gap).
- Reports/dashboards: per-student timeline (events + quiz), class heatmap of dig accuracy, engagement timeline (compass/map usage vs. time), "flag list" for teacher attention.

Post-processing (evaluation & refinement):

- Outcome metrics: post-task quiz improvement, decrease in dig attempts over sessions, change in `time_to_treasure`.
- Feedback into User Model: update prior knowledge, adapt personalization thresholds, and log teacher interventions for later analysis.

Example analytics metric definitions:

$$dig\_accuracy = 1 - (\text{mean distance to target} \times \text{dig\_times})$$

$$engmt\_score = norm\left(qz\_scr \times 0.4 + \frac{tot\_int}{sess\_time} \times 0.6\right)$$

where engmt_score= engagment score, norm=normalization, tot_int= total interactions sess_time= session time.

5.4.4 PL Model (Teacher and Automatic Interventions)

The game is designed with teacher-driven and automated personalization:

Teacher-driven PL: To enhance reproducibility, we detail how the framework's indicators and adaptive rules will function in practice. Instructors will be able to edit slides or inject hints for individual students as shown in **Figure 14** (e.g., attach a "compass tutorial" slide for students with `dig_attempts` ≥ 3 and `dig_accuracy` < 0.4). While these features of the game are still under development, the personalized elements supported by our framework advance research in e-gamification. Personalization rules as described here map these indicators to teacher-driven or automated adaptations. For example, learners who perform three consecutive incorrect digging actions or exhibit prolonged hesitation may receive additional hints, simplified tasks, or pre-topic scaffolding from teachers.

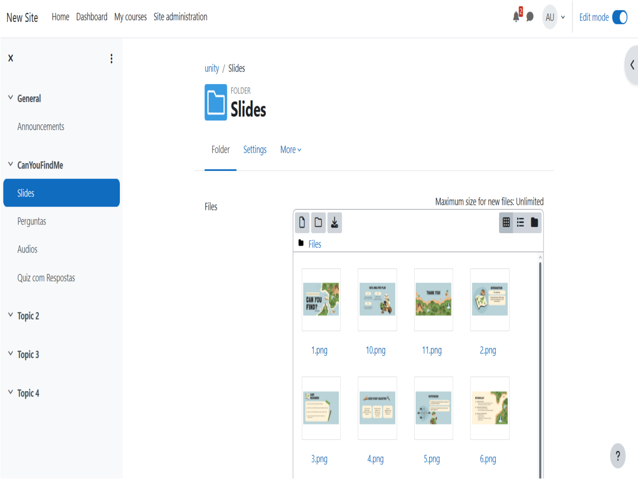

Figure 14. Screenshot of the upload slides portion of the Moodle web platform.

Automatic PL rules (examples):

- If `dig_attempts` $\geq$ 3 and `time_to_treasure` increases $\rightarrow$ auto-suggest targeted slide + short compass micro-lesson.
- If `quiz_score` $<$ threshold $\rightarrow$ route student to indoor conceptual module before outdoor exploration.
- If engagement score drops by 30% mid-session $\rightarrow$ spawn an in-game prompt (motivational hint).

These rules are defined as modular components, enabling their integration into VR learning scenarios and future analytics pipelines.

5.4.5 Student Behavior Model (Observable Proxies and Interpretation)

We mapped the game signals to three behavior dimensions:

Cognitive behavior (motivation, adaptability):

- Proxies: `time_to_treasure` (fast completion suggests motivation), reduction in dig attempts across sessions (adaptability/learning), quiz improvement.
- Interpretation cautions: low `time_to_treasure` could reflect guesswork; must combine with accuracy metrics.

Social interaction (engagement, collaboration):

- Proxies: shared task logs via Moodle (e.g., forum posts linked to map tasks), frequency of group activity markers (if multi-player), message/voice interactions.
- Usage: identify peer scaffolding or the need for teacher-mediated group support.

Emotional & motivational state (attention, cognitive load):

- Proxies: rapid increases in dig attempts with falling accuracy (frustration), erratic movement patterns (distraction), long idle times (boredom).
- If available, physiological or eye-tracking data could be layered to strengthen inferences.

