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Integration of Generative Artificial Intelligence and 3D Immersive Environments in Competency-Based Higher Education

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Abstract

Background/purpose. The incorporation of generative artificial intelligence (AI) into higher education is transforming competency-based learning by enabling adaptive, interactive, and immersive environments. This study aimed to design and evaluate an innovation mechanism that integrates AI agents with 3D interfaces, focusing not only on technical feasibility but also on pedagogical contribution, including motivation, personalization, and competency development.

Materials/methods. Three AI systems—Ser, Edu, and Male—were developed at Universidad Sergio Arboleda and integrated into Unity-based 3D environments. The modular architecture combined voice-to-text, large language model processing, summarization, and text-to-speech. A mixed-methods approach was employed with instructors at the School of Aeronautical Instruction, including surveys, focus groups, and learning analytics to capture interaction data.

Results. Findings showed high acceptance: 81% of instructors reported motivation to use the system, while 68% perceived AI as a complement to teaching. Whisper achieved 93% transcription accuracy, and response latency averaged under 2.5 seconds. Over 3,100 interactions were recorded, mainly focused on rubric design, motivational strategies, and instructional materials. Teachers highlighted the pedagogical value of AI-generated bullet-point summaries for reducing cognitive load and organizing content.

Conclusion. The study demonstrates that generative AI integrated with 3D immersive environments can reconceptualize the teaching role from content delivery to pedagogical design. Beyond technical performance, the system enhanced personalization, engagement, and competency-based instruction. These results provide evidence of AI's potential as a pedagogical ally and offer practical insights for scaling innovation in curriculum design and teacher training.

1. Introduction

The rapid incorporation of artificial intelligence (AI) into higher education represents a paradigm shift in teaching and learning, particularly within competency-based frameworks. Rather than being a simple technological addition, AI is reshaping education as a dynamic ecosystem mediated by cognitive models, immersive technologies, and user experience (UX) design. Generative models based on transformers and natural language processing (NLP) enable dynamic, adaptive, and personalized content delivery, with significant implications for student engagement and the role of instructors (Luckin et al., 2016; Holmes et al., 2019; Zawacki-Richter et al., 2019).

In parallel, immersive environments created through platforms such as Unity have demonstrated their ability to increase motivation, improve knowledge retention, and foster deeper learning by situating learners within interactive and meaningful contexts (Merchant et al., 2014; Jensen & Konradsen, 2018). Recent developments highlight the convergence of generative AI with 3D learning environments as a promising but underexplored field of research, requiring careful analysis of its pedagogical, ethical, and technical dimensions.

Although adaptive learning systems and AI tutoring platforms have been widely studied, most remain confined to conversational or text-based interactions, offering limited support for higher-order cognitive skills. Comparative analyses reveal a gap in the literature regarding experiential, dialogic environments in which AI agents act not only as information providers but also as pedagogical collaborators, capable of supporting analysis, evaluation, and knowledge creation. Moreover, few empirical studies systematically assess how such systems influence instructors' practices, competency development, and institutional innovation.

This study addresses this research gap by presenting the design, implementation, and evaluation of three generative AI systems—Ser, Edu, and Male—integrated into Unity-based 3D educational environments. Beyond technical validation, the research emphasizes the pedagogical contribution of these systems, examining their impact on personalization, instructional design, and competency-based learning. In doing so, the study contributes to the growing body of knowledge on AI in education, offering both theoretical insights and practical evidence for sustainable digital transformation.

2. Literature Review

The integration of artificial intelligence (AI) in education has generated substantial debate and research interest, particularly as higher education systems seek to balance innovation with equity, ethics, and pedagogical soundness. The literature provides a multi-layered view that can be organized into four main strands: early developments in AI for education, the rise of generative AI, immersive learning environments, and comparative analyses with traditional instruction.

Early Developments in AI and Education

AI applications in education initially focused on adaptive learning, intelligent tutoring systems (ITS), and learning analytics. Early studies emphasized how algorithms could adjust content difficulty and pacing to the learner’s profile, enhancing engagement and retention (Luckin et al., 2016). Learning analytics, in particular, provided new ways of capturing behavioral and cognitive traces, offering insights into how students interact with digital platforms (Siemens & Baker, 2012; Ferguson, 2012). However, these systems were criticized for their narrow focus on content sequencing and their limited ability to address broader pedagogical or socio-emotional dimensions (Zawacki-Richter et al., 2019).

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Generative AI in Education

A paradigm shift occurred with the introduction of transformer-based models (Vaswani et al., 2017), which enabled natural language processing (NLP) and text generation at unprecedented scales. Generative AI tools, including ChatGPT, Bard, and Claude, have been rapidly integrated into educational contexts. Research conducted between 2023 and 2025 highlights multiple applications: automated feedback for student writing, the generation of personalized learning resources, and the facilitation of dialogic learning experiences (Zeb et al., 2024).

