Assessing Behavioral Intention of University Students to Adopt VR-Based Virtual Classrooms: A Hybrid SEM–ANN Approach

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Abstract

The rapid advancement of virtual reality technologies has created opportunities for immersive learning, yet adoption of VR-based virtual classrooms in Pakistani universities remains limited, particularly among students who can benefit most from innovative digital learning tools. This study aims to examine the determinants of university students' behavioral intention to adopt VR-Based virtual classrooms, focusing on technology acceptance theories like TAM and UTAUT. This study follows positivism research philosophy based on quantitative, cross-sectional research design. A survey of 373 students across different universities was conducted, and data were analyzed using Structural Equation Modeling for hypothesis testing and Artificial Neural Networks for predictive validation. Results indicate that Performance Expectancy, Perceived Usefulness, and Perceived Enjoyment are the strongest predictors of both students' attitude and behavioral intentions. By using a hybrid SEM–ANN approach the study provides actionable insights for universities, policymakers, and VR developers to enhance VR classroom adoption among higher education.

Keywords: Higher education, Immersive learning, Student behavior, UTAUT, Virtual reality

1. Introduction

Since the COVID-19 pandemic began, higher education globally has undergone an unprecedented transformation (Dhawan, 2020; Pokhrel & Chhetri, 2021). With lockdowns and social distancing mandates forcing educational institutes to close physical campuses, institutions rapidly adopted remote learning modalities to ensure continuity of education (Ahmad Samed Al-Adwan & Al-Debei, 2024; Kalınkara & Özdemir, 2024). This shift accelerated digital learning technologies such as video conferencing, learning management systems, virtual and augmented reality in education system (Yang, Ren, & Gu, 2022). Even beyond the crisis, many universities are now considering permanent or hybrid models integrating remote instruction. This is because students and faculty have become more comfortable with and reliant upon virtual and online learning tools due to immersive experience (Conrad, Kablitz, & Schumann, 2024; Naseer et al., 2025). But the rise of such technologies has highlighted both opportunities like, wider reach, flexibility, cost savings, and challenges such as, engagement, assessment, and digital fatigue in delivering quality education.

In Pakistan, the adoption of digital and virtual learning has been more uneven, with multiple structural and socio-economic barriers slowing progress (Akram et al., 2021). The digital divide remains a persistent issue, many students, especially in rural or lower-income regions, lack reliable access to devices, high-speed internet, or conducive learning environments for remote or virtual instruction (Naveeda & Wajahat, 2024). For instance, studies have found that access to ICT infrastructure and internet-enabled devices in Pakistan is significantly influenced by socio-economic status, regional location, and gender (Shair et al., 2022; Zeewaqar, 2024). Moreover, while the higher education commission (HEC) has initiated projects to digitize services, connect universities via PERN (Pakistan Education & Research Network), and set up digital datacenters (HEC, 2025), gaps in implementation, software/hardware availability, and digital literacy among both students and faculty remain. Among educational institute in Pakistan university students are relatively better positioned with respect to technical familiarity, which makes them ideal subjects for exploring the acceptance of more advanced technologies such as virtual classrooms or VR-based learning. Yet even within this group, acceptance and intentions to use virtual learning tools can be hampered by usability concerns, lack of enjoyment, perceived usefulness, or social and infrastructural constraints.

Virtual reality (VR) and related immersive technologies have the potential to reshape educational experiences beyond what standard online classrooms provide (Wiangkham & Vongvit, 2024). VR-based virtual classrooms can offer strong sensory immersion, interactivity, simulation of real-world or complex environments, and experiential learning that traditional lectures or flat online content cannot match (Abdulmuhsin, Owain, & Alkhwaldi, 2024; Nguyen et al., 2024; Yang et al., 2022). Empirical studies have shown that immersive VR classrooms increase attention, concentration, sense of presence, and emotional engagement, which often translate into higher retention and understanding of complex subject matter (A. S. Al-Adwan et al., 2024; Liu et al., 2025). However, for such potential to be realized, students' intention to use VR-based virtual classrooms is crucial because acceptance, attitude, behavioral intention precede actual use (Ajzen, 1991; İbili et al., 2024). Understanding what drives intention is therefore vital, especially in settings like Pakistan where technological and socio-contextual constraints may moderate or influence those drivers differently than in developed countries.

Although numerous studies have examined technology acceptance in online learning environments, most focus on traditional e-learning platforms, learning management systems, or video-based instruction (Ahmad Samed Al-Adwan, Al-Madadha, & Zvirzdinaite, 2018; Tabassum, Akram, & Moazzam, 2022). Research on immersive technologies such as VR in higher education remains relatively limited, particularly in developing countries. Studies in Western contexts have highlighted the potential of VR for improving learning outcomes, engagement, and satisfaction (Aman, Aziz, & Abbas, 2023; Radianti et al., 2020), but there is little empirical evidence on students' readiness and behavioral intentions in South Asian contexts. In Pakistan, where infrastructural, cultural, and pedagogical barriers persist, VR adoption in education is still in its infancy. This creates a significant gap in understanding how students perceive and intend to use VR-based virtual classrooms. More importantly, while the acceptance of online platforms has been studied, little is known about how multiple cognitive, social, and affective factors jointly shape intentions in this emerging learning paradigm.

