Est. 1841 | YORK ST JOHN UNIVERSITY

Aluko, Henry Adeyemi, Aluko, Ayodele, Ogunjimi, Funke, Offiah, Goodness Amaka, Islam, MD Nazmul and Fernanades, Fatima A. P. (2026) Application of AI-Driven Virtual Reality (VR) in Improving Higher Education Student's Learning and Engagement. Education and Information Technologies.

Downloaded from: https://ray.yorksj.ac.uk/id/eprint/14023/

The version presented here may differ from the published version or version of record. If you intend to cite from the work you are advised to consult the publisher's version: https://doi.org/10.1007/s10639-026-13912-6

Research at York St John (RaY) is an institutional repository. It supports the principles of open access by making the research outputs of the University available in digital form. Copyright of the items stored in RaY reside with the authors and/or other copyright owners. Users may access full text items free of charge, and may download a copy for private study or non-commercial research. For further reuse terms, see licence terms governing individual outputs. Institutional Repositories Policy Statement

RaY

Research at the University of York St John

For more information please contact RaY at ray@yorksj.ac.uk

Education and Information Technologies
https://doi.org/10.1007/s10639-026-13912-6

Application of AI-driven virtual reality (VR) in improving higher education student's learning and engagement

Henry Adeyemi Aluko[1] · Ayodele Aluko[2] · Funke Ogunjimi[3] · Goodness Amaka Offiah[4] · MD Nazmul Islam[5] · Fatima Araujo Pereira Fernandes[5]

Received: 20 January 2025 / Accepted: 26 January 2026
© The Author(s) 2026

Abstract

Purpose: Calls for personalised learning have increased interest in AI-enabled virtual reality (AI-VR) as a tool that can adapt instruction and support diverse learner needs. This study investigates the adoption and applicability of AI-VR in higher education and examines its influence on students' learning and engagement. **Design/methodology/approach**: A quantitative design was used. Structured questionnaires were distributed through Google Forms to lecturers and students in UK higher education using judgemental sampling. A total of 278 respondents (69 lecturers and 209 students) completed the survey. Data were analysed using descriptive and inferential statistics in SPSS. **Findings**: Results indicate that AI-VR improves learning outcomes by strengthening knowledge acquisition, retention, and conceptual understanding. Participants reported higher engagement due to immersive, interactive environments that build confidence and support inclusive learning. Despite these benefits, levels of adoption and consistent applicability in higher education remain below expectation, influenced by digital readiness and infrastructure constraints. **Originality/value**: The study contributes to immersive learning research through the development of the AI-VR Immersive Learning Adoption Model (AILAM). The framework synthesises insights from existing literature to explain how adaptive AI-VR environments influence engagement, learning processes, and user readiness in higher education. AILAM clarifies the mechanisms through which AI-VR produces learning benefits and provides a structured foundation for future empirical inquiry and institutional decision-making.

Keywords AI-Driven Virtual Reality · Higher Education · Learning · Engagement

Extended author information available on the last page of the article

Published online: 03 March 2026

1 Introduction

Due to rapid advancement in technology, higher education landscape has gone through profound transformation whereby AI-VR is gaining importance as a veritable tool for enhancing student learning and engagement. Lin et al. (2023) aver that with the continuous development of social productivity as well as science and technology, the demand for VR technology in different fields is becoming increasingly vigorous; hence VR devices are not only used in games but is now a newly advancing technology recipe for education betterment. In recent years, educational games and technologies have become research hotspot for teaching and learning exploration as Researchers are committing more to designing learning environments/activities aided by AI-VR (Hamilton et al., 2022; Young et al., 2021). Artificial intelligence (AI) is one of the most transformative technologies of our time which has been around for over six decades since John McCarthy and his colleagues developed the word "Artificial Intelligence" in 1956 (Radanliev, 2023; Global Times, 2024).

As stated by Holmes et al., (2022) and supported by Lin et al., (2023), Artificial Intelligence is the simulation of computer to perform the activities supposedly performed by human being excellently. It simply refers to any devices or computer system able to perform tasks that generally require human intelligence; it can approximate human reasoning with environmental adaptability pivotal to education systems (Buchmeister et al., 2019). Scholars emphasize that among the numerous technological innovations, AI-VR technology has emerged as a promising tool with the potential to revolutionize the traditional classroom experience (Hamilton et al., 2022; Young et al., 2021). They argue that the applications and educational benefits of such technology-aided instruction has been studied for more than half a century, buttressing that VR is a blend of technologies used to visualize and provide interaction with a virtual environment. Christou (2020) reiterates that a crucial feature of VR is that it permits multi-sensory interaction with the space visualized.

A virtual reality environment is usually depicted as a 3-dimensional world that tries to replicate the real world both in appearance and in the way that objects behave (such as the simulation of gravity). Farris et al., (2019) buttress that at the core of the synergy between AI and VR is the provision of heightened immersion, since AI-driven algorithms, particularly those supported by machine learning, can analyze and respond to user behavior in real-time. Hence this adaptability enables VR environments to dynamically adjust, creating a more personalized and engaging experience quintessential for students learning and engagement. According to Krust (2021), virtual environments simulate students learning environment in which they will eventually operate and provide a safe environment in which to test scenarios that would be either too difficult or dangerous to perform in real life.

Virtual reality (VR), as an informative medium for learning, possesses the potential to engage students with immersive, interactive, and informative experiences (Zhao et al., 2021; Hussein and Reilly, 2018). These scholars emphasize that when presented in VR, immersive virtual environments (IVEs) can provide three-dimensional visual simulations that can be used to inform students about concepts in specific contexts that would be near impossible to achieve with more traditional teaching methodologies. Lin et al., (2023) argue that the combination of AI technology and VR educational

games not only combines the teaching content with the game, but also considers the students' sense of learning experience; thus combining teaching with fun in such ways that more effectively improve students enthusiasm for learning while optimizing the teaching effect better, and improving the teaching efficiency. With its ability to create immersive and interactive learning experiences, it is argued that AI-enabled VR has the potential to better enhance student engagement, foster deeper comprehension of complex concepts, and ultimately improve learning outcomes.

However, despite the transformative potential of AI-VR to enhance educational experiences, a critical knowledge gap remains regarding its practical implementation and verifiable impact within Higher Education. The central research problem lies in the insufficient empirical evidence concerning the accessibility of these technologies for diverse learners, their comparative effectiveness against traditional pedagogical methods, and the specific mechanisms required to successfully integrate them into existing curricula. Consequently, this study addresses these challenges by examining four pivotal research questions: determining the accessibility and inclusion implications of AI-VR for students with varied needs; evaluating its impact on key learning outcomes such as knowledge retention and critical thinking compared to conventional approaches; analysing the specific effects of immersion and gamification on student engagement; and identifying the most effective pedagogical techniques for embedding AI-VR simulations into higher education programmes.

This paper sought to provide deeper understanding on the adoption/applicability of AI-VR in Higher Education, including the effects on student engagement and learning, accessibility and inclusion implications, as well as various pedagogical techniques for incorporating AI-VR into higher education programmes. The second section of the paper provides the review of related literature with various theoretical perspectives on technology acceptance and need for proper utilization. The third section presents the methodology and draws upon the research context, data collection and analysis. Finally, the paper concludes by discussing key findings, limitations contributions of the paper with directions for forthcoming research.

1.1 Research aim

This study aims to investigate the application of artificial intelligence (AI) driven virtual reality (VR) in improving higher education students learning experiences and engagement.

