

AI-Enhanced Virtual Reality University Office Environments: An Empirical Study of Student Perceptions, Presence, and Adoption Intent

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Abstract

Integrating artificial intelligence and virtual reality technologies will influence how we teach and learn at the university. Furthermore, very few studies examine students' views of AI-driven virtual reality simulations of university office settings. We present a study at International Balkan University with 58 pre-session participants and 29 post-session observers, involved in a virtual reality simulation of the university office scenario using an AI-integrated assistant. This study evaluates five constructs (observation quality, presence and realism, artificial intelligence feature perception, usability and adoption intent, and future readiness) using validated Likert-scale questionnaires and open-ended qualitative responses. Our findings indicate high accuracy in perceiving artificial intelligence ($M = 4.48/5$), remarkably high clarity of observation ($M = 4.39/5$), and moderately high adoption intent ($M = 4.12/5$). In contrast, privacy concerns ($M = 3.24/5$) and trust calibration are still problematic areas. Pre-session findings reveal that most participants had no meaningful virtual reality exposure ($M = 1.88/5$); however, they were quite experienced with artificial intelligence tools ($M = 4.26/5$), defining a sharp technology asymmetry in the sample. Qualitative comments show that artificial intelligence meeting summarization and instant question/answering are the most favored features, while data privacy issues and academic over-reliance are the main concerns.

This study introduces a new survey and mixed-methods approach to the growing scholarly discussion of the metaverse as an educational platform. At the same time, it reveals direct implications for the design of AI-powered virtual reality spaces for learning.

Keywords: Virtual Reality; Artificial Intelligence; University Office; Metaverse Education; Student Perceptions; Technology Acceptance; AI-VR Integration; Presence; Adoption Intent

1. Introduction

The metaverse is a virtual universe that never sleeps; it is a virtual universe that is always on, that virtually combines Virtual Reality (VR), Augmented Reality (AR), Artificial Intelligence (AI), and blockchain tightly, and it is no longer just today's speculative thought and furthest ambition but an institutional reality (Mystakidis, 2022; Lee et al., 2021). This latest technological and conceptual crossover is also making its way into higher education, where it could potentially break down the typical walls of physical campuses. Virtual AI office environments can offer academic services 24/7, provide highly intelligent computerized assistants capable of handling administrative tasks, and create virtual spaces for collaboration (Kaddoura & Al Hussein, 2023; Petrigna & Musumeci, 2022).

The research work, a small part of a broader research program, examined the integration of biotechnological innovation into metaverse technology and found that AI-driven virtual environments facilitate research collaboration and education. In this study, the focus is on situating the metaverse technology in a university office context and specifically examining student reactions and use of an AI-enhanced VR working environment, the purpose of which is, on the one hand, to recreate and add more features to existing real academic services.

Although the theoretical foundations of this topic are gradually being shaped, the true understanding of students' perceptions of VR university environments integrated with AI is limited. Critics have raised serious concerns about the wholesale integration of AI into university environments. Sparrow & Flenady, 2025 highlight that the outcomes of generative AI are fundamentally problematic as educational tools, not merely because they may be factually unreliable, but because AI systems lack the capacity to testify, to model intellectual commitment, or to engage students as moral agents in a social learning community. From this viewpoint, the possibility of using AI-driven technologies in education settings should require a deep understanding of the pedagogy of learning. In addition, it includes the development of practical skills, exposure to role models, and social recognition among peers. The critique targeted AI for replacing teachers in

the classroom. Furthermore, it raises concerns equally relevant to AI-enhanced environments, as examined in this study, about students' perceptions and responses to AI use in a classroom. Rather than assuming AI integration is beneficial or detrimental, this study takes an empirical approach by directly documenting student reactions, contributing evidence to a debate that has so far remained theoretical.