To address this gap, this study draws upon two well-established frameworks in information systems research, the unified theory of acceptance and use of technology (UTAUT) proposed by (Venkatesh et al., 2003) and the technology acceptance model (TAM) proposed by (Davis, 1989). UTAUT explains technology adoption through factors such as performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC), while TAM emphasizes the roles of perceived usefulness (PU) and attitude (ATT) in predicting behavioral intention (BI). To capture the hedonic dimension, this study also includes perceived enjoyment (ENJ), which previous research has shown to be a strong predictor of intention to use immersive technologies (Sun et al., 2014; Van der Heijden, 2004). By combining utilitarian, social, and hedonic constructs, this framework provides a holistic understanding of what drives students' intention to use virtual classrooms in higher education. Furthermore, this approach allows the simultaneous testing of both direct and indirect effects via attitude, offering deeper theoretical insights into technology acceptance in VR contexts.

This study aims to examine the determinants of university students' attitudes and behavioral intentions to use VR-based virtual classrooms in higher education of Pakistan, focusing on universities students who are more technologically literate and thus more relevant for early adoption. Using a dual methodological approach, structural equation modeling (SEM) to test causal relationships and artificial neural networks (ANN) to assess predictive accuracy, this study makes both theoretical and methodological contributions. Theoretically, it extends UTAUT and TAM to a new context, Pakistani higher education with VR classrooms and incorporates perceived enjoyment as a hedonic factor. Practically, the findings will help universities, policymakers, and educators design strategies to promote effective integration of VR in learning. By addressing both cognitive, social, and affective drivers, this study provides a comprehensive model for understanding technology acceptance in emerging educational contexts.

2. Literature Review

Virtual Reality (VR) refers to computer-generated environments that simulate real or imagined worlds, enabling users to experience a sense of presence and immersion through interaction with digital objects and spaces (Burdea & Coiffet, 2003; Wohlgenannt, Simons, & Stieglitz, 2020). In education, VR technologies are increasingly being recognized as powerful tools for enhancing student learning by providing experiential, interactive, and engaging experiences beyond what traditional classroom methods can deliver (Radianti et al., 2020). Unlike conventional e-learning platforms, which rely on two-dimensional interfaces such as slides or videos, VR-based classrooms offer three-dimensional, immersive environments where learners can visualize complex concepts, perform simulations, and engage in experiential learning. This immersive quality makes VR particularly relevant for higher education disciplines that require abstract reasoning, laboratory-based experimentation, or visualization of complex processes.

The application of VR in virtual classrooms has gained attention as it addresses some of the limitations of standard online learning, such as reduced engagement, lack of interaction, and digital fatigue. Studies have shown that VR-supported learning environments can foster higher levels of attention, motivation, and enjoyment compared to traditional online platforms (Bower, DeWitt, & Lai, 2020; Jensen & Konradsen, 2018; Villena-Taranilla et al., 2022). In a VR classroom, students can interact with instructors and peers in a simulated environment that mimics the dynamics of face-to-face classes, thereby enhancing social presence and collaboration (Dunmoye et al., 2024; Hodge et al., 2008). Moreover, VR allows for real-time simulations, such as virtual laboratories, field trips, or interactive role-playing which can significantly improve comprehension and knowledge retention. Given these benefits, exploring the factors that influence students' intention to adopt VR-based virtual classrooms is essential, especially in contexts like Pakistan where digital adoption is still evolving and educational institutions are searching for innovative ways to engage students.

2.1. Theoretical Lens

Two of the most influential models in technology acceptance research are the technology acceptance model (TAM) proposed by (Davis, 1989) and the unified theory of acceptance and use of technology (UTAUT) which is proposed by (Venkatesh et al., 2003). TAM emphasizes that users' attitudes and behaviors to accept a technology are shaped by their perceptions of usefulness (PU) and ease of use (PEU) of that technology, while UTAUT incorporates broader determinants such as performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). Together, these frameworks provide a comprehensive explanation of how cognitive, social, and contextual determinants influence technology usage and adoption among users.

This study combines TAM and UTAUT to capture both utilitarian efficiency factors (e.g., PE, PU, EE, FC) and hedonic or affective factors (e.g., enjoyment and attitude). Prior research suggests that TAM alone may not fully capture the social and contextual determinants of technology adoption, while UTAUT underrepresents the role of affective motivations such as perceived enjoyment (ENJ) (Guo & Barnes, 2011; Sun et al., 2014; Van der Heijden, 2004). Therefore, an integrated model is better suited to explaining the complex nature of adopting VR-based virtual classrooms, where both the perceived usefulness of learning outcomes and the enjoyment of immersive experiences matter.

2.2. Hypothesis Development

2.2.1. Performance Expectancy

Performance Expectancy (PE) refers to the degree to which an individual believes that using a particular technology will improve their performance (Venkatesh et al., 2003; Venkatesh, Thong, & Xu, 2012). In educational contexts, PE captures the belief that digital or immersive platforms can enhance learning effectiveness, productivity, and outcomes. Prior studies have consistently shown PE to be a strong predictor of technology adoption in education domain (Abbad, 2021; Rashid, 2025). Specifically, in VR-based learning, students are more likely to adopt such tools if they believe that virtual learning will improve their understanding, engagement, and performance (Yang et al., 2022). Based on these insights, this study posits that PE will have a significant effect on both students' attitudes toward using VR classrooms and their behavioral intentions to adopt them:

H1a: Performance Expectancy positively influences Attitude toward VR classrooms.
H1b: Performance Expectancy positively influences Behavioral Intention to use VR classrooms.