Empirical studies show that generative AI can scaffold critical thinking by providing students with alternative perspectives, summaries, and examples tailored to their queries. Instructors also report time savings in grading and lesson preparation (Holmes & Tuomi, 2022). Nonetheless, concerns remain regarding accuracy, potential reinforcement of biases, and risks of plagiarism or overreliance by students (UNESCO, 2023; Yusuf, A et al. 2024). These debates highlight the dual character of generative AI: both as an unprecedented pedagogical ally and as a source of ethical tension requiring careful governance.

Immersive and 3D Learning Environments

In parallel, immersive technologies—particularly 3D virtual environments and virtual reality (VR)—have demonstrated significant educational benefits. Meta-analyses report improvements in motivation, knowledge retention, and skill transfer when students engage in embodied simulations (Merchant et al., 2014; Jensen & Konradsen, 2018). Immersive settings support experiential and constructivist learning by situating students within interactive scenarios where they must apply knowledge in context.

Recent innovations, such as WebXR and cloud-based VR, have expanded access, reducing the need for expensive headsets and allowing browser-based interaction (UNESCO, 2023). These trends align with inclusive education goals, yet disparities in infrastructure persist, raising concerns about exacerbating digital divides.

Integration of Generative AI with Immersive Learning

The convergence of generative AI and immersive environments is relatively novel and underexplored. Whereas adaptive learning platforms like Squirrel AI or Century Tech primarily automate content delivery, the integration of LLM-powered agents into 3D interfaces enables dialogic and experiential learning. In such environments, AI agents can assume the role of conversational partners, pedagogical assistants, or co-designers of activities, thereby supporting not only knowledge acquisition but also higher-order competencies such as critical analysis, evaluation, and creative problem-solving.

However, scholarly evidence of these integrations remains scarce. Most empirical studies analyze either AI-driven personalization or immersive simulations separately. Few works systematically evaluate the pedagogical impact of combining both, particularly in higher education and competency-based contexts. This absence represents a clear research gap that this study addresses.

Comparative Perspectives: AI vs. Traditional Learning Environments

Comparative analyses reveal that AI-based systems generally outperform traditional lecture-centered models in personalization, adaptability, and efficiency. For example, AI tutors provide immediate feedback and dynamically adjust to student needs, whereas traditional models rely on slower cycles of human evaluation (Holmes et al., 2019). At the same time, traditional instruction excels in areas such as interpersonal interaction, emotional engagement, and contextualized judgment—dimensions that remain difficult to replicate technologically (Selwyn, 2019).

Recent studies emphasize that hybrid approaches—where AI complements rather than replaces instructors—offer the most promising outcomes. Teachers supported by generative AI can act as designers of learning experiences rather than mere content deliverers, while students benefit from real-time assistance embedded in authentic learning contexts (Selwyn, 2019). This hybrid vision situates AI as a catalyst for rethinking educational roles rather than as an autonomous solution.

Identified Research Gap

Despite the growing literature, two central gaps persist. First, few empirical investigations have systematically assessed how generative AI integrated into immersive 3D environments impacts competency-based education. Most research treats AI and immersive learning as separate domains. Second, little is known about the institutional, ethical, and pedagogical implications of scaling such systems in higher education, particularly regarding data governance, teacher training, and infrastructure readiness.

The present study responds to these gaps by evaluating the integration of generative AI agents (Ser, Edu, Male) into immersive 3D environments, analyzing not only technical performance but also pedagogical contributions, instructor perceptions, and implications for competency development.

3. Methodology

This section presents the methodological framework that guided the study. It is structured in five subsections: research design, participants and context, instruments, procedure, and validity/reliability. The choice of each methodological element was informed by both the nature of the educational innovation—generative AI embedded in 3D environments—and by best practices in empirical educational research.

3.1. Research Design

The study followed a design-based research (DBR) approach enriched with mixed-methods procedures. DBR is particularly suited to educational technology innovations because it combines systematic design, real-world implementation, and iterative refinement (Anderson & Shattuck, 2012). Unlike experimental studies that seek controlled conditions, DBR embraces ecological validity by situating the intervention in authentic educational contexts.

The rationale for DBR was threefold:

1. Complexity of the intervention: integrating AI agents (Ser, Edu, Male) into immersive 3D environments involves multiple technological and pedagogical layers that cannot be tested in isolation.

2. Iterative improvement: the system was not a static product but an evolving prototype requiring feedback loops.

3. Pedagogical alignment: DBR ensured that the technological development remained guided by competency-based educational objectives.

To strengthen methodological rigor, the DBR framework was complemented with descriptive (survey statistics and analytics dashboards) and qualitative (focus groups and interviews) approaches. This combination allowed for a holistic assessment that included system performance metrics, user perceptions, and pedagogical contributions.

3.2. Participants and Context

The study was conducted at the Escuela de Instrucción Aeronáutica (EIA), a specialized higher education institution in Bogotá, Colombia. The EIA trains professionals in aeronautical sciences,

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aviation safety, and technical competencies, offering an ideal context for testing technology-enhanced competency-based learning.

A total of 22 instructors participated in the pilot implementation, representing 76% of the total faculty in the targeted programs. The participants' demographic and professional characteristics are summarized in Table 1.