1.2 Objectives

Examine the accessibility, adoption and inclusion implications of AI-VR in higher education: *This will assess the ways in which VR technology is been adopted and provided to students, especially those with varied learning challenges and requirements, while also overcoming any obstacles to their involvement.*

Explore the effects of AI-VR on student learning outcomes: *This involve assessing enhancements in knowledge retention, critical thinking skills, problem-solving capabilities, and other educational goals in comparison to conventional teaching approaches.*

Evaluate the impact of AI-VR on student engagement and learning: *This will investigate the impact of heightened immersion, interaction, and gamification in virtual reality settings on student engagement and involvement in educational tasks.*

Investigate various pedagogical techniques for truly incorporating AI-VR into higher education programmes: *This include investigating the effectiveness of experiential learning, collaborative activities, and simulations in virtual reality environments with the use of artificial intelligence technologies.*

2 Literature review

2.1 Artificial intelligence and virtual reality in higher education

Artificial intelligence has become central to contemporary educational technologies as systems now learn, reason, and support complex cognitive tasks through adaptive processing (Sheikh et al., 2023; Ghosh & Arunachalam, 2022). Its integration into higher education signals a shift from static digital tools to intelligent systems that interpret learner behaviour and adjust instructional input accordingly. Virtual reality has advanced alongside these developments, offering simulated three-dimensional environments where learners interact with digital objects through motion tracking and immersive displays (Wu, 2024; Hornsey & Hibbard, 2024). Recent research shows growing interest in the pedagogical value of immersive technologies. Sakr and Abdullah (2024) observe that VR, AR, and learning analytics are increasingly used to enhance learner experiences and support data-informed instructional practices.

Evidence from higher education suggests that traditional teaching models struggle to sustain attention and address diverse learning needs in cognitively demanding domains (Lin et al., 2023; Young et al., 2021). AI-VR offer alternative pathways by positioning learners as active participants who explore, manipulate, and test ideas in controlled virtual contexts (Harake & Rijjal, 2024; Bhatt et al., 2024). These benefits have been observed beyond theory. Long et al. (2025) report that VR-based training environments significantly improve mastery of theoretical and practical skills, indicating that immersive tools enhance learning efficiency. Similarly, Godsk and Møller (2025) show that educational technologies, including VR, contribute to deeper engagement and participation when integrated purposefully into higher education environments.

The relevance of AI and VR to the present study lies in how they align with immersive learning, engagement, and knowledge construction. Hamilton et al. (2022) demonstrate that learning improves when students engage with environments that replicate real-world settings. VR supports such experiences by replacing real-world sensory input with responsive, computer-generated stimuli, while AI enhances these environments through adaptive feedback and personalised support. These qualities directly connect to this study's focus on learning outcomes, engagement, accessibility, and the conditions that influence meaningful adoption of AI-VR in higher education.

2.2 AI-driven virtual reality as an emerging pedagogical tool

Recent research positions the convergence of artificial intelligence and virtual reality as a significant development in higher education. Scholars note that VR supports immersion, experiential interaction, and contextualised learning, yet its effectiveness increases when environments adapt to learner needs (Harake & Rijjal, 2024; Sheikh et al., 2023). AI complements VR by interpreting behavioural cues, adjusting task difficulty, and providing personalised feedback, creating learning experiences that respond to the pace and performance of each student (Rong et al., 2022; Saqib & Zia, 2024).

Studies offer important empirical support for these claims. Al-Emran et al. (2025) show that students' readiness to use VR depends on perceived value, usability, and the social conditions that shape acceptance, reinforcing the need for adaptive and supportive learning environments. Bayaga (2025) demonstrates how AI-enhanced and emerging technologies expand pedagogical possibilities by enabling personalised instruction and real-time analytics, which align closely with the adaptive functions of AI-VR. Evidence from adaptive learning research also strengthens this theme. Zhou et al. (2025) find that AI-based adaptive tools significantly improve student motivation and engagement, which suggests that similar adaptive mechanisms in VR environments can sustain active learning. Smyrnova-Trybulska et al. (2022) add that students respond positively to adaptive learning systems that provide timely guidance, indicating that AI-VR can support learners who benefit from structured personalisation.

These insights illustrate how AI-driven VR can deepen conceptual understanding. Ghosh and Arunachalam (2022) note that AI can anticipate user preferences and guide learners through tasks that maintain challenge without inducing cognitive overload. Wu (2024) further argues that adaptive VR environments strengthen comprehension by linking abstract concepts to concrete, situated interaction. The combined evidence shows that AI-VR supports knowledge construction, enhances engagement, and offers personalised pathways that traditional learning environments cannot easily replicate. These qualities establish the rationale for examining AI-VR adoption, experience, and impact in higher education settings.

2.3 Theoretical foundation for AI-VR in student learning

This study reviewed four complementary perspectives to extract insights that clarify how AI-VR may influence engagement, learning outcomes, accessibility, and adoption in higher education. Flow Theory offered useful ideas about the conditions that support focused immersion in adaptive learning environments. Constructivist Theory provided guidance on how learners build understanding through exploration, interaction, and task-based experimentation. Embodied Cognition highlighted the role of sensory and motor processes in shaping conceptual understanding within immersive environments. The Technology Acceptance Model contributed insight into the perceptions that shape users' willingness to engage with new technologies. These perspectives did not serve as analytical lenses in the empirical phase but informed the conceptual logic used to design the AI-VR Immersive Learning Adoption Model

(AILAM). The combined insights helped clarify how users encounter AI-VR, how adoption and applicability influence meaningful use, and how immersive experiences can lead to improvements in learning and engagement.

Flow theory links directly to engagement. Csikszentmihalyi describes flow as focused immersion occurring when task challenge matches learner skill and feedback is immediate (Marougkas et al., 2023). VR creates immersion and real time feedback, while AI can tune challenge and feedback to maintain the flow state (Espinola et al., 2024; Akman et al., 2019). In empirical terms, measures of engagement capture attentional focus, enjoyment, and time on task; flow theory predicts that adaptive VR experiences will raise these measures by reducing mismatch between task demand and learner ability.

Constructivist theory locates learning in active sense making. Piagetian and social constructivist accounts emphasise exploration, prior knowledge, and social interaction as mechanisms of conceptual change (Marougkas et al., 2023). VR affords manipulable contexts for experimentation and collaboration, and AI enables scaffolding that responds to learners needs (Shin et al., 2022; Azevedo and Carvalho, 2024). Operationally, constructivist logic explains gains in higher order outcomes such as problem solving and transfer because learners practice in contexts that mirror authentic tasks.

Embodied cognition foregrounds the body in cognition and explains how action, perception, and environment jointly shape learning. The 4E account states that cognition is embodied, embedded, enacted, and extended; VR's multimodal stimuli and interactive controls instantiate these principles (Chen, 2019; Mills et al., 2022). AI augments this process by modelling sensorimotor patterns, for example by interpreting gaze and gesture to personalise the task sequence (Farris et al., 2019; Radanliev, 2023). For students with language or special educational needs, embodied and AI mediated interactions can reduce cognitive load and provide alternative pathways to comprehension.

The Technology Acceptance Model explains adoption and sustained use. TAM locates perceived usefulness and perceived ease of use as primary predictors of behavioural intention, with external variables shaping those perceptions (Ammenwerth, 2019; Lee et al., 2019). In this study, TAM predicts the initial decision to adopt AI-VR and the conditions under which adoption translates into pedagogical use. Institutional factors such as training, infrastructure, and perceived pedagogical fit function as external antecedents that modify perceived usefulness and perceived ease of use. Behavioral intention and actual use determine exposure to the immersive, constructivist, and embodied affordances that produce flow and learning gains.

Understanding instructors' and learners' attitudes toward educational technology such as AI-VR is valuable in predicting its acceptance as teaching instrument, especially in higher education institutions. The Technology Acceptance Model (TAM) as illustrated in the Fig. 1 below, was introduced by Fred Davis in 1986, and it has evolved to become a widely used framework for investigation technology adoption.