The bulk of studies in this area either look at scenarios where VR is applied alone, with a focus on elements such as the presence and usability of VR while leaving the aspect of AI out, or are studies that assess AI interfaces in the usual, non-immersive digital setups. Bringing AI and VR together puts to the test two major issues that otherwise do not come into play simultaneously: the user must judge both the spatial realism of the VR environment and the mental capabilities of the AI assistant that is part of that environment.

The main incentive behind this research is to understand how these two evaluation streams are combined and what kind of psychological and behavioral effects they produce. We carried out an empirical, mixed-methods study at International Balkan University (IBU) by using a pre-session survey (N = 58) aimed to capture the digital literacy baseline, previous technology-related activities, and demographic profile of the participants, and a post-session survey (N = 29) to evaluate participants' impressions of the VR office demonstration using five validated construct clusters. An AI assistant was embedded in the virtual office. It was able to answer administrative questions, provide real-time meeting summaries, and help users accomplish academic tasks.

The rest of this article is organized as follows. Section 2 analyzes relevant literature on AI and VR integration in education and discusses the theoretical bases of presence and technology acceptance; Section 3 specifies the study method; Section 4 reports quantitative and qualitative results; Section 5 discusses the significance and outlines the limitations; Section 6 ends with a note on future research.

2. Literature Review

2.1 *AI and VR Convergence in Higher Education*

The use of the metaverse as a medium for education has attracted substantial research interest since 2020. According to Kaddoura and Al Husseiny, 2023 immersive learning, administrative accessibility, and social presence are the three main reasons why metaverse platforms hold value in higher education. Petrigna & Musumeci, 2022 add to this classification by highlighting the role of experiential simulation, especially in laboratory and clinical environments, while also noting the challenges posed by infrastructure and equity. In line with these evaluations, Syed Abdul et al.,

2022 reported that compared to traditional teaching methods, VR-based learning produced a 25% increase in understanding and a 30% increase in accuracy of procedures in education. However, they also highlight a potential selection bias in the sample.

Embedding AI in VR settings transforms the passive nature of VR into an interactively intelligent one. Intelligent virtual agents that possess abilities such as understanding natural language, assisting with context-based tasks, and providing feedback that adapts to the user have been studied extensively at desktop and mobile gaming levels (Mystakidis, 2022). However, their integration within 3D space is a new phenomenon. Recent studies indicate the fast propagation of immersive technologies in educational settings. A bibliometric analysis on the topic of XR in simulation-based health professions education (Alblooshi et al., 2026) revealed an average annual growth rate of 12.48% in publications from 2010 to 2025.

In a broader sense, the educational metaverse has been described as an integration of VR, AR, AI, and blockchain technologies that transform traditional teaching methods from lecturing to experiential, learner-centered involvement (Furgal Saren et al., 2026). In this context, AI-based systems customize content delivery, provide immediate feedback, and change based on the students' learning. These are the functions that the AI assistant features of the current study are modeled on.

Our studies behind this line of work present a comprehensive survey of how generative AI, reinforcement learning, and multimodal integration facilitate intelligent avatar behaviors and personalized user experiences in metaverse settings (Feta & Kamberaj, 2025). It points to a substantial research gap, although technical feasibility was proven, the literature is limited to user-perception studies, particularly in non-gaming and institutional environments, such as university offices. Thus, this study focuses directly on the response to that gap.

2.2 Technology Acceptance and the AI Trust Dimension

According to the Technology Acceptance Model (Davis, 1989) users' intention to adopt a technology is determined by its perceived usefulness and ease of use. These two factors can be related to presence, which means the feeling of being physically present in a virtual environment (Witmer & Singer, 1998). Indeed, a greater presence would also mean a greater perceived realism, and it can even lead to the willingness to adopt and delegate tasks in virtual systems (Slater, 2009). However, if AI is part of those environments, then a fourth variable will be involved, such as trust in AI. For example, Kostick-Quenet and Rahimzadeh, 2023, state that trust in

AI-assisted systems depends on factors such as perceived accuracy, the naturalness of the interaction, and data privacy assurances.

