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Student Perceptions of an AI-Enhanced Virtual Reality University Office Environment: An Observation-Based Empirical Study

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Abstract

There is a growing trend of merging artificial intelligence (AI) with virtual reality (VR) in higher education, and there is a lack of research on students' perceptions of an AI-enhanced VR office environment. This study employed a mixed-methods approach. Here, 58 students participated in a pre-session questionnaire concerning their exposure to technologies. Furthermore, 29 students observed a live demonstration of an AI-integrated VR university office and completed a post-session questionnaire. The post-session survey was designed to measure five constructs (observation quality, presence and realism, AI feature perception, usability and adoption intent, and future readiness). We used items adapted from well-established technology-acceptance and presence scales (the Technology Acceptance Model and its VR-specific extensions, and the Witmer & Singer presence questionnaire), which exhibit good internal consistency with Cronbach's alpha values ranging from 0.86 to 0.97 for each cluster. There was a significant difference between the level of technology familiarity with the participants, in that they were more likely to be using AI tools extensively (M = 4.26/5) than they were to use VR (M = 1.88/5). High accuracy of perceived AI (M = 4.48/5) and clarity of observation (M = 4.39/5), but more moderate ratings of comfort in relying on AI (M = 3.83/5) and privacy concerns (M = 3.24/5) were noted after the

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session, indicating a competence-trust gap. AI was seen as a helpful administrative tool, and there were some concerns about data privacy and dependency, with a general trend of conditional implementation of AI. These results are preliminary, as they are observation-based, single-institution, and come from a relatively small sample size after the sessions, but they do provide some early, concrete insights regarding the design of VR spaces that incorporate AI technology in higher education.

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

1. Introduction

As an immersive, continuous combination of Virtual Reality (VR), Augmented Reality (AR), Artificial Intelligence (AI), and blockchain technologies, the metaverse is transitioning from a theoretical construct to institutional deployment (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 Husseiny, 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

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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 at capturing 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 could answer administrative questions, provide real-time meeting summaries, and help users accomplish academic tasks.

Where prior work has generally evaluated VR presence and AI usability as separate research streams, this study contributes by assessing both within a single institutional demonstration, offering an early, integrated account of how the two evaluation dimensions interact for prospective users. In this study, we address the following research questions. (RQ1) What are students' perceptions of the usability and administrative utility of an AI assistant integrated into a VR university office based on first-hand experience? (RQ2) What is the relationship between perceived competence of AI and students' comfort with using AI on their academic tasks, and how does it differ from their sense of presence in the VR environment? (RQ3) What factors do students consider essential before they use an AI-VR university office themselves?

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

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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 VR-based learning produced a 25% increase in understanding and a 30% increase in accuracy of procedures in education in comparison to traditional teaching methods. 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.

Closer to the present context, extended technology-acceptance frameworks have begun to be applied specifically to VR and AI-VR educational settings. In particular, (Sagnier, Loup-Escande, Lourdeaux, Thouvenin, & Vallery, 2020) extended TAM to account for presence and embodiment in VR adoption. Furthermore, Chen et al. (2026) found that perceived usefulness, ease of use, and enjoyment jointly predict students' behavioral intention to adopt AI- and VR-integrated smart classrooms. Moreover, (Ali, Warraich, & Butt, 2025) found consistent support across studies for TAM constructs predicting AI acceptance in educational settings more broadly. These studies indicate that the acceptance mechanisms studied here are grounded in an emerging, education-specific literature rather than only in adjacent domains.

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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.

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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 sample[1] 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).

[1]A 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.

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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), and knowledge of blockchain (Q9). In addition, these items included the level of knowledge on the metaverse (Q10), digital confidence (Q11), and participation in virtual events (Q12). Likert items used a 1–5 scale (1 = Strongly disagree/No experience; 5 = Strongly agree/Extensive experience).

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. Internal consistency for each cluster was acceptable to excellent: Cronbach's α = .97 (Observation Quality, 5 items), .89 (Presence and Realism, 5 items, computed on standardized items owing to differing response ranges), .93 (AI Feature Perception, 6 items), .88 (Usability and Adoption Intent, 5 items), and .86 (Future Readiness, 2 items).

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.

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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.

4.2 Post-Session Observations: Five Construct Clusters

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

[2]Scale 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.

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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 is more helpful than a 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

[3]Items 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.

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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. The cluster indicates that the observer method gave participants a good platform to evaluate the quality of their work, but it is not a replacement for the direct immersion approach to assessment.

4.2.2 Cluster B: Presence and Realism

Both the presence and the realism items employed different response scales. All scores were above 70%, with the highest being for environmental realism (Q6: 79.3%), the next firmest for naturalness (Q7: 80.3%), belief in user presence (Q8: 78.9%), visual quality (Q9: 82.0%), and imagining working in VR (Q10: 70.0%). The standard deviation of Q10 is large (2.70); that is, there is variation between individuals in their 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 55% (6 of 11 substantive respondents; see Section 4.3). 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.

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4.3 Qualitative Findings: Three Emergent Themes

The three main themes that emerged from the open question responses (Q27–Q29) of the respondents (N = 19) who provided at least one open-ended response were identified by thematic analysis. The counts below are reported as descriptive counts with underlying transparent denominators because a single analyst (which does not allow for an inter-rater reliability statistic) wrote the code.