5.4.6 Teacher dashboard Example (Operational Design)

A teacher dashboard derived from reverse engineering includes:

- Class overview: number of active sessions, average time_to_treasure, % of students flagged.
- Student cards: quiz_score, dig_accuracy, last_intervention, suggested action.
- Heatmap: map areas with high error rates (where students dig incorrectly).
- Intervention panel: one-click assign slide/hint or schedule small group remediation.

This demonstrates how the "LA $\rightarrow$ PL $\rightarrow$ User" Model flows can be operationalized in practice after being conceptualized through this VR game. However, some features of the game are still under development (quizzes, sending the collected data to Moodle, penalties for digging wrong, and score calculation).

Figure 15. Screenshot from the game, with the user opening a treasure chest with the keys and completing the task.

5.4.7 Pedagogical Decision-Making Example

This subsection demonstrates how the framework can support teachers pedagogically in decision-making. Consider a student participating in the Compass-VR game, in which the learner must use geographical knowledge, a map, and a compass to locate a target. Suppose the LA dashboard indicates that Student X has a *digging accuracy* below 0.30 after five attempts, spends substantially more time than expected on orientation tasks, and repeatedly interacts with the map without effectively using the compass. When considered together, these indicators provide more informative evidence than a single performance score. The teacher may interpret this pattern as an indication of difficulty in applying cardinal-direction concepts or coordinating spatial representations. Based on this evidence, the teacher may choose among several pedagogical interventions: (a) assign a short pre-lesson on cardinal directions and spatial orientation; (b) provide an individualized tutorial on the use of the compass; (c) modify the instructional material by adding visual or audio explanations; (d) provide an adaptive hint within the VR environment; or (e) pair the student with a peer who has demonstrated stronger performance. Thus, the framework supports the personalization of instructional content and teaching strategies based on observed learner needs rather than applying the same intervention to all students.

The framework therefore supports several forms of pedagogical decisions. First, teachers can adapt the *difficulty and sequence* of learning activities according to learner performance and progression. Second, teachers can personalize the *type and modality of instructional material*, for example by providing visual, textual, audio, or video explanations according to learner's needs and preferences. Third, teachers can select different *forms of intervention*, including additional explanations, hints, tutorials, peer collaboration, or individual support. Fourth, teachers can identify when a learner is ready to proceed to more complex activities. Finally, aggregated LA information can help teachers identify common difficulties across a group and modify lesson plans or instructional materials for the class as a whole.

In this way, the framework supports teachers in personalizing instructional materials, selecting appropriate interventions, and adjusting task difficulty based on LA and behavioral evidence. Compared with Marougkas *et al*. [2021], which mainly adapts difficulty automatically, and PERLA Chatti and Muslim [2019], which is oriented to conventional learning environments, our framework adds VR-specific spatial navigation data, teacher-mediated interpretation, and behavior-informed personalization. The contribution of this integration is therefore not simply the inclusion of additional data sources. Rather, the framework establishes a pathway from *what the learner does in the VR environment*, to *how that behavior is interpreted through analytics*, to *what pedagogical action the teacher can take*.

5.5 Illustrative Scenario of the Framework

Consider a learner navigating the compass-based VR activity. As the student repeatedly checks the map but fails to align orientation with the compass direction, the LA module collects several performance indicators in real time, including task-completion time, number of incorrect digging attempts, and hesitation patterns extracted from navigation logs. These analytics reveal increased task difficulty and rising cognitive load. The Student Behavior Model interprets these indicators as signs of struggle for students. Based on this interpretation, the PL component triggers an adaptive rule that displays a simplified guidance overlay or provides additional hints. Simultaneously, the Teacher Model receives an automated summary suggesting the need for targeted reinforcement in spatial reasoning before the next activity. This scenario illustrates how LA metrics, behavioral indicators, and personalization rules operate together within the framework: the VR environment generates actionable data; the analytics module transforms them into meaningful signals; and the PL layer adapts instruction dynamically while keeping the teacher informed for future planning.

Table 6. The game mechanism aligned with the framework for conceptual verification.