Predicting adoption of AI driven VR requires more than a conceptual restatement of the Technology Acceptance Model. Recent empirical work shows which TAM constructs matter in immersive learning contexts and how they connect to engagement and learning outcomes. Perceived usefulness predicts adoption when instruc-

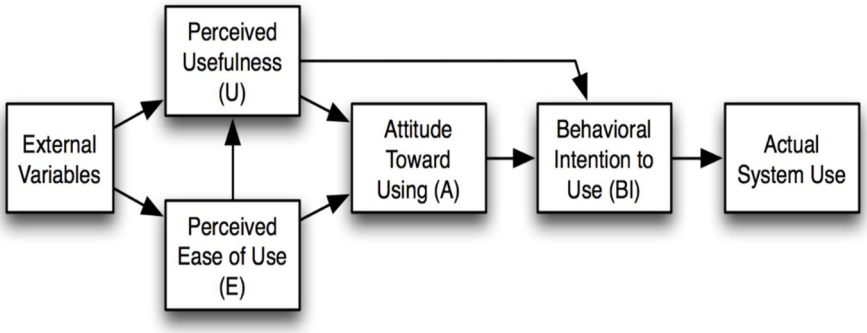

Fig. 1 Technology Acceptance Model (TAM)**Source:** Ammenwerth (2019)

tors and students see concrete gains in mastery and retention; studies report improved recall and conceptual mastery after adaptive VR interventions, which strengthens perceived usefulness. Li et al. (2025) find that real time adaptation and iterative practice in AI VR raise both immediate performance and longer-term retention, thereby increasing perceived usefulness. Lin et al. (2023) report that AI driven adaptation that adjusts difficulty and feedback supports sustained engagement, a pathway that users interpret as instrumental value.

Perceived ease of use in VR is shaped by comfort, hardware usability, and software accessibility. Hussein and Natterdal (2018) note that physical comfort and simple interface settings influence whether learners engage fully. More recent work links usability to participation across diverse student groups; accessibility barriers reduce exposure and therefore limit any downstream learning benefits. Where usability is high, users report lower cognitive load and greater willingness to persist with AI driven VR activities (Marougkas et al., 2023). These findings imply that PEU should be measured empirically in VR studies using items on hardware comfort, setup time, and interface clarity rather than generic software ease items.

Perceived enjoyment and intrinsic motivation operate as important mediators between TAM constructs and learning outcomes. Tan et al. (2025) show that motivation, not engagement alone, explains variation in retention; adaptive gamified features such as progressive challenges and competence signals sustain motivation and support deeper learning (Marougkas et al., 2023). Thus, when AI features produce timely, competence relevant feedback, perceived enjoyment rises and behavioural intention to use follows.

External variables provide the practical levers that modify perceived usefulness and perceived ease of use. Institutional training, infrastructure, and pedagogical fit are strong antecedents. Lee et al. (2019) and Al Adwan et al. (2023) show that training and perceived pedagogical alignment increase PU and PEU among lecturers. Empirical studies further show that accessibility features and embodied interaction matter for inclusion; gesture based and spatial interactions enhance conceptual understanding for many learners, but hardware cost and comfort can exclude others (Hussein & Natterdal, 2018; Mills et al., 2022).

Operational implications for measurement and modelling follow directly. In applied TAM analyses of AI-VR, perceived usefulness, perceived ease of use, per-

ceived enjoyment, and behavioural intention should be treated as distinct yet mediating constructs. Include objective exposure variables such as frequency of use and duration and measure accessibility and infrastructure as moderators. Path models should test the sequence in which institutional antecedents influence PU and PEU, which then affect BI and actual use; use then exposes learners to adaptive, embodied experiences that produce flow and, ultimately, improved learning outcomes as documented in Li et al. (2025) and Lin et al. (2023).

The insights drawn from the four perspectives clarify how the elements of the conceptual framework relate to one another. Ideas from TAM help explain the perceptions that shape initial uptake of AI-VR and the conditions under which users progress from awareness to actual use. Insights from Constructivist and Embodied Cognition perspectives illuminate how interactive design, movement, and sensory engagement shape the quality of learning once users enter the environment. AI features that adjust content and respond to user behaviour strengthen these processes by providing adaptive guidance and multimodal feedback. Concepts associated with flow offer a way to understand how immersive and responsive learning situations support sustained engagement and deeper processing. Considerations of accessibility and inclusion emerge across these insights because personalisation, comfort, and multimodal interaction influence who can participate effectively and how consistently. These theoretical insights guide the logic of the conceptual framework: adoption and usability correspond to TAM related perceptions; engagement aligns with conditions that support flow; active learning and transfer reflect constructivist pathways; and multimodal comprehension and accessibility reflect embodied interaction. This integrated understanding shaped the structure and operationalisation of variables in the AI-VR Immersive Learning Adoption Model.

2.4 Conceptual framework

The conceptual framework, AI-VR Immersive Learning Adoption Model (AILAM), in Fig. 2 (guides the analysis of how AI-VR influences learning and engagement in higher education. It is grounded in the study's aim and objectives and draws directly from the theoretical perspectives reviewed. Flow Theory informs the model by explaining how immersive and adaptive VR environments support focused engagement through balanced challenge and immediate feedback. Constructivist Theory contributes the idea that learners build understanding through exploration and interaction within rich virtual contexts. Embodied Cognition adds the view that physical movement, sensory cues, and spatial interaction strengthen conceptual processing in VR environments. The Technology Acceptance Model provides the adoption pathway, showing how perceptions of usefulness and ease of use shape behavioural intention and actual use of AI-VR tools.

These theoretical insights inform the placement and function of each variable within the model. Demographic factors operate as intervening influences on readiness and access. AI-VR features constitute the independent variable that enables immersive and adaptive learning experiences. Adoption and applicability function as mediating processes that determine whether learners and instructors meaningfully engage with the technology. Learning and engagement represent the dependent outcomes driven by the flow, constructivist, and embodied mechanisms activated during use.

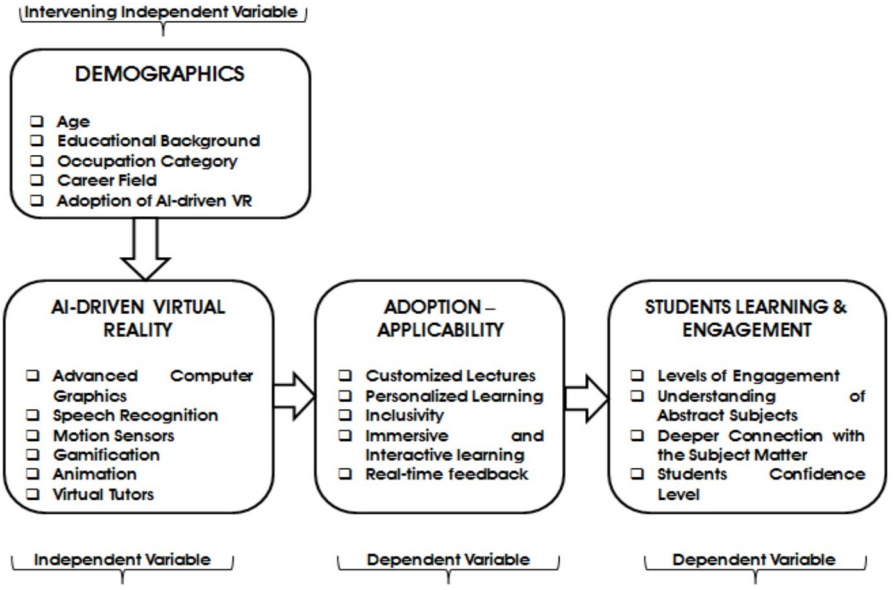

Fig. 2 AI-VR Immersive Learning Adoption Model (AILAM)**Source:** Authors (2024)

The conceptual framework explains how AI driven virtual reality contributes to learning and engagement by linking technological features, adoption processes, and learner outcomes. Demographic attributes operate as intervening factors because age, educational background, and professional experience influence familiarity with digital tools and willingness to engage with immersive systems. Studies in higher education show that younger learners and those with greater digital exposure adapt more readily to VR and AI supported environments (Lin et al., 2023).

