https://doi.org/10.2352/EI.2026.38.2.SDA-341

MAIVE: A Multi-Agent AI-Driven Immersive Virtual Reality Framework for Astronomy Education

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Abstract

Immersive VR tools simulate cosmic events interactively to improve understanding of space science, but they often prioritize visuals over learning. MAIVE navigates virtual environments with multiple AI agents and embedded tutors on demand. A central coordinator guides these tutors in explaining concepts, checking assumptions, and providing step-by-step support. By aligning motion data with activity milestones, the system captures signals that show how each user progresses through tasks. Conversation history is preserved by a memory and retrieval tool to support teachers. Separating perception tasks from teaching moves and internal model updates allows adjustments without changing virtual environments. To measure impact, we will compare an adaptive MAIVE condition to a nonadaptive condition using the same material, order, and logging. We will analyze conceptual change, user feedback scores, pause, help, and error logs.

1. Introduction

Many VR applications for astronomy provide immersive visualization but limited instructional support. At the same time, because it immerses learners in environments that integrate immersion, visualization, collaboration, and facilitation to make abstract phenomena more accessible, VR is well-suited to astronomy education [1].

In practice, classroom and outreach deployments are still limited. For example, limited headsets and staff time limit the number of learners who can participate; learners need clear instructions and training; and some users are uncomfortable or distracted by the technology [1,2]. As a result, when learners use 3D spatial and temporal reasoning but are assessed using traditional methods, assessment becomes difficult [2].

In fact, a systematic review of immersive VR classroom studies found no in-class adaptive learning methods for individual learners [3]. Embodied AI assistance in VR suggests that coherent responses to natural language tutoring in virtual spaces depend on mechanisms that retain and retrieve prior interaction context [4,5]. To address this, our architectures support adaptivity by separating evidence collection, learner state inference, and pedagogical action, allowing guidance updates without rebuilding scene content [6].

Against this backdrop, we introduce MAIVE, a multi-agent AI-driven immersive VR framework for astronomy education that triggers in-scene conceptual and procedural tutoring using continuous interaction telemetry [1,6]. In addition, we define an evaluation protocol that compares adaptive MAIVE to a nonadaptive version that preserves tasks and logging to isolate the effect of adaptivity [3]. At this stage, data collection has not yet begun. At submission time, the multi-agent architecture, and evaluation protocol are specified; the VR content and results are not reported in this paper.

2. Background and Related Work

Learning inside VR is stepping into a simulated world where users interact with 3D spaces. While such settings may boost immediate knowledge retention more than traditional techniques [7], their real impact depends heavily on how lessons are structured and evaluated; however, poor planning can undermine potential advantages [3,7]. Moreover, gains might fade if practice happens only occasionally without consistent review [7]. Nevertheless, customizing experiences based on learner needs remains limited; current classroom-based immersive systems rarely adjust to individuals despite growing interest [3]. Consequently, this space points to unexplored territory where research must advance adaptive tools tailored to personal ways of learning. For example, when students interacted with tailored 3D classroom layouts, one study showed gains in test scores and faster reaction times compared with generic designs [20]. In addition, clunky interfaces drain mental effort, dragging down progress [7]. Therefore, VR teaching should weave support and real-time guidance directly into the setting, rather than relying solely on sensory depth [3,7].

Despite its potential, VR in astronomy education often falls short when used only for display. Through interactive 3D models, celestial movements become visible; however, a deeper understanding emerges when users ask questions, test ideas, and actively navigate the content [8]. Even so, numerous digital planetariums rely on passive formats that limit discovery and reduce mental engagement [8]. When brought into schools, such tools require significant time, equipment, support, and prepared educators, often resulting in brief segments for limited numbers of students [2]. As a result, attention may shift towards the spectacle itself, pulling focus away from core scientific principles [2]. Moreover, traditional assessments often miss insights gained in spatial, immersive environments [2]. For instance, a learner might spot errors when a built-in concept map flags misunderstandings, nudging them to revisit key ideas and attempt the answers again [9]. Still, much of today's VR work in astronomy follows fixed scripts or relies on instructors, which slows broad adoption and often misses opportunities for personal guidance [1,2].

One way to offer tailored help in immersive VR is to observe user behavior, infer their mental state, and respond quickly [6,23]. Specifically, advanced analysis systems make this possible by logging actions and shaping lessons around personal progress. In multi-agent setups, different parts handle tracking, judging, or teaching, each working alone yet together [6,22]. Furthermore, help from lifelike digital guides may improve results and make tasks feel easier [5]. Likewise, systems that talk like people do make interactions feel more fluid than those that use only menus and buttons [5]. When large models guide interactions, staying aligned with past steps relies on tracking with memory, which helps preserve context across moves a person made before [4]. Additionally, pulling facts from trusted sources while generating answers reduces the inclusion of made-up details and anchors outputs in real data [11]. Finally, how quickly someone moves through virtual tasks, captured via usage signals, provides clues about progress and shapes real-time support [23].