User Model: Teacher	
Category	**Information from Game**
Description	Geography teacher
Curriculum	Cardinal points, maps, compass, location, and spatial orientation
Strategy	Find the treasure by applying geographical knowledge
User Model: Student	
Category	**Information from Game**
Age	9–10 years old
Grade	4th–5th grade
Prior Knowledge	Limited prior knowledge, particularly of maps and compasses
Interest	Games and outdoor exploration
Goals	Complete the game within the allotted time and achieve a high score
LA Model	
Category	**Information from Game**
Data	Timer (time spent searching for the treasure), quiz results, number of digging attempts, and distance from the correct digging location
Analysis	Statistical analysis
Reports	Graphical and numerical representations based on the collected statistics
PL Model	
The teacher can modify the slides and provide specific hints for individual students. For example, after a predefined number of incorrect digging attempts, the player can receive an adaptive hint.	
User Behavior Model	
Category	**Information from Game**
Motivation	Persistence in completing the task, number of voluntary interactions, and willingness to continue after errors
Attention	Time-on-task, and interaction with intentionally distracting elements, such as moving animals and environmental features
Engagement	Use of game objects, including the shovel, map, compass, keys, and treasures
Cognitive Load	Simultaneous use of the map and compass

6 Discussion

6.1 Personalized Feedback and Student–Teacher Interaction

We propose to use personalized feedback based on data generated by the LA model to improve individual learning needs, student preferences, and overall learning outcomes. Student–teacher interaction and the implementation of the defined questionnaire modes provide better key insights from students' perspectives and support their future learning. LA enables adaptive learning paths by identifying each student's strengths, weaknesses, and preferences [Hernández Cárdenas *et al.*, 2022].

The User Model, combined with the three-mode questionnaire, bridges automatic adaptation and teacher agency. This dual-level design positions teachers not only as facilitators but also as informed decision-makers, empowered with real-time insights from LA dashboards and behavioral metrics. In doing so, the framework extends prior work such as PERLA [Chatti and Muslim, 2019] and gamified VR models [Srimadhaven *et al.*, 2020] by embedding richer behavioral and contextual signals into personalization strategies. The systematic application of the questionnaire enables teachers to design tailored lesson plans, while the generated LA data informs algorithms that automatically adapt tasks to learners' performance and styles.

6.2 Behavioral Modeling in VR Simulations

We also gather student behavior data through the proposed behavior model during VR simulations to better understand each student's real-time behavior and continuously refine instructional approaches. After each VR experiment, the behavior model updates the LA and PL models, thus improving the learning capabilities of the students in a cyclic process. Findings contribute critical insights for designing future VR-based systems that prioritize personalization and meaningful human–data interactions. Under an HCI-centered design, this framework provides responsive systems that adapt to students' needs while enhancing interactions between learners and instructors.

6.3 Advancing Theoretical Integration

Beyond immediate contributions, this framework advances the theoretical integration of LA, PL, and VR by offering a structured approach that unifies cognitive, social, and emotional aspects of learning. Unlike frameworks that emphasize gamification or data collection in isolation, our model explicitly connects behavioral insights with adaptive learning pathways and teacher-driven personalization, ensuring pedagogical relevance rather than purely technical adaptation.

6.4 Practical Implications and Scalability

The framework supports scalability through hybrid delivery modes: immersive VR for institutions with advanced infrastructure and screen-based adaptations for low-resource contexts. This flexibility ensures that even schools with limited VR devices can benefit from personalized insights, aligning with the goals of inclusive and equitable access to next-generation educational technologies. The design also aligns with the Brazilian HCI Grand Challenges GC1 and GC5, advancing new theoretical models while emphasizing human–data interaction for meaningful educational outcomes.

6.5 Verified Outcomes from the Reverse-Engineering Exercise

The reverse-engineering exercise with a VR game demonstrates how the framework can be operationalized:

- **Proof of fit:** Game telemetry naturally maps onto our LA three-phase model and supplies the inputs required by the User Model and PL rules.
- **Behavioral coverage:** The game mechanics provide observable proxies for cognitive, social, and emotional constructs of the Student Behavior Model (though emotional inference remains weak without physiological sensors).
- **Teacher support:** Moodle integration enables teacher authoring and human-in-the-loop interventions as envisioned in the framework.
- **Gaps identified:** Emotional inference requires richer sensing; lifelong modeling demands persistent identifiers; and predictive analytics need larger datasets.