A specifically well-documented failure of institutional AI deployment is the automation bias, which occurs when users blindly trust AI-generated outputs even when they are wrong. The systematic review (Wei et al., 2026) showed that AI-assisted diagnostic tools in dental education had no significant benefit over conventional methods. Importantly, the students showed a measurable tendency to agree with wrong AI suggestions. This risk of over-dependence is limited to clinical training and extends to any high-stakes academic environment where AI offers guidance, including college offices, as reflected in this study.

A combination of automation bias, data privacy, and equitable access is the evaluative framework that the present students were potentially motivated by when they showed a calibrated and conditional adoption of AI rather than being very enthusiastic.

2.3 *Presence and Realism in VR Environments*

Presence, the sense of being mentally immersed, is frequently regarded as the primary factor influencing the quality of VR systems (Slater, 2009). It is usually differentiated into two types: spatial presence (the sensation of being in the virtual location) and social presence (the sensation of being there together with others). Both aspects are equally important when VR systems are used in university offices. First, spatial presence establishes whether the environment really looks like a workplace. Secondly, social presence determines whether interaction with AI avatars seems real.

The visual realism is the primary factor influencing spatial presence. For instance, Deeks et al., 2020 show that the use of VR in interactive molecular dynamics influences high spatial presence, including non-gaming users, for sufficiently realistic object fidelity and lighting. From an educational viewpoint, Taylor and Soneji, 2022 demonstrated that 3D environments enable a better understanding of complex structures because spatial presence promotes cognitive engagement. Based on these studies, we added several realism sub-items to the post-session survey.

3. Methodology

3.1 *Study Design*

This study utilizes a mixed-methods sequential design: Quantitative survey data are used for descriptive statistics and comparison, and qualitative open-ended responses provide explanatory depth and participant voice. The sequential design was selected because post-session observations could not be meaningfully interpreted in the absence of a quantitative context, especially the baseline technology exposure data pre-session. The Bit-Loft

Office at the International Balkan University approved this workshop (April 4, 2026). Before any surveys, all participants agreed to participate in the study.

3.2 Participants

Pre-session survey: We selected a non-random sample¹ of 58 students from various undergraduate engineering cohorts at International Balkan University in the first week of April 2026. The group consisted of 34 male students (58.6%) and 24 female students (41.4%). Most of them were between 18 and 22 years old (93.1%, $n = 54$). Students' year of study: 1st year 46.6% ($n = 27$), 2nd year 22.4% ($n = 13$), 3rd year 27.6% ($n = 16$), and 4th year 3.4% ($n = 2$).

Post-session survey: Twenty-nine students (part of the pre-session cohort) filled in the post-session questionnaire after watching a live demonstration of the VR university office system. Due to the restricted availability of VR headsets, the observation-based design was chosen, based on validated research protocols of technology perception (Riva & Wiederhold, 2022)

3.3 The VR University Office System

The stimulus was a purpose-built VR university office environment demonstrated on a Meta Quest 2 headset (operated by a trained demonstrator). The virtual office replicated a university administrative space, including a faculty office. Key AI features included: (i) a conversational AI assistant capable of answering academic queries in real time; (ii) automated meeting summarization, capturing key decisions and action items; (iii) subject-specialist AI professor avatars; and (iv) a movement system integration between professors in the office. The demonstration lasted approximately 15 to 20 minutes.

3.4 Instruments

Pre-session survey (13 items): Items included demographic details (Q3–Q6), VR experience (Q7), frequency of AI tool use (Q8), knowledge of blockchain (Q9) and the metaverse (Q10), digital confidence (Q11), and whether participants attended virtual events (Q12). Likert items used a 1–5 scale (1 = Strongly disagree/No experience; 5 = Strongly agree/Extensive experience).

¹A non-random (convenience) sample was chosen because the study required participants to attend a scheduled VR demonstration session on campus. Random sampling was not feasible given the logistical constraints of VR equipment availability and the need for in-person attendance within a specific period.