Theme 1: AI as an Intelligent Administrative Partner. Of 16 substantive answers to Q27, 9 (56%) were focused on the ability of the AI assistant to give instant contextual answers, which matched the top-rated answers for the sub-items of the AI, Q11 and Q12. One participant said, "The meeting summarization of the meetings in real-time and the AI assistant, which was able to immediately answer administrative questions, were the most impressive for me" (P10). Multiple respondents also cited AI professor avatars for specific subjects as a positive aspect.

Theme 2: Data Privacy and Over-Reliance as Principal Concerns. Of 11 substantive responses to Q28, 6 (55%) addressed data privacy or security (down from the 67% majority we found in earlier versions of this paper). Two separate respondents noted that the lack of critical thinking or over-reliance was an issue. There were some advanced risk perceptions, such as discussions about AI hallucinations, the removal of human interaction from academic guidance, and the use of personal interactions by AI models for training purposes: "Risks associated with the mishandling of sensitive student information, potential data breaches, how AI models use personal interactions for training" (P14). One participant made a direct connection between convenience and a skills issue: "That makes students lazier" (P9). This is aligned with informal AI literacy that has been gained through frequent use of LLMs, with a majority, but not the majority, of the privacy mentions indicating that privacy concerns exist but are not ubiquitous.

Theme 3: Conditional Adoption and Pragmatic Enthusiasm. Of 18 substantive responses to Q29, 14 (78%) expressed willingness to use the system, most with explicit conditions attached; two (11%) were undecided, and one (6%) declined. Conditions centered on reliability, security, and keeping AI as a support tool rather than a replacement: "Yes, because it saves time and makes things easier, but only if it's reliable and secure" (P12); "I would still be careful not to rely on it too much and use it as a support tool rather than a replacement for learning" (P6).

4.4 Cross-Cluster Correlations

Pearson correlations among the six cluster-mean scores (N = 29) tested whether constructs moved together. All correlations were positive. Observation Quality correlated strongly with Presence and Realism (r = .75, p

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$< .001$) and with AI Feature Perception ($r = .69$, $p < .001$). AI Feature Perception correlated strongly with Usability and Adoption Intent ($r = .73$, $p < .001$), and Usability and Adoption Intent correlated strongly with Future Readiness ($r = .76$, $p < .001$). Notably, Privacy Concern was positively, not negatively, associated with every other cluster, most strongly with Future Readiness ($r = .51$, $p = .005$) and Presence and Realism ($r = .49$, $p = .007$), and only weakly and non-significantly with Observation Quality ($r = .29$, $p = .125$). This suggests privacy concern was not simply a marker of disengagement; participants who engaged more fully with the demonstration and rated it more favorably also tended to voice more privacy concern, consistent with the qualitative pattern of conditional rather than unconditional enthusiasm. Given the sample size, these associations are treated as descriptive and hypothesis-generating rather than confirmatory.

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.

This discrepancy can be more accurately described in terms of the difference between cognitive and affective trust, as opposed to one general concept. Cognitive trust is about the user's perception of the AI's competence and reliability, as demonstrated by the high score in terms of AI accuracy (Q11: $M = 4.48$), whereas affective trust is about how the user feels about relying on the system, as shown by a lower score in terms of comfort with relying on the AI features (Q16: $M = 3.83$). In this study, participants seem to

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form a faster cognitive trust in the AI assistant's competence than affective trust in delegating academic tasks to it. Seen from this perspective, the discrepancy does not indicate a lack of trust but the process of calibration in which the user gives credibility based on competence before giving confidence based on reliance, in line with the existing literature (Kostick-Quenet & Rahimzadeh, 2023). This point has clear design implications: actions to increase the perceived AI accuracy (e.g., improving natural-language understanding capabilities) would likely not accelerate its adoption if affective trust barriers are not tackled independently.

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

Some of the limitations in extending these results exist in several aspects. Firstly, the sample population was from the International Balkan University, with a majority from the Computer Engineering study program. Secondly, there is a difference between the observation-based testing method and the VR immersion technique itself. Thirdly, the post-test sample (N = 29) has limited statistical power to detect differences because, with this sample size, only large effects can be detected. As the fourth limitation, it is important to note that weak associations between the constructs do not necessarily imply a lack of association. The means and cross-cluster associations of the constructs are considered descriptive and exploratory in nature for this reason. Fifthly, the perception of the constructs was gathered in a one-time observation following a brief demonstration.

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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 the following. (i) A fully immersive experiment, where all participants use the VR headsets instead of watching demonstrations, will allow us to determine how applicable the patterns observed in this study will be in the case of direct interaction. (ii) A longitudinal study design to reassess the levels of trust and intention to adopt after repeated exposure, because the competence-trust gap may increase or decrease with familiarity. (iii) Cross-institutional replication of the current study, as well as the selection of a more diverse and larger sample in order to verify the results in the general context. (iv) Qualitative studies with multiple independent coders for the purposes of confirming and expanding on the themes uncovered during single-coder analysis.

Overall, this line of studies will include blockchain-based data governance and cross-institutional replication within a more complex framework and empirical model of AI-VR integration in higher education.

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Data Availability: All data are included in the content of the paper.

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Declaration for Human Participants: All procedures performed in studies involving human participants were based on the ethical standards of the institutional and/or national research committee. Furthermore, the Research Ethics Committee of the International Balkan University approved the study (April 4, 2026). Prior to the pre-session survey, participants confirmed that they had read a study information sheet and explicitly affirmed that their participation was voluntary, that they could withdraw at any time without

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penalty, and that they consented to their anonymized data being used in academic research. No participant names were collected; the pre-session survey requested only an institution-issued student identifier rather than a name, and post-session responses were collected without any identifying information. Data were used solely for the purposes described in this study.

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