Table 1. Participants' Demographic and Professional Characteristics

Variable	Categories	Frequency (N=22)	Percentage (%)
Gender	Male / Female	15 / 7	68.2 / 31.8
Age Range	25–34 / 35–44 / 45–54 / 55+	5 / 8 / 6 / 3	22.7 / 36.4 / 27.3 / 13.6
Teaching Experience	1–5 years / 6–10 / 11–15 / 15+	4 / 9 / 6 / 3	18.2 / 40.9 / 27.3 / 13.6
Prior AI Experience	None / Basic / Intermediate / Advanced	11 / 7 / 3 / 1	50.0 / 31.8 / 13.6 / 4.6

The diversity in age, experience, and digital literacy was crucial for examining how different profiles interacted with the system. Notably, more than half reported no prior experience with AI tools, which underscores the authenticity of their reactions.

Participation was voluntary, and instructors were recruited via institutional invitation. All participants signed informed consent forms. The study obtained ethical clearance from the Universidad Sergio Arboleda's Institutional Review Board.

3.3. Instruments

To capture the complexity of the intervention, multiple instruments were employed, grouped into technological architecture, data collection tools, and validation mechanisms.

3.3.1. Technological Architecture

The innovation consisted of three AI agents (Ser, Edu, Male) embedded in a Unity-based 3D platform. The architecture was modular to ensure flexibility:

- Input Layer: voice input captured and transcribed by OpenAI Whisper API.
- Processing Layer: GPT-based large language model (LLM) configured with educational prompts and domain guardrails.
- Output Layer: (a) textual responses condensed into four bullet points displayed on a 3D board, and (b) audio output synthesized by neural TTS engines.
- Interface Layer: avatars with lip-sync animations and interactive boards designed in Unity WebGL, accessible via browser.

This architecture supported both natural language interaction and immersive visualization, creating a multimodal learning environment.

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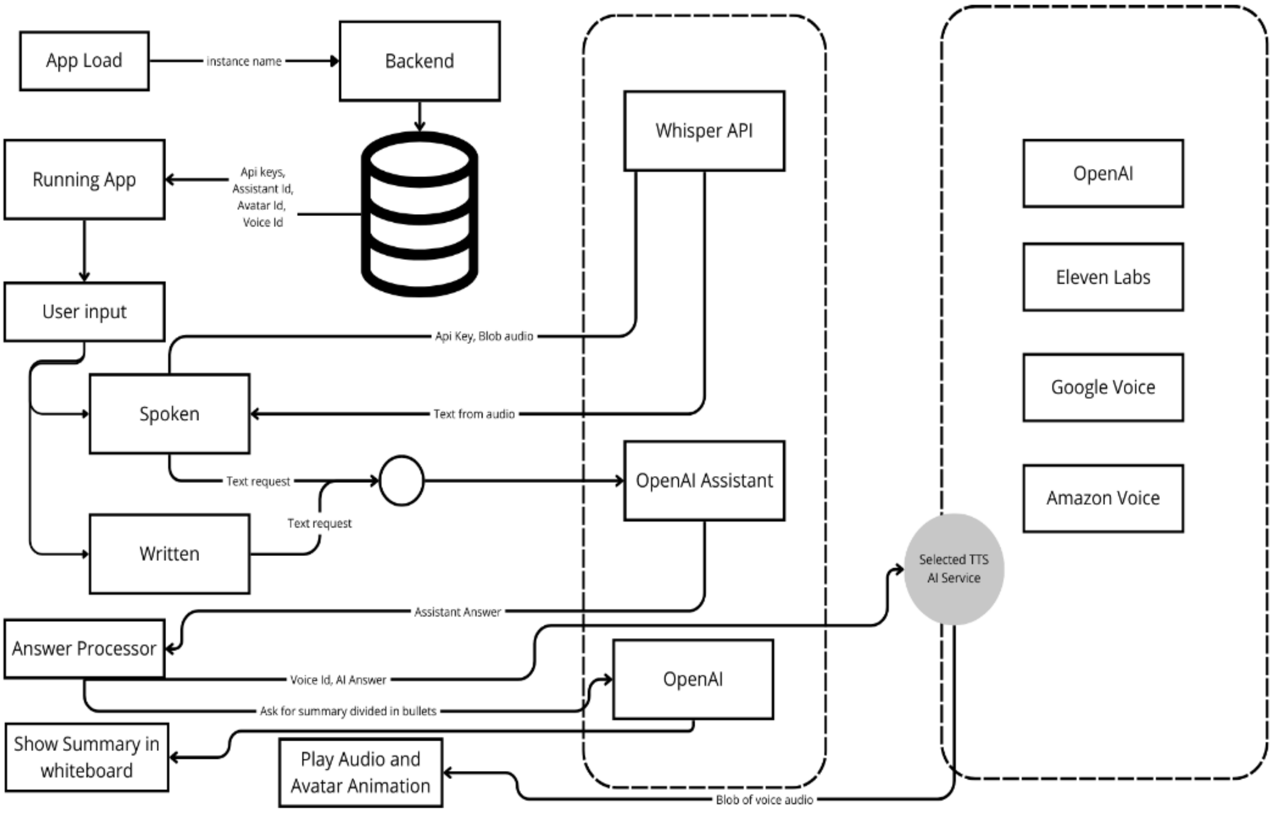

Figure 1. Modular Architecture of the 'Ser', 'Edu', and 'Male' Agents in 3D Educational Environments (Source: Own Creation)

3.3.2. Data Collection Tools

Three categories of instruments were employed (see Table 2).