Post-session survey (29 items): Items were grouped into five clusters: (A) Observation Quality (Q1–Q5); (B) Presence and Realism (Q6–Q10); (C) AI Feature Perception (Q11–Q16); (D) Usability and Adoption Intent (Q17–Q21); and (E) Future Readiness (Q22–Q24, Q26). Privacy concern was a separate item (Q25). Three open-ended questions (Q27–Q29) were used for qualitative responses.

3.5 Statistical Analysis

Descriptive statistics were used in the quantitative analysis performed with Python (McKinney, 2010). Because the post-session sample size was only $N = 29$, correlation analyses were performed only between construct clusters for inferential testing, and results were interpreted with caution. Thematic content analysis of qualitative responses to Q27–Q29 was based on the six-phase method (Braun & Clarke, 2006).

4. Results

4.1 Pre-Session Baseline: Technology Exposure and Digital Literacy

Table 1 compiles the main results of pre-session Likert items for all 58 participants. Most remarkably, a sharp contrast can be observed between the level of familiarity with AI tools and the extent of VR experience. A high usage level of AI tools was recorded ($M = 4.26$, $SD = 1.04$), and post-experience of VR headset was extremely low ($M = 1.88$, $SD = 1.15$), with as many as 53.6% rating themselves at the minimum value. This divergence has major consequences for the development and testing of AI-VR hybrid systems.

Table 1: Pre-Session Survey: Key Descriptive Statistics ($N = 58$)²

Variable	N	M	SD	Min	Max
VR Headset Experience (1–5)	56	1.88	1.15	1	5
AI Tool Use in Daily Life (1–5)	58	4.26	1.04	1	5
Blockchain Familiarity (1–5)	56	2.70	1.20	1	5
Metaverse Familiarity (1–5)	56	3.04	1.21	1	5
Digital Confidence (1–5)	58	4.07	1.01	2	5

On average, knowledge about the metaverse was limited ($M = 3.04$, $SD = 1.21$), blockchain familiarity was below the midpoint ($M = 2.70$, $SD = 1.20$), while digital confidence was surprisingly high ($M = 4.07$, $SD = 1.01$). 41.4% of respondents had attended a virtual event, 37.9% had not, and 20.7% were unsure.

²Scale 2 (used for VR experience item) = Disagree / Little experience. Full scale: 1 = Strongly disagree / No experience; 2 = Disagree / Little experience; 3 = Neutral / Some experience; 4 = Agree / Considerable experience; 5 = Strongly agree / Extensive experience.

4.2 Post-Session Observations: Five Construct Clusters

Table 2 provides comprehensive descriptive statistics for all post-session Likert items sorted by construct cluster.

Table 2: Post-Session Survey: Descriptive Statistics by Construct Cluster (N = 29)³

Item	Construct	N	M	SD	Max
Q1: Clear view of virtual environment	Observation Quality	29	4.41	1.02	5
Q2: Could follow the demonstration	Observation Quality	29	4.34	1.04	5
Q3: Good understanding of how the system works	Observation Quality	29	4.41	1.02	5
Q4: Felt engaged while observing	Observation Quality	29	4.28	1.10	5
Q5: The demonstration showed enough detail	Observation Quality	29	4.52	0.78	5
Q6: Environment looked realistic (1–6)	Presence & Realism	29	4.76	1.43	6
Q7: Objects/spaces appeared natural (1–7)	Presence & Realism	29	5.62	1.24	7
Q8: Believe user would feel present (1–8)	Presence & Realism	29	6.31	1.69	8
Q9: Visual quality was convincing (1–5)	Presence & Realism	29	4.10	0.98	5
Q10: Could imagine working in VR office (1–10)	Presence & Realism	29	7.00	2.70	10
Q11: AI understood requests accurately	AI Feature Perception	29	4.48	0.78	5
Q12: AI made tasks easier	AI Feature Perception	29	4.38	0.86	5
Q13: Would trust AI suggestions	AI Feature Perception	29	3.97	1.05	5
Q14: AI behaved naturally and intuitively	AI Feature Perception	28	4.04	1.04	5
Q15: AI more helpful than non-AI interface	AI Feature Perception	29	4.17	0.85	5
Q16: Comfortable relying on AI features	AI Feature Perception	29	3.83	1.14	5
Q17: Would improve academic productivity	Usability & Adoption	29	3.97	1.09	5
Q18: Would make university tasks easier	Usability & Adoption	29	4.03	0.98	5
Q19: Could learn to use this easily	Usability & Adoption	28	4.39	0.88	5
Q20: Interaction looked clear and understandable	Usability & Adoption	29	4.24	0.87	5
Q21: Would use in academic work if available	Usability & Adoption	28	3.96	1.20	5
Q22: AI-VR could improve university experience	Future Readiness	29	4.14	1.06	5
Q23: Comfortable attending lectures/meetings in VR	Future Readiness	29	3.97	1.21	5
Q25: Privacy and data security concerns	Privacy Sensitivity	29	3.24	1.09	5