AI driven virtual reality forms the central independent construct and captures the technological affordances that make immersive learning possible. Advanced graphics, motion sensing, speech recognition, and intelligent tutoring systems create interactive conditions that promote experiential understanding. Evidence shows that such features strengthen conceptual comprehension and retention because learners interact with dynamic environments rather than abstract descriptions (Christou, 2020).

Adoption and applicability function as mediating variables. Drawing from applied interpretations of the Technology Acceptance Model, adoption depends on perceived usefulness and perceived ease of use, while applicability reflects whether AI VR supports personalised learning, inclusivity, and real time feedback (Al Adwan et al., 2023). Empirical work confirms that adaptive VR systems promote sustained use when learners recognise clear instructional benefits and when the tools are comfortable and accessible (Hussein & Natterdal, 2018).

The final component captures learning and engagement outcomes. Immersive VR environments improve motivation, support deeper processing of abstract concepts, and enhance confidence as learners receive immediate feedback on actions (Tan et

al., 2025). The framework therefore models a sequential process: demographic factors influence adoption, adoption determines exposure to immersive AI VR features, and this exposure predicts higher engagement and improved learning outcomes. This structure guides both the study's variable operationalisation and its analytical approach.

3 Methodology

The paper involved primary research based on quantitative approach whereby structured questionnaire was distributed through Google Form, targeting lecturers and students across the UK Higher Education. Based on judgmental sampling technique, the study purposively restricted participation to only lecturers and students, particularly those in the UK higher education system. This sampling method ensured that the researchers were guided to select typical sample elements that in their judgment possess the qualities needed to provide the required information for the study.

There are over 233,930 staff employed across UK higher education institutions (Universities UK, 2024). In addition, the House of Commons Library (2024) reports that more than 2.86 million students are enrolled in various higher education institutions in the UK. Going by these figures, the population relevant to this study is 3,930,130 (Three Million, Nine Hundred and Thirty Thousand, One Hundred and Thirty). Therefore, the convenience sampling, under the non-probability techniques was applied in targeting 278 lecturers (69) and students (209). This number of participants was targeted to ensure an achievable sample size comprised of those readily accessible by the study; but particularly because using an online survey as part of the research, convenience method enabled the study to cover participant sample of lecturers and students everywhere/anywhere around the UK.

Data were analysed through descriptive statistics with the aid of Statistical Package for Social Sciences (SPSS). Correlation test was adopted in order to determine the strength of any monotonic or non-monotonic relationship between the variables (which is given by the correlation coefficient); and also, to describe the direction of the relationship which can be positive or negative based on the sign of the correlation coefficient. However, Regression analysis was needed to further prove the cause-and-effect relationship between the variables because correlations mainly provide evidence of association, not causation (Ursachi, Horodnic and Zait, 2015). Hence, Regression analysis helped to determine the strength of the relationship between adoption/applicability of AI-VR in Higher Education and the effects on student learning outcomes. Chi-square test is also an excellent choice of statistical tool that can be added to facilitate better understanding and interpretation of the relationship between two categorical variables. We applied the chi-square test to compare observed results with expected results; especially to determine if a difference between observed data and expected data is due to chance, or if it is due to a relationship between the variables studied. For instance, Chi-square analyses were conducted to ascertain the statistical significance of the relationship between experience and effectiveness of AI-VR.

3.1 Findings

3.1.1 Validity and reliability test

Validity in research is the ability to conduct an accurate study with the right tools and conditions to yield acceptable and reliable data that can be reproduced (Dovetail, 2024). This paper applied both face and content validity to ensure relativity of the testing method and information included in the study. The research instrument was subjected to thorough scrutiny/assessment of the questionnaire's suitability to measure the phenomena being studied. After thorough vetting by different experts, the questionnaire was considered valid since each question relatively addresses specific and relevant aspects of the study subject. The Cronbach's Alpha Coefficient reliability measure tool was used to test the research instrument for consistency and objectivity.

Cronbach's Alpha Coefficient decision rule states that where the coefficient value is 0.8 and above, the research instrument should be considered to be very reliable; acceptable at the range of 0.7. But where the calculated coefficient range is less than 0.5, the reliability of the research instrument should be considered weak and unreliable. If the Cronbach Alpha is less than 0.5, it tends to be that the items in the instrument are inappropriate. The formula is derived from the sum of item variance over the total measure variance; hence where both of the values are low, it could be due to a low number of questions, poor inter-relatedness between items or heterogeneous ideas which is an indication that respondents varied little in their answers to items or the overall test (Ursachi, Horodnic and Zait, 2015). Accordingly, a presentation of the reliability test is provided in the table below:

3.2 Reliability of research instrument

At 0.709, as clearly illustrated in the distribution above (Table 1), the overall reliability of the instrument is within acceptable criteria. The result of the Cronbach's Alpha reliability analysis presented in Table 1 above is justified since the Cronbach's Alpha is greater than 0.7, which is the acceptable range.

3.2.1 Descriptive analysis of respondents demographics

Out of the targeted 386 lecturers and students across UK higher education system, only 278 (i.e. 72%) successfully completed the questionnaire distributed online through Google form.

As evident in Fig. 3 above, most of the respondents (74) are between 25 and 34 years, while over 50% of them are in the prime youthful age which has implication for the study given that age is considered a critical factor in technology adop-

Table 1 Reliability Analysis

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.709	.692	5

Source: SPSS 25

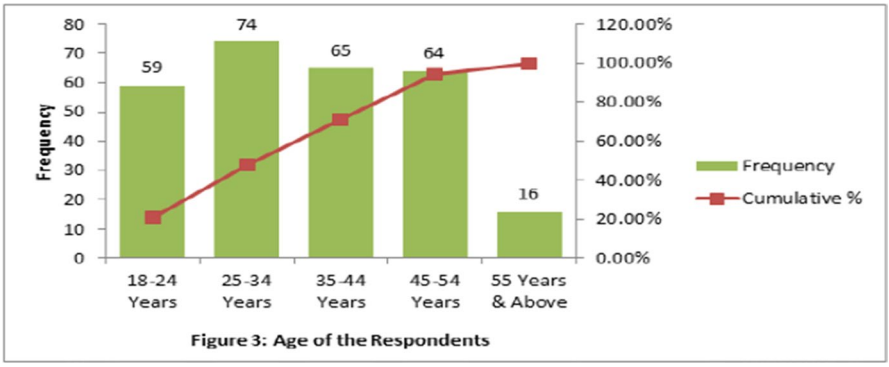

Fig. 3 Respondents Age.**Source:** SPSS 25

tion and usage. Studies have indicated that students as well as tutors in their prime are more inclined to adopt and apply AI-enabled VR tools in teaching and learning. Meanwhile, the chances of objectivity in responses are high since the other different age categories were significantly represented.

As shown in Fig. 4 above, most of the respondents are undergraduates (67), followed by master's degree holders at (61) while the different categories of educational background were significantly represented; hence showing high chances of objectivity. This demographic has core implications for the study since education level have been captured as key determinants of awareness, acceptance/adoption of technology tools in higher learning.