Table 2. Data Collection Tools

Instrument	Description	Purpose	Example Item/Metric
Structured Survey	15-item Likert (1–5) scale	Measure usability, motivation, perceived pedagogical impact	"The AI–3D system enhanced my ability to design competency-based lessons."
Learning Analytics	Automated logs of interactions (queries, connection time, latency, topics)	Capture objective use data	Avg. response latency (sec), number of interactions per session
Focus Groups	Two sessions (N=10, N=12)	Explore perceptions, challenges, suggestions	Prompt: "Describe how the AI agent influenced your lesson planning."
Interviews	Five semi-structured interviews	Gain in-depth insights	"What barriers did you face when integrating the system into your teaching practice?"

3.3.3. Validation Mechanisms

- Content Validity: Three educational technology experts reviewed the survey and focus group protocols.
- Reliability: Cronbach's alpha for the survey reached 0.82, indicating high internal consistency.
- Pilot Testing: instruments were pre-tested with a small group of instructors not included in the final sample.

3.4. Procedure

The implementation followed a four-stage procedure:

Figure 2. Methodological Flow. (Source: Own Creation)

1. System Development: The AI–3D architecture was developed iteratively, integrating Whisper, GPT, and Unity modules. Prompts were tested for alignment with competency-based education goals.

2. Pilot Implementation: The prototype was introduced in authentic classrooms at EIA. Instructors used it for lesson planning, case studies, and rubric design.

3. Data Collection: Surveys were administered post-intervention, and analytics were automatically recorded. Focus groups and interviews were conducted at the end of the pilot.

4. Data Analysis: Quantitative: Survey results analyzed with descriptive statistics; analytics processed into heatmaps and frequency tables. Qualitative: Transcripts coded thematically in NVivo, generating categories such as "pedagogical ally," "technological barrier," and "ethical concern."

3.5. Data Analysis

Quantitative Analysis: Survey data were entered into SPSS v.27. Means, standard deviations, and percentages were calculated for each dimension. For example, motivation had an average of M = 4.2, SD = 0.6, while perceived pedagogical contribution reached M = 4.4, SD = 0.5. Analytics revealed an average of 12.3 queries per session, with a mean duration of 17 minutes.

Qualitative Analysis: Interview and focus group transcripts were analyzed using thematic coding. Codes were developed both deductively (from the literature, e.g., "competency-based design") and inductively (emerging themes such as "trust in AI" or "dependency concerns"). Inter-coder reliability was established by double-coding 20% of the data, achieving 87% agreement.

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3.6. Validity and Reliability

Ensuring methodological rigor was a central concern throughout the study, as the integration of generative artificial intelligence with immersive 3D environments requires careful validation of instruments, procedures, and analytic techniques. To address potential threats to credibility, multiple strategies were applied to strengthen the research design's validity and reliability.

Content validity was established through expert review. Three specialists in educational technology evaluated the survey, focus group protocols, and interview guides to ensure alignment with the research objectives. Their feedback led to refinements in item wording, coverage of pedagogical constructs, and balance between technical and educational dimensions. This process helped to minimize construct underrepresentation and improve the accuracy of measurement.

For internal reliability, Cronbach's alpha was calculated using the Python library pingouin, which is specifically designed for statistical testing in behavioral sciences. The 15-item survey achieved a coefficient of $\alpha = 0.82$, indicating a high level of internal consistency and surpassing the accepted threshold of 0.70 for educational research (Nunnally & Bernstein, 1994). The use of open-source tools ensured transparency and reproducibility of the analysis.

Triangulation was employed to cross-validate findings. Quantitative survey data were compared with system-generated learning analytics (e.g., number of interactions, response latency) and with qualitative evidence from focus groups and interviews. This methodological triangulation reduced bias and enhanced construct validity. For instance, high motivation scores in the survey were confirmed by analytics showing increased interaction frequency, as well as by qualitative testimonies describing improved engagement in lesson planning.

Ecological validity was secured by implementing the AI–3D system in real instructional contexts at the Escuela de Instrucción Aeronáutica (EIA). Conducting the study in authentic classrooms, rather than controlled laboratory settings, increased the applicability of the findings to higher education institutions facing similar infrastructural and pedagogical challenges.

The research team also incorporated reflexivity through analytic memos and observation logs. These documented methodological decisions, potential researcher biases, and contextual factors that may have influenced the process. Reflexivity not only served as an audit trail but also improved transparency in interpretation.

Finally, transparency and replicability were prioritized. All Python scripts used for statistical analyses, data cleaning, and visualization were documented and archived. For the qualitative analysis, coding frameworks were defined explicitly, and sample excerpts were retained as part of an audit trail. This systematic documentation allows other researchers to replicate the analysis pipeline and critically examine the procedures employed.