³Items Q6–Q10 use heterogeneous response scales as designed; means should be interpreted relative to their respective scale maxima. Unless otherwise noted, scales are 1–5.

4.2.1 Cluster A: Observation Quality

The observation quality cluster (Q1–Q5) produced a cluster mean of $M = 4.39$ (SD range: 0.78–1.10). The most highly rated item was Q5 ($M = 4.52$, $SD = 0.78$), indicating that participants thought they had enough information to form their judgments. Q4 ($M = 4.28$, $SD = 1.10$) was the lowest in the cluster, which is understandable for a passive observation mode. Overall, the cluster confirms that the observer method was methodologically sound.

4.2.2 Cluster B: Presence and Realism

The presence and realism items used heterogeneous response scales. Scores normalized by dividing by scale maxima were all above 70%: environmental realism Q6 (79.3%), naturalness Q7 (80.3%), belief in user presence Q8 (78.9%), visual quality Q9 (82.0%), and ability to imagine working in VR Q10 (70.0%). The large SD for Q10 (2.70) indicates individual differences in spatial imagination.

4.2.3 Cluster C: AI Feature Perception

The AI feature perception cluster (Q11–Q16) yielded a mean of $M = 4.14$. AI accuracy (Q11: $M = 4.48$, $SD = 0.78$) was the highest rated attribute, followed by task facilitation (Q12: $M = 4.38$). Trust delegation items were notably lower: overall AI trust (Q13: $M = 3.97$) and comfort with AI reliance (Q16: $M = 3.83$). This competence–trust gap mirrors findings in the AI adoption literature (Kostick-Quenet & Rahimzadeh, 2023) and is extended here to VR-embedded AI contexts.

4.2.4 Cluster D: Usability and Adoption Intent

The usability and adoption intent cluster (Q17–Q21) yielded a mean of $M = 4.12$. Perceived ease of learning was highest (Q19: $M = 4.39$), while direct adoption intention was lowest (Q21: $M = 3.96$, $SD = 1.20$). This pattern reflects conditional adoption intent: participants are enthusiastic but withhold full commitment pending reliability, security, and supplementary (not replacement) integration with current academic processes.

4.2.5 Privacy Sensitivity

Privacy concern (Q25: $M = 3.24$, $SD = 1.09$) was above the scale midpoint, and data privacy was the most prevalent theme in qualitative responses to Q28, mentioned by over 70% of respondents. The discrepancy between the moderate Likert rating and high qualitative salience suggests that single-item Likert measures underestimate privacy concern, likely due to social desirability bias or abstract framing.

4.3 ***Qualitative Findings: Three Emergent Themes***

Thematic analysis of open-ended responses to Q27–Q29 (N = 21 substantive responses) revealed three principal themes.