The occupation category distribution in Fig. 5 above shows that more of the respondents are lecturers/tutors at 149; however, many of them are represented as students, which aid objectivity in responses. Overall teachers that are open to technology and innovative teaching methods are more likely to embrace AI-VR as a valuable tool in their teaching, likewise students.

As evident Fig. 6 above, the different categories of career fields were significantly represented among the respondents ranging from those in hospitality and tourism

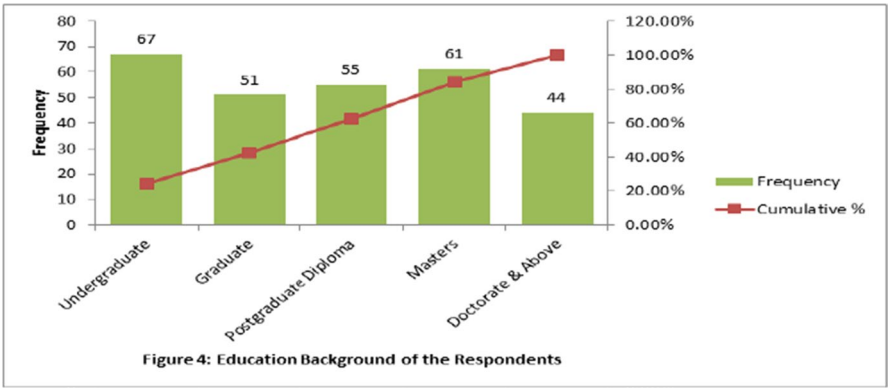

Fig. 4 Respondents education background. **Source:** SPSS 25

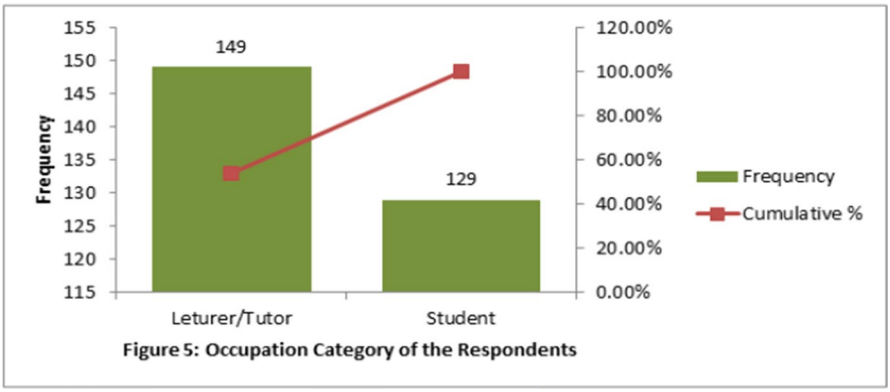

Fig. 5 Respondents Occupation category.**Source:** SPSS 25

management at 52, health and social care at 50, business and management at 44, and so on. This goes to show high level of objectivity in responses from individuals in different career fields on the application of AI-VR in enhancing learning and student engagement.

As shown in Fig. 7 above, clear majority of the respondents (239) indicated that they adopt/use AI-enabled virtual Reality in teaching and learning. Across the UK, the Department for Education (2024) had reported a significant level of improvement with the number of people who use AI – VR technology in higher education, even though there is still a wide gap compared to other sectors.

A value above 0.5 to 0.9 is acceptable and indicates that factor analysis is appropriate, however, a value less than 0.5 indicates that sample size is not sufficient to perform factor analysis. The KMO and Bartlett's Test in Table 2 above represents that the value of Kaiser–Meyer–Olkin Measure of Sampling Adequacy is $0.724 > 0.5$, and significance level of Bartlett's Test of Sphericity is $p < 0.001$. This shows that the sample size is sufficient. Bartlett's Test Values show the multivariate normality of the distribution. A 'p' value less than 0.05 indicates that data do not produce identity matrix and approximately multivariate is normal and acceptable for factor analysis. The result of Bartlett's Test of Sphericity for this study is $P < 0.001$ and suggests that data is acceptable for application of factor analysis.

a. Predictors: (Constant), Effectiveness of AI-VR on student engagement and learning, Impact of AI-VR on student engagement and learning.

Source: SPSS 25.

The two values in the model summary as illustrated in Table 3 above are (R and R^2). Term 'R' in the model represents the correlation at (.545), which indicates moderate correlation. The value of R^2 is.321 and it indicates that 32.1% is how much of the total variance explained by experience and preference of using AI-VR (independent variable) on student engagement and learning (dependent variable).

The sig. column in the ANOVA analysis in Table 4 above indicates that regression model expresses that experience of using AI-VR is significantly strong ($F = 2.936$; $p < 0.055$). This implies experience of using AI-VR to satisfy student learning outcomes expresses a strong effectiveness of AI-VR on student engagement and learning.

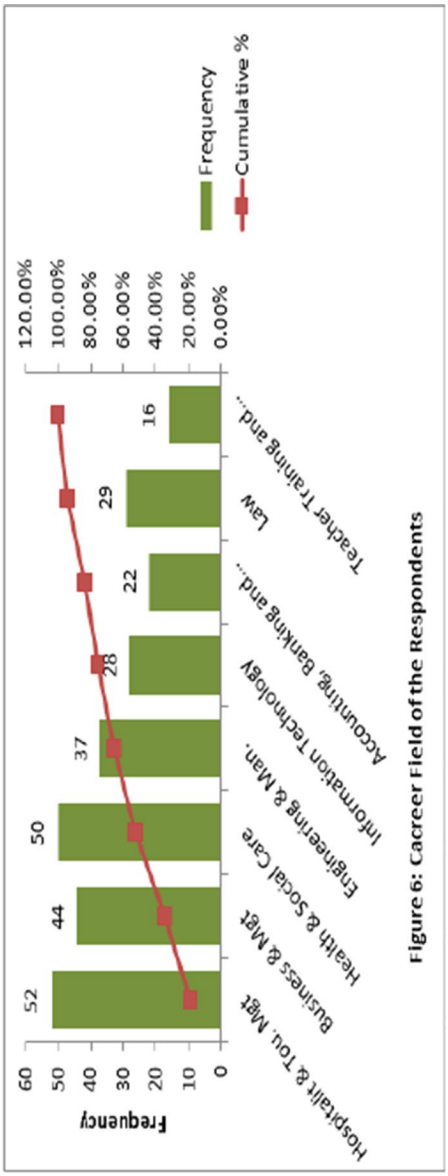

Fig. 6 Respondents Career Field.**Source:** SPSS 25

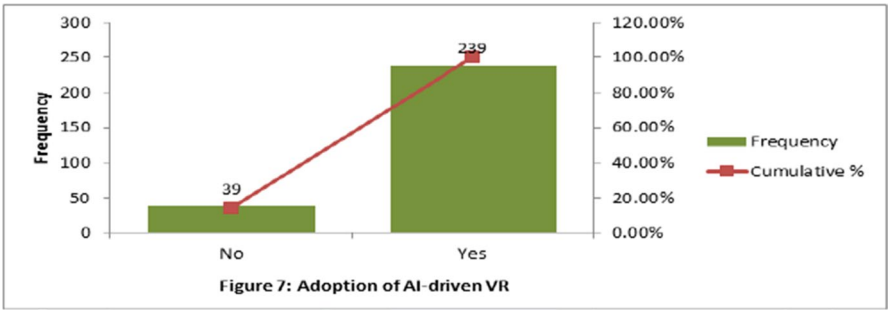

Fig. 7 Respondents Adoption of AI-VR.**Source:** SPSS 25

Table 2 Factor Analysis

KMO and Bartlett's Test		
Kaiser–Meyer–Olkin Measure of Sampling Adequacy		.724
Bartlett's Test of Sphericity	Approx. Chi-Square	423.058
	Df	10
	Sig	<.001

Source: SPSS 25

Table 3 Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.545[a]	.321	.314	.5405

Table 4 ANOVA[a]

ANOVA[a] Analysis						
Model		Sum of Squares	Df	Mean Square	F	Sig
1	Regression	1.715	2	.858	2.936	.055[b]
	Residual	80.328	275	.292		
	Total	82.043	277			

a. Predators (Constant): Experience of using AI-VR to satisfy student learning outcomes.

b. Dependent Variable: Effectiveness of AI-VR on learning, Impact of AI-VR on student engagement.