Learning goals should connect directly to how players gain understanding, respond to their decisions, and measure their own growth [12]. Within VR settings that pull users in, such cycles sustain attention while supporting steady educational outcomes through responsive systems. Moreover, studies on games meant for training emphasize blending teaching strategies naturally into play, using data-driven insights and performance checks [12]. Approaches such as G/P/S provide structure by linking game actions, instructional aims, and measures of success [13,14]. Taken together, these ideas shape MAIVE, in which multiple AI agents guide learners through an astronomical educational environment, providing real-time guidance tailored to individual paths [1,3,6]

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3. Conceptual Framework

Immersive VR shows benefits in education because assessments occur immediately after exposure within the application [7]. At the same time, despite its potential, customization in virtual environments has a small classroom adoption; systems that adjust to each student's pace or choices remain scarce [3]. In practice, instruction unfolds through guided experiences in which responses shape ongoing tasks, supported by live performance data that shifts content during active engagement. For this reason, we frame MAIVE around structured immersion, in-scene feedback, and telemetry-driven adaptation, enabling instruction to respond while the learner is still acting in the environment [3,7].

3.1 Learning rationale

Learning takes shape when students do things, talk about them, and make sense together; in this view, this underpins MAIVE's foundation in constructivist and socio-constructivist ideas. Over time, knowledge grows through lived cycles: trying, thinking, adjusting; an approach rooted in experiential learning theory [16–18]. Even though VR in astronomy offers rich visuals and deep presence, real learning progress often hinges on shared inquiry and skilled guiding that move curiosity toward clarity [1]. When this is missing, cognitive strain can swamp attention; cluttered VR designs distract more than teach, which is why MAIVE builds guidance into its core architecture [18,19]. Even then, in immersive settings, flawed ideas can go unchallenged, yet studies show that timely, built-in responses help learners rethink assumptions during space-related tasks [9]. Based on this, MAIVE draws on how users interact with telemetry to identify misconceptions and errors and to ensure correct learning [23].

3.2 Theory-to-design mapping

MAIVE missions take shape by clear conceptual aims, moments to express thinking, and feedback shaped by a learner's specific misunderstanding, so offering instant replay within the same setting [9,16–18]. Similarly, astronomy-focused VR tasks guide learners through structured visualization, 3D layout, shared activities, and attention to ideas [1]. In MAIVE, the assistant arrives when requested; as a result, we will reduce exploration, prevent long pauses, and avoid cycling errors while tracking the user experience [18,19]. Since most immersive classrooms rarely adjust to individuals [3], customization here turns user action paths into indicators of progress, helping match findings, where patterns forecast learning shifts, and helping [23]. Overall, MAIVE keeps responsive decisions within its AI multi-agent system: sensing, evaluation, and instructional action, which allows transparency between what learners do and how the system responds [6].

3.3 Why adaptivity is coupled to a multi-agent approach

Through immersion in MAIVE, adaptation operates continuously, by detecting actions and offering help without breaking engagement [5,23]. Rather than centralizing control, multiple agents divide tasks; each handles distinct roles while sharing insights via clear messaging, a method highlighted when linking virtual environments with agent networks [6,22]. Because of this, splitting duties this way keeps reactions quick and allows every interaction to be traced back to explicit evidence rather than opaque global logic [6,23].

4. MAIVE System Architecture

We designed MAIVE as an immersive VR learning environment that adapts during use by tracking learner behavior and delivering timely guidance. In VR, sensing, inference, and tutoring must operate continuously without interrupting interaction, which makes modular, multi-agent architectures a practical fit for maintaining consistency and responsiveness [21]. Figure 1 summarizes the closed loop that connects the VR scenario, telemetry features, orchestration, and in-scene tutoring. The design separates high-frequency telemetry capture from instructional decisions and then reintegrates the output as embodied guidance rendered within the scene [5,23].

4.1 System Overview

As an immersive VR scenario, telemetry, learner state pipeline, and multi-agent tutoring comprise MAIVE (Figure 1). During use, the telemetry and feature pipeline sessions rely on task markers and learner state indicators to guide tutoring decisions [23]. In practice, transforming continuous tracking streams and task events into time-aligned traces helps identify errors and misconceptions [23]. Rather than relying on end-of-task summaries, behavior can be used as a continuous signal to identify the interaction that caused a stall or misconception [23]. As a result, embodied assistance returns dialogue and scene feedback [5].