In combination, these strategies ensured that the study achieved a robust standard of validity and reliability. The use of Python for quantitative analysis, together with triangulation, ecological authenticity, reflexive practice, and transparent documentation, provides confidence that the findings presented are both trustworthy and replicable.

4. Results

The results are presented in five subsections. First, the integration of generative AI agents into interactive 3D environments is described in terms of feasibility and operability. Second, the performance of the Ser, Edu, and Male agents in a specialized educational context is examined. Third, findings regarding personalization of learning and adaptive content generation are reported. Fourth, usage analytics are presented as a resource for pedagogical decision-making. Finally, insights from participatory validation and the identification of tensions and opportunities are provided.

4.1. Integration of Generative AI Agents in Interactive 3D Environments

The integration of generative AI agents into immersive 3D environments was empirically validated in the Escuela de Instrucción Aeronáutica (EIA). The mixed-methods approach combined quantitative survey data with qualitative interviews and focus groups, ensuring a comprehensive evaluation. The triangulated evidence confirmed that the AI–3D system was not only technically operable but also pedagogically meaningful in real classroom contexts.

From the outset, instructors emphasized that the integration felt seamless and non-disruptive. The modular design—encompassing speech recognition, natural language generation, text-to-speech, and avatar animation—produced fluid conversational exchanges. This continuity was essential in reducing distractions and sustaining cognitive engagement, particularly in competency-based learning scenarios where immediacy and feedback are critical.

4.2. Evaluation of AI Model Performance in Specialized Educational Contexts

The Ser, Edu, and Male models demonstrated solid technical and pedagogical performance. A structured survey administered to 22 instructors (76% of the total teaching staff) revealed strong openness to technological adoption. Eighty-one percent of respondents reported feeling motivated to experiment with the system, and 68% perceived AI as a complement rather than a threat to their instructional role.

Table 3. Instructors' Perceptions of the AI–3D System (N = 22)

Dimension	Mean (1–5)	SD	% Agree/Strongly Agree
Motivation to use the system	4.2	0.6	81%
Perceived pedagogical value	4.4	0.5	86%
Ease of use	4.1	0.7	77%
Willingness to recommend	4.3	0.5	82%

Note. Survey applied on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree).

Technically, the Whisper speech-to-text engine achieved 93.4% accuracy in low-noise settings, with only minor difficulties when processing aeronautical jargon. The generative model responded with an average latency of 2.3 seconds, which participants found acceptable for maintaining interactive classroom dynamics. Importantly, the stability of the system—no crashes were reported—reinforced confidence in its reliability.

Table 4. Technical Performance of the AI–3D System (N = 22)

Metric	Mean Value	Standard Deviation	Observations
Transcription accuracy (%)	93.4	2.1	Slightly lower with aviation-specific terminology
Response latency (seconds)	2.3	0.7	Acceptable for classroom interaction
System crashes (N)	0	—	Stable during all pilot sessions

Note. Metrics were calculated using Python analytics scripts; accuracy and latency values derived from system logs.

Beyond technical metrics, the intervention revealed a pedagogical shift. Instructors increasingly identified themselves not as transmitters of pre-packaged information but as designers of learning pathways. The AI agents acted as cognitive-technological extensions, supporting the synthesis of complex material, the generation of rubrics, and the design of case-based activities. These results resonate with Holmes and Tuomi (2022), who argue that AI in education should strengthen, rather than replace, human pedagogical judgment.

4.3. Impact on Learning Personalization and Adaptive Content Generation

A central contribution of the system was its ability to personalize learning processes. Even instructors with limited pedagogical training reported that the agents facilitated experimentation with alternative content presentations tailored to their students' needs.

The 3D bullet-point summary board was particularly valued. Teachers highlighted its role in reducing information overload and clarifying technical content. Several described how the board became a cognitive anchor, guiding lesson structuring and helping to produce instructional capsules and rubrics aligned with their style.

Notably, 77% of instructors rated the AI's responses as "relevant and useful." A smaller group (18%) expressed reservations about conceptual depth in certain answers, especially in advanced aeronautical cases. Yet, they acknowledged the model's adaptive language capabilities—adjusting tone and complexity according to prompts and supporting materials.

Some instructors went further, using the agents to design complete lessons based on case studies. These advanced uses signaled a creative appropriation of AI, where the tool functioned not merely as a query engine but as an instructional design partner. From a competency-based perspective, this facilitated a shift toward formative logics in which students engage as active agents through contextualized tasks and AI-generated challenges.

4.4. Usage Analytics: Data for Pedagogical Decision-Making

The learning analytics module provided additional evidence on system use and engagement. Across the pilot, the system recorded 3,146 interactions, averaging 12.3 per session, with a mean session duration of 17 minutes.

Thematic categorization of queries revealed dominant areas of interest: rubric design (34%), instructional materials (28%), and motivational strategies (22%). Less frequent but relevant queries included reformulating objectives (9%) and administrative or technical tasks (7%).