Source: SPSS 25.

Table 5 above shows that the value of experience and preference of using AI-VR to satisfy student learning and outcomes is (β=.125, P<0.020). This implies experience and preference of using AI-VR to satisfy student learning and outcomes moderately contributes towards effectiveness and impact of AI-VR on student engagement and learning. The results show positive coefficients which indicate that as the value of the independent variable increases, the mean of the dependent variable also tends to increase.

Table 5 Coefficients[a] Analysis

Coefficients[a] Analysis						
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig
		B	Std. Error	Beta		
1	(Constant)	3.179	.206		15.433	<.001
	Experience and Preference of using AI-VR to satisfy student learning outcomes	.125	.053	.186	2.345	.020

a. Dependent Variable: Effectiveness and Impact of AI-VR on student engagement and learning.

Source: SPSS 25.

4 Effectiveness of AI-VR on student engagement and learning across various academic discipline

The sig. column in the ANOVA analysis shown in Table 6 above indicates that regression model expresses that effectiveness of AI-VR on student engagement and learning across various academic discipline is significantly strong ($F = 5.060$; $p < 0.002$). This implies the use of AI-VR to drive student engagement and learning across various academic disciplines is effective. Also, the sig. column in the ANOVA table indicates that regression model expresses that effectiveness of AI-VR on student engagement and learning across various academic career fields is significantly strong ($F = 5.764$; $p < 0.001$). This implies the use of AI-VR to drive student engagement and learning across various academic career fields is effective.

5 Impact of AI-VR on student engagement and learning across various academic discipline

The sig. column in the ANOVA table shown in Table 7 above indicates that regression model expresses that the impact of AI-VR is significantly strong ($F = 9.345$; $p < 0.001$). This implies the impact of AI-VR on student engagement and learning across various academic disciplines is effective. Also, the sig. column in the ANOVA table indicates

Table 6 ANOVA[a]

ANOVA						
Model		Sum of Squares	df	Mean Square	F	Sig
Occupation category	Regression	2.723	3	.908	5.060	<.002
	Residual	49.151	274	.179		
	Total	51.874	277			
Career Field	Between Groups	77.697	3	25.899	5.764	<.001
	Within Groups	1231.170	274	4.493		
	Total	1308.867	277			

Source: SPSS 25

Table 7 ANOVA[a]

ANOVA						
Model		Sum of Squares	df	Mean Square	F	Sig
Occupation category	Regression	4.815	3	1.605	9.346	<.001
	Residual	47.059	274	.172		
	Total	51.874	277			
Career Field	Between Groups	17.948	3	5.983	1.270	<.285
	Within Groups	1290.919	274	4.711		
	Total	1308.867	277			

Source: SPSS 25

that regression model expresses that the impact of AI-VR on student engagement and learning across various career fields is significantly strong ($F = 1.270$; $p < 0.285$). This implies that the impact of AI-VR on student engagement and learning across various academic disciplines is effective.

6 Contextual analysis of the use of AI-VR in classroom and online learning environment

Standard deviation rule says a high/large standard deviation indicates that there is significant variance in the observed data around the mean, and vice versa. The Table 8 above describes the distribution of the individual responses on the context AI-VR is used. As shown in the Table 8, at 0.7835 (online learning environment) and 0.8286 (classroom), the standard deviation for the effectiveness of AI-VR on student engagement and learning is an indication of a moderately high variance. Similarly for the impact of AI-VR on student engagement and learning at 0.6932 (online learning environment) and 0.5830 (classroom) is an indication of a

Table 8 Group Statistics

Group Statistics					
	In what context did you use AI driven Virtual Reality	N	Mean	Std. Deviation	Std. Error Mean
Effectiveness of AI-VR on student engagement and learning	Online Learning Environment	156	3.891	.7835	.0627
	Classroom	121	4.116	.8286	.0753
Impact of AI-VR on student engagement and learning	Online Learning Environment	156	3.942	.6932	.0555
	Classroom	121	4.041	.5830	.0530

Source: SPSS 25

moderately high variance. This implies that the observed data are quite spread out, and there is adequate variance in the observed data around the mean. Hence, there is moderately high likelihood of the effectiveness and impact of AI-VR on student engagement and learning. Higher Education institutions, therefore, should aim to make more informed decision on integrating AI-VR in both classroom and online learning environment to keep averaging higher engagement and learning outcomes.

7 Correlation analysis

The criteria suggest that a coefficient value less than or equal to 0.3 (≤ 0.3) is weak correlation, a coefficient value less than or equal to 0.5 (≤ 0.5) is moderate correlation, and a correlation equal or greater than 0.7 (≥ 0.7) is a strong correlation. As shown in the Table 9 above, all the correlation values are greater than 0.5 (≥ 0.5) thereby indicating a significantly moderate correlation across all variables.

Table 9 Correlations Analysis

Correlations						
		Experience	Preference	Impact	Accessibility and inclusion	Effectiveness
Experience	Pearson Correlation	1	.547	.636	.646	.529*
	Sig. (2-tailed)		.536	.545	.641	.531
Preference	Pearson Correlation	.547	1	.657**	.676**	.576**
	Sig. (2-tailed)	.536		.601	.531	.514
Impact	Pearson Correlation	.636	.657**	1	.590**	.661**
	Sig. (2-tailed)	.545	.601		.519	.623
Accessibility and inclusion	Pearson Correlation	.646	.676**	.590**	1	.669**
	Sig. (2-tailed)	.641	.531	.519		.541
Effectiveness	Pearson Correlation	.529*	.576**	.661**	.669**	1
	Sig. (2-tailed)	.531	.514	.623	.541	

*. Correlation is significant at the 0.05 level (2-tailed)

**. Correlation is significant at the 0.01 level (2-tailed)

Experience - Experience of using AI-VR to satisfy student learning outcomes

Preference - Preference on the effects of AI-VR to satisfy student learning outcomes

Impact - Impact of AI-VR on student engagement and learning

Accessibility & Inclusion - Accessibility and inclusion implications of AI-VR in higher education

Effectiveness—Effectiveness of AI-VR on student engagement and learning.

Source: SPSS 25.

7.1 Discussion

Findings of this paper indicated that more of lecturers/tutors have adopted and use AI-enabled virtual Reality in teaching and learning. The findings of this research corroborate recent studies findings that tutors are increasingly exploring the potentials of AI-VR technology to facilitate deeper comprehension of complex concepts to enhance learning outcomes (Lin et al., 2024; Ibrahim and Murat, 2023). The study of Saqib and Zia (2024) revealed that the notion of using a generative artificial intelligence (AI) engine for text composition has gained excessive popularity among students, educators and researchers. However, this has added another dimension to the daunting task of verifying originality in academic writing. Consequently, the market for detecting artificially generated content has seen a mushroom growth of tools that claim to be more than 90% accurate in sensing artificially written content. The UK Department for Education (2024) report corroborates these findings.