2.2.2. Effort Expectancy

Effort Expectancy (EE) is defined as the degree of ease associated with using a technology (Venkatesh et al., 2012). In educational settings, if students perceive VR classrooms as user-friendly, easy to navigate, and not cognitively demanding, they are more likely to adopt them. Previous studies have found EE to be a significant determinant of online/virtual learning acceptance, particularly among younger populations who value intuitive interfaces (Abbad, 2021; Rashid, 2025; Yang et al., 2022). In VR-based education, usability concerns (e.g., complex equipment, steep learning curves) can discourage adoption unless students perceive the technology as straightforward and easy to integrate into their learning routines. Accordingly, this study hypothesizes:

H2a: Effort Expectancy positively influences Attitude toward VR classrooms.
H2b: Effort Expectancy positively influences Behavioral Intention to use VR classrooms.

2.2.3. Social Influence

Social Influence (SI) refers to the extent to which individuals perceive that important others such as peers, instructors, or family believe they should use a particular technology (Riaz & Awais, 2024; Venkatesh et al., 2012). In higher education, social norms and peer recommendations significantly shape students' willingness to adopt new tools (Rashid, 2025). Research on e-learning and mobile learning consistently demonstrates that SI plays a critical role, especially in collectivist cultures like Pakistan where social approval influences decision-making (Du & Lv, 2024; Rashid, 2025). In VR-based learning, encouragement from faculty and peers can reduce uncertainty and motivate students to try immersive technologies. Thus, the following hypotheses are proposed:

H3a: Social Influence positively influences Attitude toward VR classrooms.
H3b: Social Influence positively influences Behavioral Intention to use VR classrooms.

2.2.4. Facilitating Conditions

Facilitating Conditions (FC) represent the availability of technical and organizational support that enables the use of new technologies (Bibi, Seher, & Aslam, 2025; Venkatesh et al., 2003). In education, this includes access to devices, internet connectivity, software platforms, and institutional support such as training and troubleshooting. Prior studies on e-learning adoption in developing countries have shown that without adequate facilitating conditions, students are less likely to adopt technology, regardless of perceived usefulness (Abbad, 2021; Rashid, 2025). In VR classrooms, where specialized equipment and stable infrastructure are required, FC become even more critical in shaping both attitude and intention. Accordingly, the following hypotheses are advanced:

H4a: Facilitating Conditions positively influence Attitude toward VR classrooms.
H4b: Facilitating Conditions positively influence Behavioral Intention to use VR classrooms.

2.2.5. *Perceived Enjoyment*

Perceived Enjoyment (ENJ) is the degree to which the activity of using a technology is perceived as enjoyable in its own right, beyond performance outcomes (Jo & Park, 2023; Van der Heijden, 2004). In VR learning environments, enjoyment is especially relevant, as immersive and interactive experiences create a sense of fun, excitement, and intrinsic motivation. Studies have demonstrated that perceived enjoyment significantly influences both attitude and behavioral intention in hedonic and learning technologies (Alalwan et al., 2019; Teo & Noyes, 2011). In VR classrooms, students who find the experience engaging and enjoyable are more likely to form positive attitudes and develop stronger intentions to use such platforms. Thus, the following hypotheses are proposed:

H5a: Perceived Enjoyment positively influences Attitude toward VR classrooms.
H5b: Perceived Enjoyment positively influences Behavioral Intention to use VR classrooms.

2.2.6. *Perceived Usefulness*

Perceived Usefulness (PU), a central construct in TAM, is defined as the degree to which a person believes that using a technology will enhance their performance (Davis, 1989; Jo & Park, 2023). In the context of education, PU reflects the belief that VR classrooms will help students achieve learning goals more effectively and efficiently. Prior research consistently identifies PU as one of the strongest predictors of attitude and intention toward educational technologies (Al-Samarraie et al., 2018; Koteczki & Balassa, 2025). For VR, students who perceive the platform as useful for improving knowledge, understanding, and skills are more likely to adopt it as a learning tool. Accordingly, this study proposes:

H6a: Perceived Usefulness positively influences Attitude toward VR classrooms.
H6b: Perceived Usefulness positively influences Behavioral Intention to use VR classrooms.

2.2.7. *Attitude*

Attitude (ATT) refers to the degree of positive or negative feelings an individual has toward using a particular technology (Ajzen, 1991; Seher, Tofique, & Afzal, 2025). In technology acceptance research, attitude is often conceptualized as a mediating factor between perceptions (e.g., usefulness, enjoyment, effort expectancy) and behavioral intention. According to the TAM, and TPB attitude toward using a system is a direct antecedent of behavioral intention (Ajzen, 1991; Davis, 1989). Empirical studies in online learning and digital classrooms confirm that students who hold favorable attitudes toward a system are more likely to express strong intentions to adopt it (Mailizar, Burg, & Maulina, 2021; Šumak, Heričko, & Pušnik, 2011). In the case of VR classrooms, where novelty and experiential elements may evoke both enthusiasm and skepticism, attitude plays a central role in shaping adoption decisions. Building on TAM and TPB foundations, this study proposes the following hypothesis:

H7: Attitude positively influences Behavioral Intention to use VR classrooms.