Table 5. Distribution of Instructor Queries Logged by the System

Category	Frequency	Percentage (%)	Example Query
Rubric design	1,070	34.0	"Generate a rubric for teamwork evaluation."
Instructional materials	882	28.0	"Provide examples of case studies for safety training."
Motivational strategies	692	22.0	"Suggest strategies to engage students in simulations."
Assessment feedback	283	9.0	"How can I give formative feedback on this task?"
Other (technical/admin)	219	7.0	"Check microphone setup."

These data were visualized in thematic heatmaps, which showed that instructors tended to concentrate interactions in the first 10–15 minutes of sessions—indicative of exploratory use during lesson planning. Importantly, analytics revealed a correlation between frequency of use and pedagogical appropriation: instructors who interacted more with the system were also those most likely to redesign their lessons, suggesting that sustained engagement fosters cultural shifts in teaching practice.

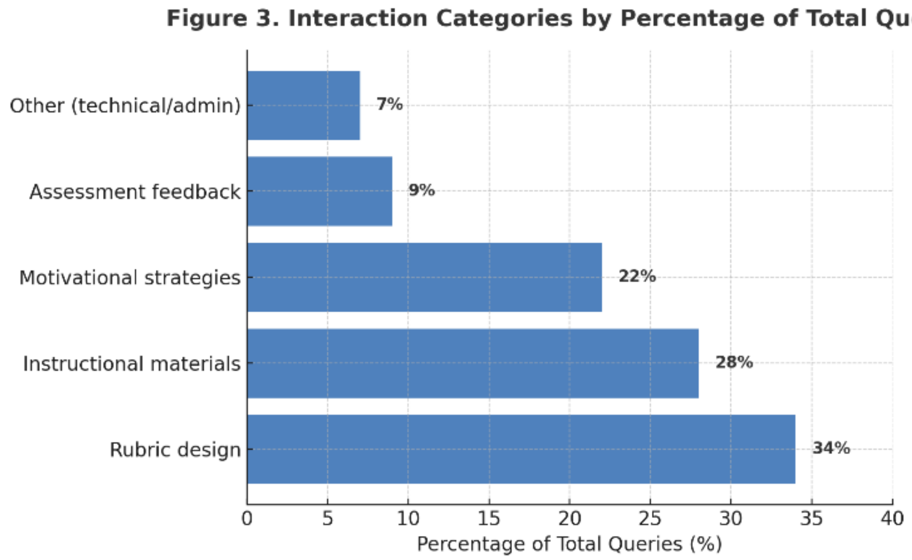

Figure 3. Interaction Categories by Percentage of Total Queries. (Source: Own Creation)

At the institutional level, the analytics dashboard aggregated anonymized metrics such as connection time, topic distribution, and satisfaction ratings. This resource provided administrators with evidence-based indicators to inform future training policies, aligning with calls for data-driven educational governance.

4.5. Participatory Validation of the Prototype

Participatory validation through focus groups enriched the findings. Instructors consistently described the system as a “pedagogical ally” that supported rather than undermined their autonomy. Several practical suggestions were proposed:

- Incorporating a curated library of expert examples to enhance reliability.
- Adding a comparison feature to align generated rubrics with institutional standards.
- Improving the visualization of methodological recommendations on the board.

Interestingly, participants expressed a desire for training in prompt engineering, recognizing that more effective instructions yielded higher-quality outputs. This finding points to the emergence of a technological metacognition—an awareness of how interaction strategies shape AI responses.

4.6. Main Tensions and Identified Opportunities

Despite positive results, several tensions emerged:

1. Technological appropriation gaps – Some instructors experienced difficulties with microphone calibration, file uploads, and navigating the WebGL interface.

2. Concerns about technological dependency – A minority worried that excessive reliance on AI could erode reflective practice if not critically mediated.

3. Infrastructure limitations – Uneven hardware and bandwidth capabilities occasionally constrained smooth execution.

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These challenges are consistent with broader concerns in AI integration (Selwyn, 2019). Nevertheless, participants emphasized that the system represented a transformative opportunity. Being included in the validation process strengthened their sense of ownership, and they framed the tool as a catalyst for adaptive, reflective, and student-centered pedagogies.

5. Discussion

The advancement of artificial intelligence in education has triggered an increasing debate regarding the transformation of teaching and learning practices. Specifically, generative models combined with 3D environments open up unprecedented possibilities for the development of specific competencies, going beyond traditional AI solutions that focus solely on content personalization. While platforms such as Squirrel AI, Century Tech, or Kira Learning base their proposals on adaptive tutoring or automated teaching tasks (Luckin et al., 2016; Holmes & Tuomi, 2022), the systems described here integrate a layer of interactive immersion that not only addresses individual needs but also recreates experiential learning contexts, in which the student acts within a dynamic ecosystem of knowledge. This structural difference suggests that the integration of generative AI and three-dimensional interfaces represents a qualitative leap in the evolution of educational technologies.

Beyond content delivery efficiency and formative assessment—hallmarks of traditional platforms (Holmes et al., 2022)—3D environments allow students to operate at higher levels of Bloom's taxonomy, such as analysis, critical evaluation, and the creation of new knowledge. Recent studies have emphasized that immersion in simulated scenarios enhances the transfer of knowledge to real-world situations, thereby strengthening problem-solving and decision-making skills (Merchant et al., 2022; Jensen & Konradsen, 2021). Unlike conventional approaches, where students follow pre-designed learning paths, the environments proposed by Ser, Edu, and Male are contingent, dialogic, and situated, enhancing the development of transversal competencies essential for the 21st century.