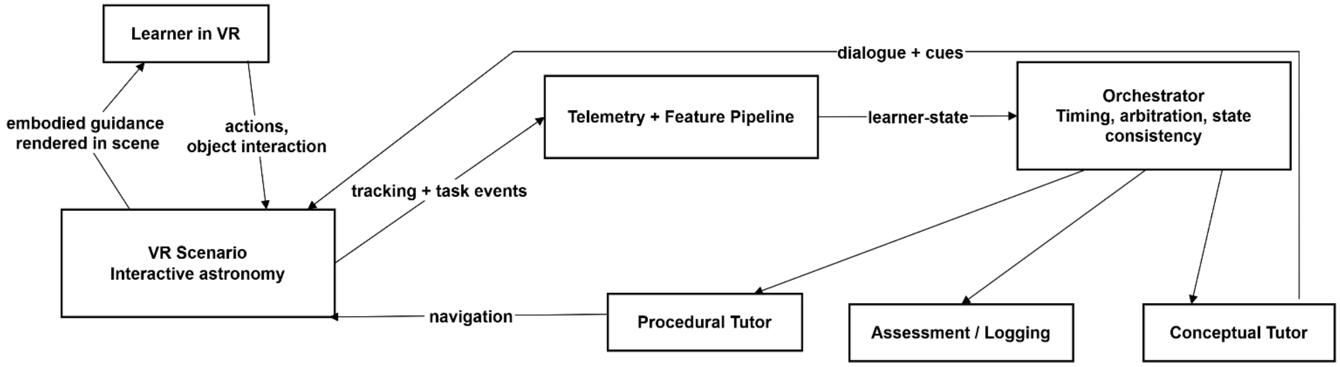

Figure 1. *The MAIVE closed-loop architecture linking VR interaction, telemetry features, orchestration, and in-scene tutoring.*

4.2 Multi-Agent Design

At the system level, MAIVE tutoring strategies are independent of VR using modular tutoring components. More broadly, a multi-agent VR framework separates data capture, evaluation, and pedagogical action for immersive adaptive instruction [6]. To keep things coordinated, under distributed VR constraints, an AI orchestrator controls tutoring actions [21]. By synchronizing controller pose streams, interaction inputs, and task markers, a telemetry agent can produce time-aligned traces and features. Based on prior work, tracking features predict VR training learning gains as evidence for learner-state inference [23]. From there, this evidence helps the learner state evaluator identify progress, difficulty, and stalls, and the assessment and logging service records indicators, interventions, and outcomes for offline analysis [14,23].

On the instructional side, the conceptual tutor provides objective-aligned astronomy prompts, explanations, and misconception checks. In line with this, multi-agent educational VR platforms motivate concept tutors rather than generic help text by tailoring content and feedback to learners [6]. Alongside this, the procedural tutor's navigation and interaction steps help students' complete tasks without instructor intervention. In practice, intelligent tutoring systems distinguish between proactive scaffolding and reactive feedback based on procedural cues, either before failure, when stalls are detected, or after errors, when recovery is needed [23]. To keep interactions coherent, the memory and retrieval service maintains session context and provides tutors with a brief history and concept of milestones. As shown in prior studies, LLM-based social VR agents demonstrate that explicit memory and retrieval improve contextual relevance and coherence across turns, which is crucial for learner history-based guidance [4]. For this reason, we ground tutor responses in retrieved context and curated resources to reduce unsupported actions [11].

4.3 Data and Telemetry Pipeline

In MAIVE, telemetry is active in instruction input, not logs. In immersive VR, fine-grained motion and interaction traces are tracked, and velocity-based tracking features estimate learner state in real time [23]. From this, continuous tracking and task events allow the telemetry pipeline to compute learner state indicators during the session and send them to the orchestrator to provide feedback on stalls or misconceptions.

At the same time, telemetry in educational VR raises privacy and ethical concerns because behavioral traces can reveal sensitive information, and prior research has shown the need for safeguards against privacy violations, algorithmic bias, and potential harm to user well-being [24]. To address this, we avoid storing personal identifiers and behavioral traces and record only what is needed for adaptability and evaluation [24]. Moreover, since serious game design frameworks emphasize early definition of research questions, metrics, data requirements, consent, and ethics review, instrumentation supports analysis without exposing unnecessary data; we are following this guide to implement our telemetry [14].