2.3. Conceptual Framework

This study integrates constructs from widely recognized theories included UTAUT, TAM, and hedonic motivation theory into a unified framework to explain students' behavioral intention (BI) to use VR-based virtual classrooms. From UTAUT, the constructs of performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) are included, as these represent core drivers of technology adoption in educational and organizational settings (Venkatesh et al., 2003). From TAM, perceived usefulness (PU) and attitude (ATT) are adopted, reflecting the utilitarian and affective dimensions of technology evaluation (Davis, 1989). Additionally, perceived enjoyment (ENJ), drawn from hedonic motivation theory (Van der Heijden, 2004), captures the intrinsic motivational aspect of technology use, which is particularly relevant for immersive and interactive VR environments.

The framework assumes that all six independent variables (PE, EE, SI, FC, ENJ, PU) influence both attitude (ATT) and behavioral intention (BI). This inclusion reflects the notion that students form cognitive, affective, and motivational judgments simultaneously when evaluating a novel learning tool like VR. Moreover, attitude itself is hypothesized to directly predict BI, consistent with TAM and the theory of planned behavior (Ajzen, 1991), which suggest that favorable attitudes strongly enhance intention to adopt. By combining utilitarian (PE, PU), affective (ATT, ENJ), social (SI), and contextual (EE, FC) factors, the framework offers a comprehensive perspective that goes beyond traditional adoption models, addressing both extrinsic and intrinsic motivations. Figure 1 presents the conceptual framework of this study, illustrating the hypothesized relationships among the constructs.

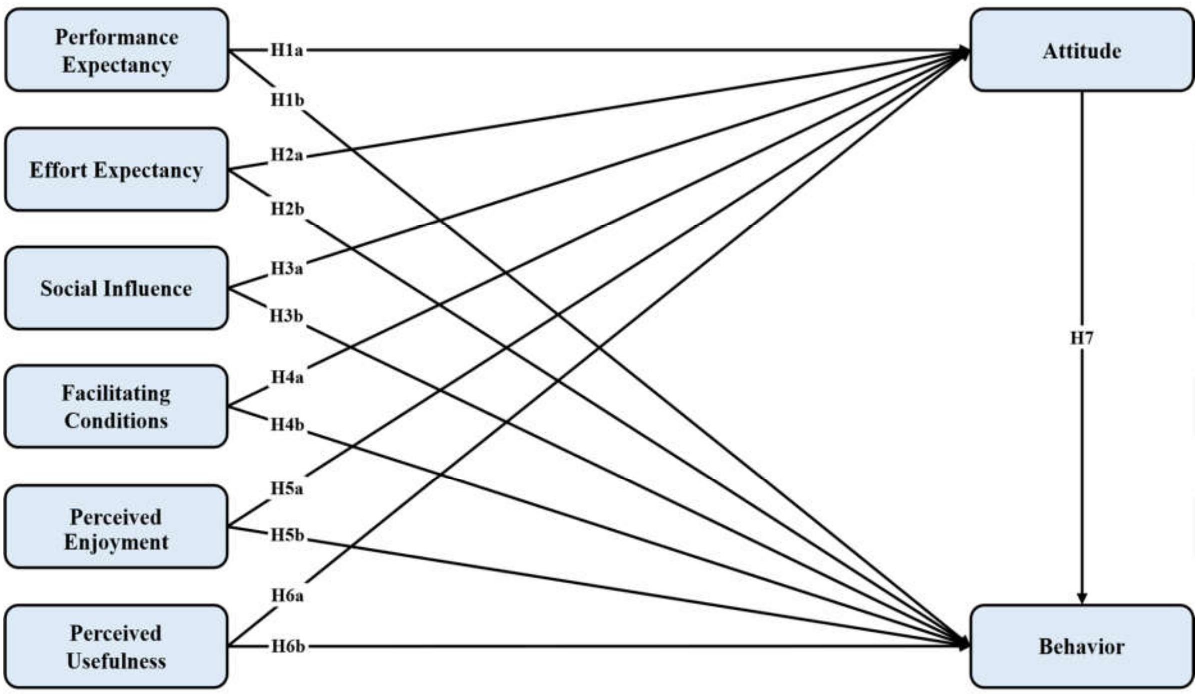

Figure 1: Conceptual Framework.

3. Methodology

3.1. Research Design

This study follows positivism research philosophy based on quantitative, cross-sectional research design to examine the determinants of students' intention to use VR-based virtual classrooms (Awais, Fatima, & Awan, 2022). A quantitative approach is appropriate because the objective is to test theoretically derived hypotheses using measurable constructs and statistical modeling (Creswell & Creswell, 2017). The study employs a dual-analytical strategy: Structural equation modeling (SEM) and artificial neural networks

(ANN). SEM is widely used in technology acceptance research as it allows simultaneous testing of measurement models and structural relationships among latent constructs. However, SEM assumes linearity and may not fully capture complex, non-linear relationships among variables. To overcome this limitation, ANN is applied as a complementary method. ANN provides high predictive accuracy and the ability to model non-linear patterns, thereby validating and strengthening the results derived from SEM. This combination of SEM for hypothesis testing and ANN for predictive validation has been increasingly recommended in recent IS and education technology research (Almarzouqi, Aburayya, & Salloum, 2022; Yakubu et al., 2020).

3.1.1. *Population and Sample*

The population of this study consists of students enrolled across universities in Pakistan. The sampling method adopted was convenience sampling, due to accessibility constraints, supplemented by stratification across different universities to enhance representativeness. For SEM, an adequate sample size is critical, a commonly accepted rule of thumb is at least 10 times the maximum number of structural paths pointing at a construct (Hair et al., 2019). Given that the conceptual model includes seven latent constructs and multiple paths, a minimum of 200 responses is considered acceptable. To ensure robustness and enable ANN analysis, a larger sample size (N > 300) was targeted, allowing data to be split into training and testing subsets for predictive modeling.