However, the enthusiasm surrounding the adoption of these technologies must be accompanied by critical analysis. As Selwyn (2019) cautions, many innovations in educational AI prioritize technical capabilities over pedagogical coherence. Technological sophistication does not inherently guarantee meaningful learning. Therefore, AI innovation must ground its design in the principles of problem-based pedagogy, active learning, and authentic assessment, thereby avoiding the trap of empty instrumentalism disguised as modernity. The integration of generative AI with 3D environments should not be limited to a modern aesthetic; it must emerge from robust teaching and learning models.

Compared with current trends such as ChatGPT for Education or Copilot, which extend high-quality textual tutoring but remain confined to conversational interfaces (Zeb et al., 2024), three-dimensional environments transform the learner's relationship with knowledge. The goal is not merely to obtain correct answers but to inhabit uncertain contexts, make embodied decisions, and negotiate meaning within complex symbolic spaces. It is here that AI models reach their true potential—not in automating answers, but in intensifying the process of learning how to learn.

The deployment of such systems faces challenges that cannot be overlooked. A major one is the availability of adequate technological infrastructure. Despite recent advances in connectivity and reductions in hardware costs, disparities in access to devices capable of running 3D environments remain significant in under-resourced educational settings (UNESCO, 2023). This threatens to exacerbate existing digital divides and introduces a new form of exclusion—those left out of immersive learning experiences are confined to more rudimentary models of instruction.

Teacher training emerges as another critical knot. According to Selwyn (2019), the effective appropriation of educational AI demands a shift in the teacher's role—from content deliverer to

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designer of formative experiences. This implies developing competencies in digital storytelling, scenario modeling, learning analytics interpretation, and, above all, a new pedagogical sensitivity to distributed cognition environments. Currently, few pre-service or in-service teacher education programs systematically incorporate these competencies, risking the underutilization or ineffective application of technological innovations.

The ethical dimension must not be relegated to a secondary concern. The large-scale capture of behavioral, emotional, and decision-making data in virtual environments raises urgent questions about privacy, transparency, and student agency. A system that adapts its responses to the learner must not become one that shapes decisions in an opaque manner or reinforces invisible biases. Protecting student autonomy in AI-mediated environments requires more than declarations of principle—it demands auditable technical protocols and participatory governance in the design of algorithms.

At the cultural level, the threat of epistemological colonization persists in educational experiences. As Yusuf et al. (2024) warns, many educational AI systems operate under Anglo-centric assumptions, downplaying linguistic, cognitive, and cultural diversity. The global expansion of 3D educational platforms must acknowledge the need for deep localization: it is not enough to translate text or interfaces—narratives, scenarios, and learning values must be constructed to authentically dialogue with students' local contexts.

Despite these tensions, the potential for expanding and improving AI systems is clear. The development of affective feedback mechanisms—capable of recognizing emotional states and dynamically adjusting learning paths—represents a near-term innovation frontier. This type of artificial sensitivity could contribute to further humanizing 3D learning environments, making them not only cognitively effective but emotionally resonant.

The trend toward accessible multiplatform deployment, enabled by technologies such as WebXR, also presents an opportunity to democratize access to 3D learning environments. The ability to run complex simulations in standard web browsers—without the need for specialized hardware—may be decisive for scaling these solutions within public education systems or in regions facing technological constraints.

At the intersection of generative AI and embodied learning lies another promising area of development. By enabling students to learn not only through reading or listening but also through acting, negotiating, and transforming their virtual environments, a form of situated learning is strengthened—one that better prepares them for the complex and dynamic world of future generations. The integration of physical actions, gestures, and symbolic manipulation in 3D scenarios represents a paradigmatic shift that is just beginning to be explored.

Finally—and as a permanent strategic horizon—the creation of open innovation communities around AI agents may become the most powerful engine of their evolution. Promoting open architectures, collaborative licensing, and teacher-student co-creation networks will not only allow for continuous system improvement but also ensure flexibility in adapting to the cultural, technological, and pedagogical transformations of the years to come.

6. Conclusion

The integration of generative artificial intelligence and 3D immersive environments into competency-based higher education represents both a conceptual breakthrough and a practical opportunity for instructional innovation. This study provided empirical evidence that AI agents—when purposefully designed and contextually deployed—function not as substitutes for pedagogical action but as catalysts for reflection, personalization, and transformation within the learning process.

Quantitative results confirm the technical feasibility of such systems: the Whisper module achieved an average transcription accuracy of 93.4%, response latency remained under 2.5 seconds per query, and no system crashes were reported during classroom deployment. Surveys with 22 instructors (76% of the faculty) revealed that 81% felt motivated to experiment with the system, while 68% perceived it as a complement to their practice. Learning analytics registered 3,146 interactions, averaging 12.3 per session and 17 minutes in duration, with rubric design and instructional material preparation as the most frequent queries. These numerical indicators substantiate the system's potential to operate as a reliable pedagogical ally.