4.4 Implementation Context

MAIVE targets classroom and outreach settings where headset availability, time, and staffing constrain what can be delivered in a single session [2]. In the planned study, VR exposure will be reported as checkpoint time derived from task-marker timestamps. To compensate, screen casting lets learners without headsets observe, discuss, and influence decisions about astronomy VR deployment and navigation, supporting collaborative learning and reducing equipment needs [1,2]. With these constraints in mind, MAIVE's fast entry, step-by-step progression, and in-scene guidance reduce the need for instructor intervention. At the architectural level, modules, and the tutoring layer updates telemetry features and tutoring policies, as in modular multi-agent VR systems [6,21,22].

4.5 Adaptation, Tuning, and Feedback

During sessions, MAIVE guides learning with real-time analytics and tunes behavior between sessions with batch analytics. In operation, the AI orchestrator selects a conceptual prompt or procedural cue from learner-state indicators derived from telemetry and task performance, using predefined decision rules and constraints [21,23]. Using short dialogue turns and cues feedback, MAIVE supports users without breaking immersion [5]. Afterward, logged traces and assessment outcomes are analyzed to adjust thresholds, priorities, and message templates while maintaining stable agent interfaces for version tracking [14,23].

5. Research Design and Evaluation Methodology

In serious game creation, evaluation begins when research questions define what data to collect and how tools are shaped within the framework [14]. Serious game design methodologies emphasize that the concept-development stage must explicitly integrate learning outcomes, because an inadequate design process can produce costly, time-intensive systems that still fail to achieve the intended educational results [15]. Because insights into learning rely on behavior during the session, the assessment strategies highlighted are critical [10]. In MAIVE, the astronomy scenarios, guidance mechanisms, and logging features evolve together, so adaptivity testing does not alter foundational activities. To study performance differences, MAIVE pits an adaptive version against a static counterpart through randomly assigned user groups. Identical material, goals, and activity order across versions make it possible to detect effects tied solely to real-time customization, a feature seldom seen in current VR-based education. What sets the test apart is just one change: AI multi-agent support with everything else held steady, like data tracking and job layout, limiting outside influence [6,23]. Factual accuracy in answers comes from pulling verified details during response creation and blending them into open-ended output.

5.1 Research Questions

Prior VR astronomy studies indicate that misconceptions can persist when guidance is limited, and that feedback delivered during the session can prompt learners to reexamine their reasoning and revise their answers in context [1,9]. RQ1 asks whether the adaptive condition yields larger conceptual gains on an astronomy concept inventory from pretest to posttest, and whether this improvement is reflected in fewer repeated misconceptions and more in-session correction events [1,9]. RQ2 asks whether learners report greater clarity, support, and usability of guidance in adaptive conditions, and whether these reports align with behavioral indicators such as reduced stall time, lower help-seeking friction, and more consistent task completion [10,23]. RQ3 asks whether adaptive tutoring improves problem-solving behavior, as measured by performance on open-ended and telemetry-derived indicators of strategy efficiency and repeated error patterns [23].

5.2 Planned Study Design

As shown in Figure 2, sessions unfold across two distinct setups, assigned at random. Participants complete consent and safety screening, as well as a baseline astronomy concept inventory, before orientation and control familiarization. The guide is organized into checkpoints that correspond to learning tasks. VR exposure will be reported as time derived from task-marker timestamps. In the adaptive condition, AI multi-agent guidance delivers tutoring inside the scene at defined touchpoints. The AI agents offer idea-based cues and step-by-step help at specific moments within the environment [6]. When adaptation is turned off, interaction continues without agent input, keeping tasks and recordings unchanged to isolate effects tied to responsiveness rather than setup differences [23]. Each teaching moment is recorded as a timed entry, enabling closer study of how advice influences actions based on when and what kind of advice appears [6,23]. During these interactions, the privacy rules described in Section 4.3 limit data access, require masking identities, and reduce tracking to the essentials, ensuring personal details remain secure [14,24]. After VR, participants complete a post-test concept of inventory, a short learner experience questionnaire, and brief exit prompts to contextualize outlier responses.

5.3 Measures and Data Streams

Before and after each session, understanding is assessed through tests tied to the learning goals, along with real-time error spotting, the moments when mistakes are corrected, and how learners adjust their actions once feedback arrives [1,9]. The clarity, support, and guidance participants feel is captured later via survey questions about their experience [10]. Learner behavior arises from constant telemetry, which is translated into measurable signs [23]. Both groups have these tracked logs, so that differences can be clearly compared during the analysis [23].