3.1.2. *Data Collection*

Data was collected using a structured questionnaire survey, with measurement items adapted from validated scales in prior studies grounded in technology acceptance models like TAM and UTAUT (Davis, 1989; Venkatesh et al., 2012). The questionnaire was distributed through online link created on Google forms to reach a broad range of students across universities in Pakistan. Also, on top of questionnaire link of two YouTube videos: Video 1: (https://bit.ly/4pJ1eQu), Video 2: (https://bit.ly/46koUCT) about VR technologies in education was linked to make better understand for respondents about this technology. The data collection took place over a three-month period. To ensure ethical compliance, respondents were informed about the purpose of the study and assured of the confidentiality and anonymity of their responses. Participation was voluntary, and students had the right to withdraw at any stage without penalty.

3.2. Measures

All constructs in this study were measured using reflective indicators, adapted from previously validated scales in technology acceptance literature. A 5-point Likert scale (ranging from1 = Strongly Disagree to 5 = Strongly Agree) was used to capture responses, as it is widely applied in behavioral intention and technology adoption studies. Performance expectancy (PE) is measured using 4 items adapted from Ahmad Samed Al-Adwan and Al-Debei (2024), reflecting students' beliefs about the degree to which VR classrooms would enhance their learning performance. For effort expectancy (EE), 4 items also adapted from Ahmad Samed Al-Adwan and Al-Debei (2024), assessing the perceived ease of using VR classroom systems. Social influence (SI) is measure through 3 items adapted from Abdulmuhsin et al. (2025), focusing on peer, instructor, and institutional expectations regarding VR use. Also for facilitating conditions (FC), 4 items adapted from Abdulmuhsin et al. (2025), measuring the availability of technical and institutional support for VR classroom adoption. Perceived enjoyment (ENJ), 3 items adapted from Rosli and Saleh (2024), capturing intrinsic enjoyment and fun in using VR classrooms. Perceived usefulness (PU), 4 items also from Rosli and Saleh (2024), reflecting beliefs about the usefulness of VR classrooms in achieving academic outcomes. For attitude (ATT), 4 items adapted from Mehta et al. (2025), reflecting students' overall evaluative feelings toward using VR classrooms. Behavioral intention (BI), measured using 5 items adapted from Rosli and Saleh (2024), focusing students' intention to adopt VR classrooms in the future. All items were slightly rephrased to fit the VR classroom context in Pakistan. Table 2 presents the constructs and measurement items statement.

3.3. Data Analysis

The data analysis was conducted in two stages, combining Structural Equation Modeling (SEM) and Artificial Neural Networks (ANN) to achieve both theory testing and predictive validation (Raut et al., 2018; Sternad Zabukovšek et al., 2019).

3.3.1. Structural Equation Modeling (SEM)

Structural equation modeling (SEM) was applied using Smart-PLS software. SEM was chosen because it enables simultaneous assessment of the measurement model (validity and reliability) and the structural model (hypothesized relationships among constructs). In the measurement model, reliability was assessed using cronbach's alpha and composite reliability (CR), while convergent validity was confirmed through average variance extracted (AVE) (Hair et al., 2019; Hair Jr et al., 2021). Discriminant validity was tested using the heterotrait-monotrait ratio (HTMT). In the structural model, path coefficients, p-value, t-value and explained variance (R^2) were analyzed using bootstrapping with 5,000 resamples, consistent with recommendations by (Hair et al., 2019).

3.3.2. Artificial Neural Network (ANN)

To complement SEM, an artificial neural network (ANN) analysis was conducted using a multilayer perceptron with one hidden layer, implemented in IBM SPSS neural network module. ANN was chosen because it overcomes SEM's assumption of linearity, allowing exploration of complex, non-linear interactions among predictors (Almarzouqi et al., 2022; Sternad Zabukovšek et al., 2019). The dataset was randomly split into training (70%) and testing (30%) subsets. Predictive accuracy was evaluated using root mean squared error (RMSE), ensuring robustness through 10-fold cross-validation. Finally, ANN produced a normalized importance ranking of predictors, showing which independent variables had the greatest influence on dependent variables, like attitude and behavioral intention. This hybrid approach (SEM + ANN) enhances both explanatory power and predictive validity, a practice increasingly adopted in technology acceptance research (Akour et al., 2022; Ali et al., 2025).

4. Results

4.1. Demographics Information of Respondents

The first part of questionnaire was designed to collect demographics information of respondents. A total of 373 valid responses were collected from students across several universities in Pakistan. Table 1 presents the demographic profile of respondents. The sample included 61% male, and 39% female students, with the majority aged between 18–25 years, reflecting the typical undergraduate student population. In terms of academic level, 55% were pursuing Bachelor, 36% Master, and 9% Doctoral degree indicating representation from different stages of higher education.