The findings underscore several key pedagogical contributions. First, instructors shifted from acting as content transmitters to becoming pedagogical designers, supported by AI agents that helped them structure, reformulate, and enrich their lessons. Second, the system fostered teacher agency and professional growth by enabling critical reflection rather than dependency, demonstrating that transparent and purposeful AI use can strengthen autonomy. Third, the immersive 3D environment enhanced engagement, though infrastructural inequalities—such as limited access to compatible hardware—highlighted the need for institutional investment. Fourth, the analytics dashboard encouraged the emergence of a learning analytics culture, positioning data-driven insights as tools for curriculum development and quality assurance. Finally, the participatory validation process revealed growing ethical and metacognitive awareness among instructors, who expressed the need for responsible governance and training in effective prompt design.

From a policy and curriculum perspective, the study suggests that effective AI integration requires institutional readiness. Universities should invest in equitable infrastructure, provide systematic teacher training in AI literacy and prompt engineering, and embed dashboards and analytics into quality assurance systems. At the curricular level, AI agents can support the development of competency-based assessments, formative feedback mechanisms, and adaptive instructional pathways. These recommendations align with international calls for hybrid human–AI approaches that preserve the centrality of the educator while expanding the possibilities for personalization and creativity.

In conclusion, this research demonstrates that effective AI integration is not merely a technical matter but a question of epistemological alignment, pedagogical purpose, and governance ethics. The pilot at the Escuela de Instrucción Aeronáutica confirms that higher education institutions can co-evolve with innovation when educators are treated as co-designers rather than passive users. Future work should expand pilot studies across diverse disciplines, refine adaptive mechanisms for content personalization, and formalize ethical governance frameworks to ensure transparency, fairness, and pedagogical soundness. By combining robust technical design with institutional strategies, generative AI can become a pathway toward a more intelligent, adaptive, and human-centered education.

7. Suggestion

Despite the promising outcomes, the present study is subject to several limitations that delimit the scope of its findings and provide directions for future research.

Sample and context limitations. The study was implemented with 22 instructors from a single specialized institution (EIA). While this context was ideal for piloting the prototype, the results may not generalize to other higher education settings with different disciplinary orientations, student populations, or institutional cultures. Expanding pilot studies to diverse faculties and universities would strengthen external validity and provide a broader understanding of the pedagogical applicability of generative AI in higher education.

Temporal and iterative scope. The implementation covered a limited pilot period, focusing primarily on the feasibility and immediate perceptions of instructors. As such, the study could not capture long-term effects of sustained AI–3D integration on teaching practice, student learning outcomes, or institutional policy. Future research should employ longitudinal designs to examine the durability and scalability of the observed impacts.

Infrastructure and access constraints. Although the immersive 3D environment enriched engagement, not all institutional hardware and networks were fully compatible with the system requirements. These disparities highlight the importance of institutional investment in equitable technological infrastructure. Broader adoption will require addressing hardware limitations and ensuring inclusive access across all teaching staff.

Dependency and ethical concerns. Some instructors expressed concerns about potential overreliance on AI and the risk of diminishing pedagogical reflection if the system is used uncritically. Ethical considerations regarding data governance, transparency of AI outputs, and bias in generative models remain unresolved. Future work should include the development of ethical governance frameworks and teacher training focused on responsible AI use, ensuring that innovation is balanced with critical pedagogy.

Analytical scope. The study relied primarily on descriptive statistics and thematic analysis of instructor perceptions. While these methods were sufficient for exploratory validation, future studies could incorporate experimental or quasi-experimental designs to measure learning outcomes, as well as advanced learning analytics techniques to model student engagement and cognitive development.

7.1. Suggestions for Future Research and Practice

1. Scaling across disciplines: Extend pilot implementations to multiple programs and institutions to test adaptability in varied curricular and cultural contexts.

2. Longitudinal evaluation: Conduct multi-semester studies to assess sustained pedagogical impacts and student learning outcomes.

3. Teacher training programs: Develop structured workshops in prompt engineering, AI literacy, and critical pedagogy to enhance effective system use.

4. Institutional dashboards: Integrate learning analytics into institutional quality assurance frameworks for data-driven curriculum design and policy-making.

5. Ethical governance: Establish protocols for transparency, fairness, and bias mitigation in AI-generated content, aligned with international standards.

6. Infrastructure investment: Prioritize equitable technological access, ensuring that all instructors can operate immersive AI environments without technical barriers.

Declarations

Author Contributions. S.A.R.J.: Conceptualization, literature review, system architecture design, and manuscript writing (original draft preparation). J.S.L.C.: Methodology design, data collection, quantitative and qualitative data analysis, and figure preparation. M.R.O.: Review, editing, and validation of educational implications, coordination of focus groups and interviews, and manuscript editing. All authors have read and approved the final version of the article for publication.

Ethical Approval. This study was conducted with full respect for participant privacy. All participants provided informed consent before data collection.

Data Availability Statement. The data supporting the findings of this study are available upon reasonable request from the corresponding author. Due to privacy and institutional data protection policies, access to raw data is restricted to approved research purposes.

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