Overall, this verification demonstrates feasibility and illustrates how behavioral data, LA, and PL rules can be aligned within a single system. At the same time, it points to the need for future empirical testing, teacher validation, and long-term deployment.

7 Threats to Validity

The reverse engineering of the educational game against our proposed framework demonstrates conceptual applicability, but it does not substitute for empirical validation with real learners or domain specialists. Several limitations must therefore be acknowledged. First, behavioral inferences derived from in-game telemetry (e.g., number of digs, time-on-task) are inherently probabilistic and should be triangulated with ground-truth evidence such as classroom observation, interviews, or expert judgment. Second, the framework has not yet been validated through pilot studies with students, nor has it been reviewed by LA specialists who could further assess its methodological soundness. Third, practical constraints, including limited access to VR devices, the absence of a fully integrated LMS-based system, and the lack of empirical testing of the three-mode questionnaire, restricted our ability to implement and test personalization features in authentic classroom contexts. These limitations highlight that the present work should be viewed as a theoretical and conceptual contribution, providing a foundation for future empirical studies. Subsequent research will need to validate the framework in authentic educational settings, incorporating feedback from both learners and educators, and leveraging scalable infrastructure to evaluate usability, pedagogical impact, and system-level feasibility.

8 Ethical and Methodological Considerations

Although this study is conceptual and does not involve empirical data collection with human participants, ethical considerations were integrated throughout the framework design process due to its educational context and anticipated future deployment involving sensitive learner data. Ethical principles directly influenced four key design decisions. First, we prioritized teacher agency from the User Model (Section 4.1.1) over automated personalization, maintaining human-in-the-loop oversight rather than relying exclusively on algorithmic control. Second, the three-mode questionnaire system as mentioned in **Table 3** provides students' voice in their learning pathways, respecting autonomy by balancing system recommendations with learner preferences [Parsons, 2021].

Third, the LA Model (4.1.2) generates interpretable dashboards with explicit decision rationales rather than opaque predictive scores, preventing "black-box" profiling that could stigmatize struggling learners [Ferguson, 2019]. Fourth, we emphasized scalable hybrid modalities to prevent technological exclusion of under-resourced schools. These choices embed fairness, transparency, and privacy protection from the conceptual phase.

Future implementation will integrate physiological, cognitive, and behavioral VR data (eye-tracking, EEG, heart rate), raising important privacy concerns. As Tzimas and Demetriadis [2021] emphasizes, LA research must address ethics proactively from design phases rather than as reactive measures. Similarly, Misiejuk *et al.* [2025] highlights the need for individualized learning technologies to incorporate principles of privacy, transparency, fairness, and informed consent, while Parsons [2021] argues that educational technology must be value-oriented, respecting learner autonomy and protecting vulnerable populations. The study protocol will be submitted for formal ethics committee review, including a detailed description of procedures and participant protections, including: (1) explicit informed consent from students, parents, and teachers, (2) data minimization capturing only pedagogically necessary information, (3) secure storage with access controls, and (4) withdrawal rights without penalty. All research phases will strictly follow approved ethical guidelines safeguarding participant privacy and vulnerable learners. Any committee feedback will be incorporated to ensure full compliance with ethical standards. All future research phases will strictly follow approved ethical guidelines, with particular attention to safeguarding participant privacy and rights.

9 Final Remarks and Future Work

This study proposed a conceptual framework that integrates LA, PL, a structured User Model, and a Student Behavior Model within immersive VR-based education. Guided by a DBR methodology, the framework was conceptually evaluated by theory and verified through reverse engineering using a VR-based educational game. This dual approach ensured coherence with established educational theories while also demonstrating practical alignment with VR game environments. The User Model systematically supports teaching methodology, lesson planning, and the design of customized teaching strategies, while the Student Behavior Model captures behavioral and affective dimensions such as motivation, collaboration, and cognitive load through VR-enabled interactions and analytics. The framework enables teachers to align instructional planning with students' real-time performance, supported by the integration of LA and PL models that dynamically adjust learning activities to individual pace, interests, and cognitive profiles that support personalized learning. In doing so, it enhances engagement, learning outcomes, and collaborative processes, fostering more human-centered and effective educational environments. The personalized feature of our framework contributes to advancing future research in gamification and personalized learning. In particular, this feature offers a new perspective for designing innovative gamification strategies for promoting education in immersive learning experiences for individual students.