Table 1. Demographic Characteristics of Respondents

Characteristics	Items	Frequency	Percentage
Gender	Female	146	39
	Male	227	61
Age	Between 18 to 25	153	41
	Between 26 to 30	93	25
	Between 31 to 35	78	21
	36 and above	49	13
Education qualification	Bachelor	205	55
	Master	134	36
	Doctorate	34	9

4.2. Common Method Bias (CMB)

Since data were collected using a self-reported survey, common method bias (CMB) was assessed using two approaches. First, Harman's single-factor test was conducted in IBM SPSS 22 by loading all measurement items into an exploratory factor analysis. The results indicated that the first factor accounted for only 34.418% of the total variance, which is well below the recommended threshold of 50%, suggesting that no single factor dominated the variance in the data (Podsakoff et al., 2003). Second, variance inflation factor (VIF) values were calculated for all constructs using Smart-PLS tool. As presented in Table 5, the VIF values ranged between 1.190 (minimum) and 2.650 (maximum), all of which fall below the conservative threshold of 3.3, thereby confirming the absence of multicollinearity and CMB issues (Kock, 2015). Collectively, these diagnostic checks confirm that common method bias was not a major concern in this study, thereby ensuring the robustness of the structural model results.

4.3. Measurement Model

The measurement model was first assessed to ensure construct reliability and validity before testing the structural relationships. Indicator reliability was examined through outer loadings, where all items exceeded the recommended threshold of 0.70 (Hair et al., 2019; Hair Jr et al., 2021), indicating that the items shared sufficient variance with their respective constructs. One exception was item BI5, which had a loading of 0.632. However, this item was retained because it was above the minimum acceptable cutoff of 0.60 suggested by (Hulland, 1999), and because its removal did not substantially improve the reliability of the construct. This decision aligns with the argument that slightly lower loadings may be acceptable if the overall construct reliability is preserved. In addition, multicollinearity was examined by assessing the variance inflation factor (VIF) values of all indicators. All VIF values were well below the conservative threshold of 3.3 (Kock, 2015), confirming that collinearity was not a concern and ensuring stable estimation of the outer model. The results for indicator loadings and VIF values are reported in Table 2.

Table 2: Items, Source, Outer Loading and VIF Values

Items	Statement	Loadings	VIF
Performance expectancy			
PE1	Using a VR-based virtual classroom would enable me to accomplish my learning tasks more quickly.	0.798	1.732
PE2	Using a VR-based virtual classroom would enhance my learning effectiveness.	0.841	2.006
PE3	A VR-based virtual classroom would improve the quality of my learning.	0.830	1.943
PE4	I find a VR-based virtual classroom useful for my university studies.	0.818	1.792
Effort expectancy			
EE1	Learning to use a VR-based virtual classroom would be easy for me.	0.805	1.674
EE2	It would be easy for me to become skillful at using a VR-based virtual classroom.	0.792	1.854
EE3	I find that using a VR-based virtual classroom would not require much mental effort.	0.762	1.914
EE4	My interaction with a VR-based virtual classroom would be clear and understandable.	0.809	1.661
Social influence			
SI1	People whose opinions I value would encourage me to use a VR-based virtual classroom.	0.876	1.860
SI2	People who influence my learning decisions would support me in using a VR-based virtual classroom.	0.859	1.896

Items	Statement	Loadings	VIF
SI3	My classmates and teachers would prefer that I use a VR-based virtual classroom.	0.822	1.657
Facilitating conditions			
FC1	Guidance would be available to me in using a VR-based virtual classroom.	0.754	1.576
FC2	Specialized instruction or training would be available for using a VR-based virtual classroom.	0.717	1.488
FC3	A specific person (or group) would be available to help me with VR-based virtual classroom difficulties.	0.828	2.167
FC4	I would have the necessary resources (equipment, internet, support) to use a VR-based virtual classroom.	0.849	2.282
Perceived usefulness			
PU1	Using a VR-based virtual classroom would improve my learning performance.	0.828	1.871
PU2	Using a VR-based virtual classroom would increase my productivity in learning.	0.755	1.549
PU3	Using a VR-based virtual classroom would enhance my effectiveness in learning.	0.765	1.642
PU4	I would find a VR-based virtual classroom useful for my learning.	0.838	2.019
Perceived enjoyment			
ENJ1	I think that using a VR-based virtual classroom would be enjoyable for learning.	0.869	1.954
ENJ2	I think a VR-based virtual classroom would be fun to use as a learning resource.	0.884	2.084
ENJ3	I would enjoy using a VR-based virtual classroom for my education.	0.852	1.858
Attitude			
ATT1	I have a positive attitude toward using a VR-based virtual classroom for learning.	0.848	1.996
ATT2	I believe a VR-based virtual classroom will be a valuable approach for future education.	0.828	1.947
ATT3	A VR-based virtual classroom aligns well with modern learning needs.	0.852	2.085
ATT4	I think a VR-based virtual classroom is an innovative and exciting learning tool.	0.785	1.751
Behavioral intention			
BI1	I plan to use a VR-based virtual classroom for my learning in the future.	0.795	1.802
BI2	If I have access, I plan to use a VR-based virtual classroom.	0.730	1.558
BI3	I intend to learn using VR-based virtual classroom in the future.	0.767	1.639
BI4	Assuming I have access to VR-based virtual classroom, I intend to use it.	0.793	1.791
BI5	I will frequently use a VR-based virtual classroom for learning in the future.	0.632	1.220

Construct reliability and convergent validity were evaluated using Cronbach's alpha, composite reliability, and average variance extracted (AVE). As shown in Table 3, Cronbach's alpha values ranged from 0.796 to 0.848, and composite reliability values ranged from 0.862 to 0.902, both exceeding the 0.70 threshold. Similarly, all AVE values were greater than the recommended 0.50 cutoff (Fornell & Larcker, 1981), indicating that each construct captured more than half of the variance of its respective indicators.