5.4 Planned Analyses and Reporting

Because we set analytical plans early, tools and outputs remain tied to study goals without growing once systems go live [14]. Starting from where students stand, the focus is on how understanding grows across groups through post-testing. Other checks examine whether adaptive learning support increases satisfaction scores, improves real-time fixes, reduces recurring errors and pauses, and alters patterns observed in digital traces [1,9,10,23]. Session logs with tracking signals tied to behavior changes, behavioral shifts, specific tutoring actions, and their timing within the session [6,23]. Data collection has not yet begun, and results are not yet available; therefore, this reports on the evaluation protocol and the instrumentation to test MAIVE under controlled conditions.

6. Discussion and Future Work

The goal of MAIVE is to engage students in astronomy through VR experiences [1]. Immersive VR studies have reported positive learning outcomes, but most interventions are short, and retention is rarely tested, so impact claims remain uncertain [7]. Because adaptive learning techniques tailored to individual learners are rare in-class immersive VR, MAIVE treats personalization as a system requirement rather than a feature.

MAIVE implements serious game design with early goal setting, learner agency, and measurement [12,14]. Multiple AI agents separate learner state evidence, instructional decisions, and in-scene tutoring for consistent teaching while learners are immersed [6,21]. As evidenced by MAIVE's distinction between conceptual support for reasoning and misconception checking and procedural support for navigation and interaction, astronomy learners benefit from timely feedback [1,9]. Telemetry adapts sessions, and logged traces and assessment results tuned [14,23]. Evidence that motion and interaction features can predict learning gains, and time-adaptive scaffolding suggests that telemetry and intervention logs link tutoring to observed behavior [23].

This paper describes the framework and evaluation protocol, but participant outcomes are unavailable. Adaptive multi-agent guidance will be compared to nonadaptive tasks and logging for conceptual learning, learner experience, and problem-solving [20,23]. Classroom deployment is limited by headset availability, staff time, and training overhead, which encourages in-scene assistance to reduce instructor intervention [2]. VR telemetry can reveal sensitive behavioral information, so we collect only essential signals, obtain consent, and avoid storing direct identifiers in logged traces [14,24]. We ground language generation tutoring in retrieval-based resources to reduce unsupported responses and oversee AI behavior [11].

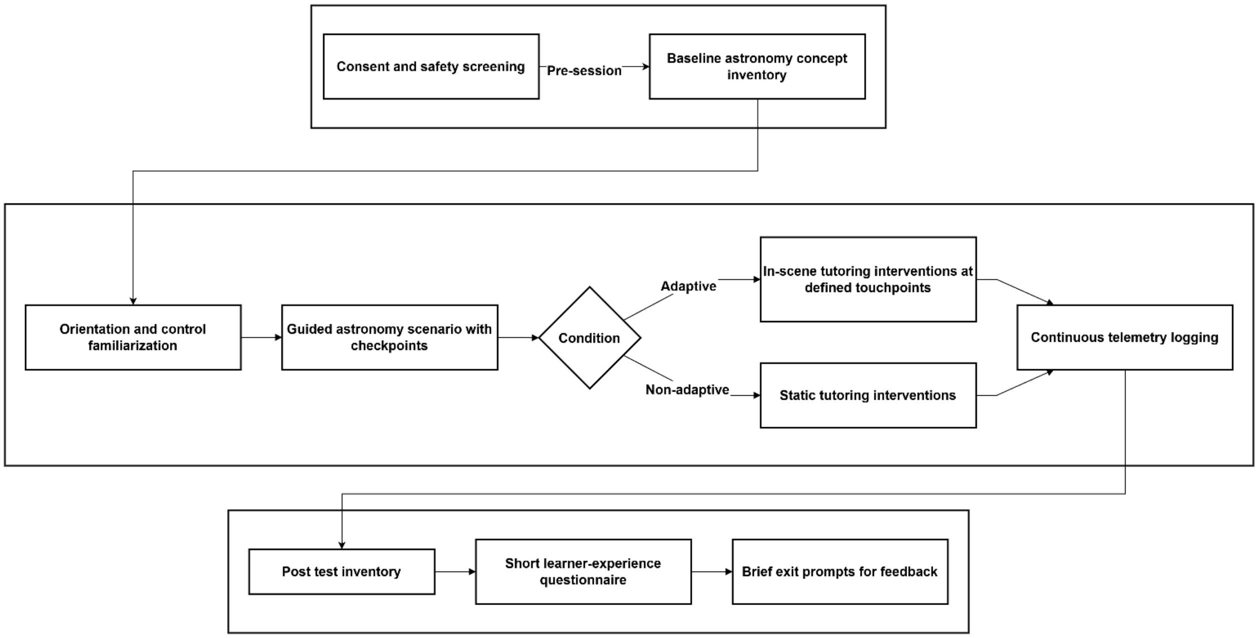

Figure 2. *Planned participant flow and adaptivity touchpoints.*

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