Importantly, the research aligns with the Brazilian HCI Grand Challenges [Pereira *et al.*, 2024], specifically GC1 by advancing theoretical and methodological models for VR in education, and GC5 by enabling meaningful human–data interaction through LA dashboards and feedback-driven instructional planning. By aligning with the Brazilian HCI Grand Challenges (GC1 and GC5) and emphasizing low-barrier, teacher-supported personalization, the framework offers a viable path for scalable adoption in Brazilian public schools. The reverse-engineering exercise further demonstrated that an off-the-shelf Unity/Moodle educational game can instantiate core elements of the framework, generating relevant telemetry, supporting teacher interventions, and offering observable behavioral signals. At the same time, this exercise revealed gaps such as the need for richer sensing and empirical calibration that highlight the distinction between conceptual verification and robust deployment.

This paper primarily illustrates the *Modeling step* of the proposed framework as illustrated in **Figure 3** as a conceptual model, while the *Technological step* remains as future work where actual empirical validation of the proposed framework will take place. Future iterations will incorporate established HCI methods such as participatory design, usability evaluation, and UX assessment. Also, we plan to develop VR-based games for users with no or less programming expertise in the next phase of the research. Accordingly, this study does not yet include empirical user validation, which will be undertaken in follow-up research. Planned next steps include pilot studies in VR-based STEM classrooms to assess the framework's effectiveness in enhancing student–teacher interaction, adaptability, and engagement, particularly in Brazilian high schools. Longitudinal studies and expert reviews will also be conducted to refine the framework further and assess its long-term impact on personalized learning outcomes.

Declarations

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Authors' Contributions

Muhammad Ahsan led the conceptualization and methodology of the study, coordinated the overall project administration, and was primarily responsible for the formal analysis, visualization, and preparation of the original draft, as well as subsequent revisions. Ulfat Tahireen contributed to the investigation by designing the three-mode questionnaire for student–teacher interaction. Filza Javed contributed by developing the PL model and aligning it with the proposed framework. Matheus Gonçalves developed the VR-based educational game used in the reverse-engineering verification. Laura Coura assisted in the reverse-engineering tasks, mapping the game mechanics to the framework models and supporting data analysis. Daniel Guidoni guided the review analysis, modeling, and paper structure. Saul Delabrida provided supervision, critical review, methodological guidance throughout the research process, and funding acquisition. All authors reviewed and approved the final manuscript.

Competing interests

The authors declare they have no competing interests.

Availability of data and materials

The manuscript promotes rigor and reproducibility that can be replicated in future empirical studies. While no human-subject data was collected at this stage, the conceptual framework is transparent and theoretically aligned as well as conceptually verified with a VR-based game. The empirical validation will be conducted in future research. The game used in this research is available at the link `https://github.com/xr4good/Compass-VR`. Also, the questionnaire and the details regarding the reverse engineering process are available at the link `https://github.com/xr4good/LA-PL-VR_Model`.

Further relevant information

It is explicitly stated that Generative Artificial Intelligence (AI) tools were used exclusively in the stages of grammatical review, stylistic improvement of content, and refinement of the textual cohesion of excerpts from this article. It is noteworthy that such computational tools were not listed, nor do they meet the requirements for authorship or co-authorship of the work. Human authors assume full and complete responsibility for all intellectual and scientific content presented, guaranteeing the originality of the text and the absence of plagiarism in all sections of the article.

This study recognizes the importance of citation diversity. Our reference list reflects contributions from scholars representing a variety of backgrounds, institutions, and geographic regions, offering a broad range of perspectives within the field. All references were selected on the basis of relevance to the research topic. Factors such as authors' gender, nationality, or other personal characteristics were not considered. By explicitly stating this commitment, we aim to raise awareness of citation bias and support more equitable and inclusive referencing practices in future research.

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