Table 3: Constructs Reliability and Validity

Constructs	α	CR (rho_a)	CR (rho_c)	AVE
ATT	0.848	0.853	0.898	0.687
BI	0.798	0.800	0.862	0.556
EE	0.809	0.835	0.871	0.627
ENJ	0.836	0.838	0.902	0.754
FC	0.796	0.806	0.868	0.622
PE	0.840	0.841	0.893	0.676
PU	0.809	0.817	0.874	0.636
SI	0.813	0.821	0.889	0.727

Discriminant validity was assessed using the HTMT criterion. All HTMT ratios were below the conservative threshold of 0.85 as shown in Table 4 (Henseler, Ringle, & Sarstedt, 2015), supporting discriminant validity among the constructs. These results collectively demonstrate that the measurement model achieved adequate reliability, convergent validity, and discriminant validity, providing a solid foundation for structural model assessment.

Table 4: Discriminant Validity (HTMT Ratios)

Constructs	ATT	BI	EE	ENJ	FC	PE	PU	SI
ATT								
BI	0.707							
EE	0.347	0.338						
ENJ	0.779	0.673	0.217					
FC	0.454	0.337	0.255	0.515				
PE	0.811	0.676	0.150	0.834	0.508			
PU	0.780	0.686	0.326	0.734	0.470	0.747		
SI	0.619	0.523	0.410	0.484	0.245	0.474	0.569	

4.4. Structural Model

The structural model was evaluated using PLS-SEM, with results summarized in Table 5 and the overall model presented in Figure 2. The analysis demonstrated substantial explanatory power, with the model explaining 62.3% of the variance in Attitude ($R^2 = 0.623$) and 45.3% of the variance in Behavioral Intention ($R^2 = 0.453$). These values indicate a moderate-to-strong predictive capacity in line with recommended thresholds for behavioral research (Hair et al., 2019). Among the hypothesized relationships, Performance Expectancy (PE) significantly influenced both Attitude ($\beta = 0.321$, $p < 0.001$) and Behavioral Intention ($\beta = 0.176$, $p = 0.025$) which supporting hypothesis, H1a and H1b. Effort Expectancy (EE) also had positive effects on ATT ($\beta = 0.102$, $p = 0.003$) and BI ($\beta = 0.109$, $p = 0.026$) which support hypothesis, H2a and H2b. Social Influence (SI) significantly predicted ATT ($\beta = 0.167$, $p < 0.001$), but not BI ($\beta = 0.082$, $p = 0.119$) which support hypothesis, H3a, but reject hypothesis H3b. Similarly, Facilitating Conditions (FC) were not significant for both ATT ($\beta = 0.017$, $p = 0.645$) and BI ($\beta = –0.045$, $p = 0.292$), leading to rejection of two hypothesis, H4a and H4b. For hedonic and utilitarian factors, Perceived Enjoyment (ENJ) was positively related to ATT ($\beta = 0.211$, $p = 0.001$) and BI ($\beta = 0.169$, $p = 0.012$) supporting both hypothesized relations, H5a and H5b. Likewise, Perceived Usefulness (PU) also support the hypothesized relations, H6a and H6b as significantly influenced both ATT ($\beta = 0.212$, $p = 0.003$) and BI ($\beta = 0.170$, $p = 0.012$). Finally, Attitude itself found to be a significant predictor of BI ($\beta = 0.188$, $p = 0.007$), which further supporting the hypothesis, H7.