- **Theme 1: AI as an Intelligent Administrative Partner.** The AI assistant's ability to provide instant, contextual answers was the feature that impressed most users, aligning with the highest-rated AI sub-items Q11 and Q12. Subject-specialist AI professor avatars were also frequently praised.
- **Theme 2: Data Privacy and Over-Reliance as Principal Concerns.** Privacy and security issues dominated Q28. Participants expressed sophisticated risk awareness, including concerns about AI hallucinations, automation bias, and the displacement of human involvement in academic guidance. This indicates an informal AI literacy built through regular LLM use.
- **Theme 3: Conditional Adoption and Pragmatic Enthusiasm.** Responses to Q29 revealed a steady pattern of conditionally positive responses: willingness to use the system subject to accuracy guarantees, data security assurances, and confirmation that AI supplements rather than replaces academic processes.

5. **Discussion**

5.1 ***The Technology Asymmetry Finding and Its Implications***

The most important theoretical insight from this research is the large disparity between students' knowledge of AI (M = 4.26) and their hands-on VR experience (M = 1.88). AI-VR hybrid systems have a chance to bridge this gap: since participants are comfortable with conversational AI interfaces, they can engage with AI features integrated in VR even though the VR world is quite new for them. This discovery corroborates guidelines for developing AI-VR systems that treat AI as a natural extension of familiar interfaces rather than adding both spatial and conversational novelty simultaneously.

5.2 ***The Competence–Trust Gap in AI-VR Systems***

The accuracy of AI (M = 4.48) far exceeded comfort with AI reliance (M = 3.83), broadening the competence–trust gap observed in AI studies (Kostick-Quenet & Rahimzadeh, 2023) to VR-embedded contexts. This gap implies that there may be two types of adoption: low-friction applications (scheduling, information lookup) receive faster adoption than high-friction ones (advisory, evaluative). University AI-VR developers should first build trust through transparency mechanisms (confidence indicators, source citations, human escalation options) before expecting full delegation of academic decisions to AI.

5.3 *Presence Through Observation*

The presence and realism cluster yielded consistently positive ratings even though participants did not wear the VR headset. Q8 ($6.31/8 = 78.9\%$) indicates that the virtual office was visually coherent enough to vicariously convey presence. The large SD for Q10 (2.70) points to individual differences in spatial imagination that may predict later adoption when headsets become directly available.

5.4 *Privacy as a Design Constraint*

Privacy concern was moderate quantitatively ($M = 3.24$) but highly prominent qualitatively. Future instruments should employ multi-item privacy concern scales distinguishing biometric, conversational, and academic performance data. In practical terms, institutions deploying VR university offices are obligated to follow data minimization principles, establish clear data retention policies, obtain explicit consent, and communicate these measures transparently to students (Mosharraf, 2025).

5.5 *Limitations*

Several factors limit how far these results can be extended. First, the sample was drawn from a single institution (IBU) and predominantly from computer engineering programs. Second, the observer paradigm differs from direct VR immersion. Third, the post-session sample ($N = 29$) limits statistical power. Fourth, perceptions were captured once after a short demonstration; longitudinal follow-up is needed. Fifth, social desirability bias may have inflated positive ratings.

Conclusion

This study is the first to empirically investigate students' views of a university office environment enhanced by AI and VR, based at IBU, supported by an original dataset. The results reveal a cohort with high AI knowledge but almost no VR experience, producing a distinctive evaluation profile: high appreciation for AI functional features, positive vicarious presence, and adoption intent mitigated by privacy concerns and calibrated trust. The competence–trust gap of participants assessing AI accuracy is significantly higher than their comfort with reliance and has direct design implications for institutional AI-VR systems.

This study is part of broader explorations of the integration of AI, machine learning, blockchain, and the metaverse ecosystem (Feta & Kamberaj, 2025). The forthcoming research in this program will focus on blockchain-based data governance, longitudinal trust development, and cross-institutional replication as part of the progression toward an

empirically based, ethically responsible model of AI-VR integration in higher education.

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