Chen et al. (2024) conducted research that revealed most respondents used generative AI to generate ideas for papers, projects or assignments, and they also used AI to assist with their original ideas. Despite their use of AI assistance, most students were critical of generative AI output, and this mindset was reflected in their reported interactions with ChatGPT. Respondents expressed a need for explicit guidance from course syllabi and university policies regarding generative AI's ethical and appropriate use. Likewise, Hamilton et al., (2022) had employed a qualitative design to interview HE instructors from several disciplines and institutions. Based on thematic analysis of five major themes that included: (a) applications and benefits (b) curriculum integration (c) classroom logistics (d) barriers to application and (e) evaluation; their findings revealed that tutors were generally positive about using AI-VR as a pedagogical tool, proposing a range of novel applications and uses. However, logistical and technical problems were prominent which made implementation and wide scale adoption challenging.

Findings of this paper further revealed that AI-VR largely improves students learning outcomes by increasing their knowledge acquisition and retention. Unlike the traditional means that mostly struggle to captivate student's attention, AI-VR enhances students' engagement. It creates immersive and interactive learning experience that builds students confidence, removes the four-wall barriers to permit inclusivity. Scholars argue that students exposed to Virtual Reality-enhanced learning experiences exhibit higher levels of engagement, improved understanding of abstract subjects, and increased retention rates (Hamilton et al., 2022; Sun et al., 2022). The discoveries are that AI-VR enables deep engagement in highly realistic representations of actual or fictional environments with advanced computer graphics, motion sensors, and display technologies (Lin et al., 2023; Young et al., 2021; Christou, 2020; Servotte et al., 2020). The exploration of AI-VR in improving Higher Education student learning and engagement shows that it offers students immersive digital experiences that cannot be replicated through standard instructional methods (Azevedo & Carvalho, 2023; Sun et al., 2022; Elliot & Joey, 2019). Students can engage more efficiently with AI-VR content beyond traditional teaching approach, enabling tutors to customise their lectures to match their students' individual learning preferences for adaptive learning.

7.2 Limitations

Methodological limitations in terms of approach, scope and sampling are major areas future research can improve on. In terms of approach, future studies can align with the pragmatist mixed-research approach that permits the use of qualitative method of data collection (such as interviews and focus group discussion) to inform more in-depth knowledge for such invaluable education research area. Future research can apply a broadened scope (beyond the UK) to investigate AI-VR tools utilization and impact on learning outcomes; considering that technological changes are occurring rapidly at global level. Sampling of future studies can also adopt the probability sampling that would help ensure equal representations of the sample elements, to help inform more objective investigation. AI-VR offers the potential for personalized learning experiences; hence future studies can concretely look into how adaptive VR environments can be properly integrated for students with special education needs and disabilities (SEND) to adjust content and difficulty levels to their individual student needs, as this adaptability holds the promise of more efficient and effective learning with such technology.

8 Conclusions and Implications

This study examined how AI-VR supports learning and engagement in higher education and used these insights to develop the AI-VR Immersive Learning Adoption Model (AILAM). The findings show that adaptive VR environments strengthen learning by adjusting task difficulty, providing real time feedback, and enabling sensory rich interaction. Students reported deeper understanding and higher engagement when learning tasks were supported through immersive and responsive virtual environments. Although adoption levels are promising, challenges linked to digital readiness, infrastructure, and institutional capacity continue to shape who benefits from AI-VR and how consistently it is applied in teaching.

AILAM represents the main conceptual contribution of the study. The framework integrates the mechanisms that emerged across the literature and the theoretical foundations reviewed, combining them into a single pathway that explains how learners and instructors encounter, adopt, and experience AI-VR. AILAM therefore extends current discussions in the wider literature by consolidating dispersed insights on immersion, adaptation, and user readiness into a single coherent pathway that clarifies when and how AI-VR produces meaningful educational value. The model positions AI-VR features as the core driver of immersive learning, adoption and applicability as the mediating processes that determine meaningful use and learning and engagement as the outcome constructs shaped through exposure to adaptive environments. Demographic and contextual factors moderate these relationships by influencing readiness, access, and the ease with which users interact with the technology. This integrated structure provides a clear foundation for examining the conditions under which AI-VR yields measurable improvements in higher education settings.

The practical implications flow directly from the model. Universities should equip staff with the skills needed to design and facilitate immersive activities and build reliable digital infrastructure that supports stable use of AI-VR systems. Curriculum teams can embed AI-VR activities into modules where experiential and simulation-based learning improve understanding. Clear communication of expected benefits will help lecturers and students integrate the technology with confidence.

Policy implications also arise from AILAM. Institutions should prioritise digital inclusion by ensuring that AI-VR tools are accessible and adaptable for diverse learners. Guidance on responsible and ethical AI use will be essential for maintaining trust and protecting learners' data. Broader innovation strategies can support sector wide collaboration and investment in emerging immersive technologies.

The study's design reveals some limitations worthy of acknowledgement to further shape future inquiry. Cross sectional data limit causal interpretation, and self-reported perceptions may not capture behavioural nuances. Future research could apply longitudinal or comparative methods to observe changes in learning outcomes over time, or use mixed method designs to examine how learners experience adaptive VR in practice. Further work is also needed on students with special educational needs to determine how adaptive VR environments can reduce cognitive load and support personalised learning pathways.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

References

Akman, E., & Çakır, R. (2019). Learners' opinions on an educational virtual reality game in terms of flow experience. *International Journal of Emerging Technologies in Learning, 14*, 121–137. https://doi.org/10.3991/ijet.v14i15.10576

Al-Adwan, A. S., Li, N., & Al-Adwan, A. (2023). Extending the Technology Acceptance Model (TAM) to predict university students' intentions to use metaverse-based learning platforms. *Education and Information Technologies, 28*(1), 15381–15413. https://doi.org/10.1007/s10639-023-11816-3

Al-Emran, M., Al-Sharafi, M. A., Foroughi, B., Al-Qaysi, N., Leung, N. K., Yaseen, Z. M., & Ali, N. (2025). From adoption to social sustainability: Examining the factors affecting students' use of virtual reality in higher education. *Education and Information Technologies*. https://doi.org/10.1007/s10639-025-13720-4

Ammenwerth, E. (2019). Technology acceptance models in health informatics: TAM and UTAUT. *Studies in Health Technology and Informatics, 263*, 64–71. https://doi.org/10.3233/SHTI190111

Azevedo, M. J., & Carvalho, A. A. (2023). Learning with virtual reality (VR) and augmented reality (AR). In *International Conference on Lifelong Education and Leadership for All (ICLEL 2023)* (pp. 118–127).

Bayaga, A. (2025). Leveraging AI-enhanced and emerging technologies for pedagogical innovations in higher education. *Education and Information Technologies, 30*(1), 1045–1072. https://doi.org/10.1007/s10639-024-13122-y

Chen, J. C. (2019). Theoretical bases for using virtual reality in education. [Online] Available at: https://www.semanticscholar.org/paper/Theoretical-Bases-for-Using-Virtual-Reality-in-Chen/f6b4882a93a6d3cc35fa090a4c9f7927b12d01fc [Accessed June 10, 2024]

Chen, K., Tallant, A. C., & Selig, I. (2024). Exploring generative AI literacy in higher education: Student adoption, interaction, evaluation and ethical perceptions. *Information and Learning Sciences*. https://doi.org/10.1108/ILS-10-2023-0160

Christou, C. (2020). 'Virtual Reality in Education' *In book: Affective, Interactive and Cognitive Methods for E-Learning Design: Creating an Optimal Education Experience (pp.228–243).* https://doi.org/10.4018/978-1-60566-940-3.ch012

Elliot, H., & Joey, J. L. (2019). Virtual reality in education: A tool for learning in the experience age. [Online] Available at: https://www.semanticscholar.org/paper/Virtual-reality-in-education%3A-a-tool-for-learning-Hu-Au-Lee/8fd102d83be5a9c9a6129d1849d8dfa6b09d8c8e [Accessed June 10, 2024]

Espinola, V. B., Zahnow, E., O'Bryan, C. J., & Fuller, R. A. (2024). Virtual reality for nature experiences. *Nature Human Behaviour, 2*(1), 8–14. https://doi.org/10.1038/s41562-024-01857-0

Farris, C. P., Rathner, J., Fong, A., & Sevigny, C. P. (2019). Virtual reality in higher education. *International Journal of Innovation in Science and Mathematics Education, 27*(8), 69–80. https://doi.org/10.30722/IJISME.27.08.006

Fussell, S. G., & Truong, D. (2021). Accepting virtual reality for dynamic learning: An extension of the Technology Acceptance Model. *Interactive Learning Environments, 31*(9), 5442–5459. https://doi.org/10.1080/10494820.2021.2009880

Godsk, M., & Møller, K. L. (2025). Engaging students in higher education with educational technology. *Education and Information Technologies, 30*(3), 2941–2976. https://doi.org/10.1007/s10639-024-12901-x

Hamilton, D., McKechnie, J., Edgerton, E., & Wilson, C. (2022). Implementing immersive virtual reality in higher education: A qualitative study of instructor attitudes and perspectives. *Innovative Practice in Higher Education, 4*(2), 206–238.

Hussein, M., & Natterdal, C. (2018). *The benefits of virtual reality in education: A comparison study*. *Bachelor of Science Thesis in Software Engineering and Management* [Online] Available at: https://core.ac.uk/download/pdf/43559881.pdf [Accessed June 10, 2024]

Kavanagh, S., Reilly, A. L., Wuensche, B., & Plimmer, B. (2017). A systematic review of virtual reality in education. *Themes in Science and Technology Education, 10*(2), 85–119. https://doi.org/10.4236/ce.2024.158102

Kunst, A. (2021). In general, which types of video games do you play? [Online] Available at: https://www.statista.com/forecasts/997858/videogame-preferences-by-genre-in-the-uk [Accessed June 10, 2024]

Lee, J., Kim, J., & Choi, J. Y. (2019). The adoption of virtual reality devices: The Technology Acceptance Model integrating enjoyment, social interaction, and strength of social ties. *Telematics and Informatics, 39*, 37–48. https://doi.org/10.1016/j.tele.2018.12.006

Li, J., & Feng, Q. (2025). Research on dual impact of AI-VR integrated immersive STEM teaching model on learning motivation and academic performance. In *Proceedings of the 2nd Guangdong-Hong Kong-Macao Greater Bay Area Education Digitalization and Computer Science International Conference* (pp. 279–283).

Lin, Y., You, Y., & Zhou, Z. (2023). Application of VR in the field of education. *Highlights in Science, Engineering and Technology, 68*, 11–20. https://doi.org/10.1177/14604582241259331

Long, Y., Zhang, X., & Zeng, X. (2025). Application and effect analysis of virtual reality technology in vocational education practical training. *Education and Information Technologies, 30*(7), 9755–9786. https://doi.org/10.1007/s10639-024-13197-7

Marks, B., & Thomas, J. (2022). Adoption of virtual reality technology in higher education: An evaluation of five teaching semesters in a purpose-designed laboratory. *Education and Information Technologies, 27*(1), 1287–1305. https://doi.org/10.1007/s10639-021-10653-6

Marougkas, A., Troussas, C., Krouska, A., & Sqouropowou, C. (2023). Virtual reality in education: A review of learning theories, approaches and methodologies for the last decade. *Electronics, 12*(13), 1–22.

Mills, K. A., Scholes, L., & Brown, A. (2022). Virtual reality and embodiment in multimodal meaning making. *Journal of Visual Literacy, 29*(3), 118–125. https://doi.org/10.1177/07410883221083517

Radanliev, P. (2023). Artificial intelligence: Reflecting on the past and looking towards the next paradigm shift. *Journal of Experimental and Theoretical Artificial Intelligence, 1*(10), 1–18. https://doi.org/10.1080/0952813X.2024.2323042

Raja, M., & Priya, G. G. (2021). Conceptual origins, technological advancements, and impacts of using virtual reality technology in education. *Webology, 18*(2), 11–23. https://doi.org/10.14704/WEB/V18I2/WEB18311

Sakr, A., & Abdullah, T. (2024). Virtual, augmented reality and learning analytics impact on learners, and educators: A systematic review. *Education and Information Technologies, 29*(15), 19913–19962. https://doi.org/10.1007/s10639-024-12602-5

Sharma, U., Tomar, P., Bhardwaj, H., & Sakalle, A. (2021). Artificial intelligence and its implications in education. In *Impact of AI Technologies on Teaching, Learning, and Research in Higher Education* (pp. 222–235). https://doi.org/10.4018/978-1-7998-4763-2.ch014

Shin, Y., Lin, J., Kim, Y., Seo, D. G., & Lim, J. (2022). Effects of VR body representation on motor skill learning. *International Journal of Legal Medicine, 12*(1), 1–9. https://doi.org/10.1038/s41598-022-19514-9

Smyrnova-Trybulska, E., Morze, N., & Varchenko-Trotsenko, L. (2022). Adaptive learning in university students' opinions: Cross-border research. *Education and Information Technologies, 27*(5), 6787–6818. https://doi.org/10.1007/s10639-021-10830-7

Tan, L. Y., Hu, S., Yeo, D. J., & Cheong, K. H. (2025). Artificial-intelligence-enabled adaptive learning platforms: A review. *Computers and Education: Artificial Intelligence, 9*, Article 100429.

Tatnall, A. (2022). Editorial: EAIT 21–8 (September 2022). *Education and Information Technologies, 27*(8), 10455–10467. https://doi.org/10.1007/s10639-022-11314-y

Vincent-Lancrin, S., & Vlies, R. (2020). *Trustworthy artificial intelligence (AI) in education: Promises and challenges*. OECD Publishing.

Young, G. W., Stehle, S., Yazgi, B., & Tiri, E. (2021). Exploring virtual reality in the higher education classroom: Using VR to build knowledge and understanding. *Journal of Universal Computer Science, 26*(8), 904–928.

Yuan, L. (2023). Regarding the immersion of VR: What do we need to do to make it better? *Highlights in Science, Engineering and Technology, 39*, 121–130. https://doi.org/10.54097/hset.v39i.6511

Zhao, H., Kelly, A., Hulusic, V., & Charles, F. (2021). The application of virtual reality in student recruitment. *Journal of Advanced Technology & Science, 8*(1), 107–126. https://doi.org/10.1145/3489849.3489936

Zhou, C., Ren, T., & Lang, L. (2025). The impact of AI-based adaptive learning technologies on motivation and engagement of higher education students. *Education and Information Technologies*. https://doi.org/10.1007/s10639-025-13646-x

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Authors and Affiliations

Henry Adeyemi Aluko[1] · Ayodele Aluko[2] · Funke Ogunjimi[3] · Goodness Amaka Offiah[4] · MD Nazmul Islam[5] · Fatima Araujo Pereira Fernandes[5]

✉ Henry Adeyemi Aluko
h.aluko@yorksj.ac.uk; henry@henryaluko.com

Ayodele Aluko
alukoa@regents.ac.uk

Funke Ogunjimi
f.ogunjimi@mrcollege.ac.uk

Goodness Amaka Offiah
goodness.titus04@gmail.com

MD Nazmul Islam
nislam@arden.ac.uk

[1] Department of Business Management and Health Studies, York St John University, London, UK

[2] Department of Business Finance and Entrepreneurship, Regents University, London, UK

[3] Department of Hospitality Management, Mont Rose College, London, UK

[4] Department of Public Administration, Ebonyi State University, Abakaliki, Nigeria

[5] School of Business Management and Creativity, Arden University, London, UK