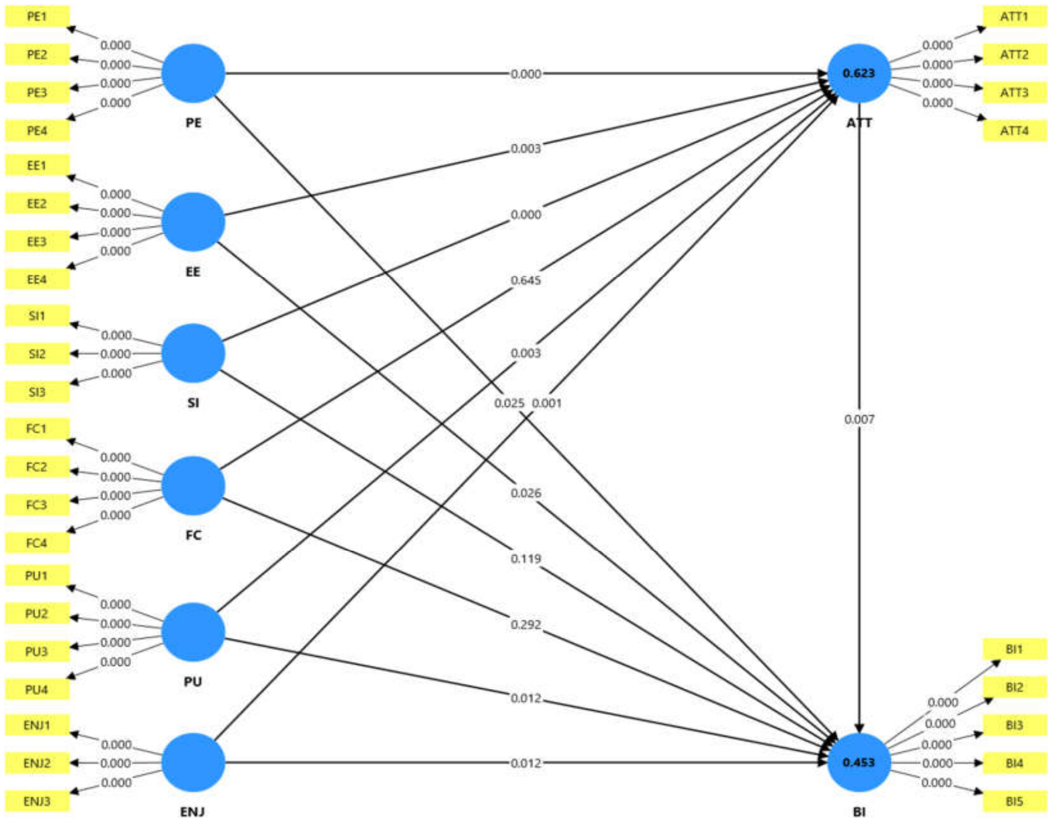

Figure 2: Structural Model

Taken together, these results highlight that PE, PU, and ENJ are the most consistent predictors of both ATT and BI, whereas FC did not play a significant role. This pattern suggests that in the Pakistani higher education context, students' intentions to use VR-based classrooms are shaped more by performance and enjoyment considerations.

Table 5: Hypothesis Testing Results

Hypothesis	Relation	β	STD	T-values	P-values	Decision	VIF
H1a	PE → ATT	0.321	0.066	4.874	0.000	Accepted	2.324
H1b	PE → BI	0.176	0.078	2.243	0.025	Accepted	2.597
H2a	EE → ATT	0.102	0.035	2.937	0.003	Accepted	1.190
H2b	EE → BI	0.109	0.049	2.224	0.026	Accepted	1.218
H3a	SI → ATT	0.167	0.042	3.949	0.000	Accepted	1.422
H3b	SI → BI	0.082	0.053	1.558	0.119	Rejected	1.496
H4a	FC → ATT	0.017	0.037	0.461	0.645	Rejected	1.301
H4b	FC → BI	-0.045	0.043	1.054	0.292	Rejected	1.302
H5a	ENJ → ATT	0.211	0.061	3.438	0.001	Accepted	2.243
H5b	ENJ → BI	0.169	0.068	2.499	0.012	Accepted	2.361
H6a	PU → ATT	0.212	0.071	2.964	0.003	Accepted	1.992
H6b	PU → BI	0.170	0.068	2.501	0.012	Accepted	2.111
H7	ATT → BI	0.188	0.070	2.693	0.007	Accepted	2.650

4.5. PLS Predict

To further assess the predictive relevance of the model, a PLS-predict procedure was performed (Shmueli et al., 2019). The manifest variable (MV) results presented in Table 6 show that the Q^2predict values for all indicators were positive (ranging from 0.177 to 0.481), confirming predictive validity. Moreover, for all items of dependent constructs (e.g., ATT1–ATT4 and BI1–BI5), the PLS-SEM models yielded lower RMSE and MAE values compared to both the linear regression (LM) and item-averaging (IA) benchmarks, indicating superior out-of-sample predictive power.

Table 6: PLS-Predict MV Summary

Items	Q^2predict	PLS-SEM		LM		IA	
		RMSE	MAE	RMSE	MAE	RMSE	MAE
ATT1	0.481	0.659	0.505	0.683	0.514	0.914	0.724
ATT2	0.424	0.734	0.535	0.759	0.555	0.967	0.739
ATT3	0.408	0.683	0.525	0.711	0.537	0.887	0.694
ATT4	0.328	0.748	0.563	0.784	0.593	0.912	0.712
BI1	0.286	0.721	0.575	0.741	0.577	0.853	0.713
BI2	0.177	0.834	0.671	0.862	0.695	0.919	0.752
BI3	0.203	0.830	0.646	0.868	0.681	0.929	0.689
BI4	0.223	0.803	0.634	0.839	0.656	0.911	0.742
BI5	0.223	0.832	0.659	0.859	0.682	0.944	0.712

At the latent variable (LV) level (Table 7), the results demonstrated strong predictive performance for Attitude (Q^2predict = 0.601, RMSE = 0.637, MAE = 0.480) and moderate predictive power for Behavioral Intention (Q^2predict = 0.410, RMSE = 0.773, MAE = 0.604). According to established guidelines (Shmueli et al., 2019), these values suggest that the model provides robust predictive accuracy, especially for Attitude, while maintaining moderate accuracy for Behavioral Intention.

Table 7: PLS-Predict LV Summary

Constructs	Q^2predict	RMSE	MAE
ATT	0.601	0.637	0.480
BI	0.410	0.773	0.604

Overall, the PLS-predict analysis confirms that the model demonstrates robust out-of-sample predictive ability, adding further credibility to the SEM findings. These results align with recent calls in the literature to evaluate both explanatory power (R^2, path coefficients) and predictive validity (PLS-predict) for a more comprehensive model assessment (Hair Jr et al., 2021; Shmueli et al., 2019).

4.6. Artificial Neural Network (ANN) Results

To complement the SEM analysis, an artificial neural network (ANN) was applied using IBM SPSS 22. The data were split into training (70%) and testing (30%). Further for ANN analysis only constructs having significant impact in SEM were considered as recommended (Sternad Zabukovšek et al., 2019). Since facilitating conditions (FC) was not significant in SEM for attitude (ATT) and behavioral intention (BI), and social influence (SI) was not significant for BI, these constructs were excluded from the respective ANN models. The ANN architectures are shown in Figure 3 for ATT and Figure 4 for BI.

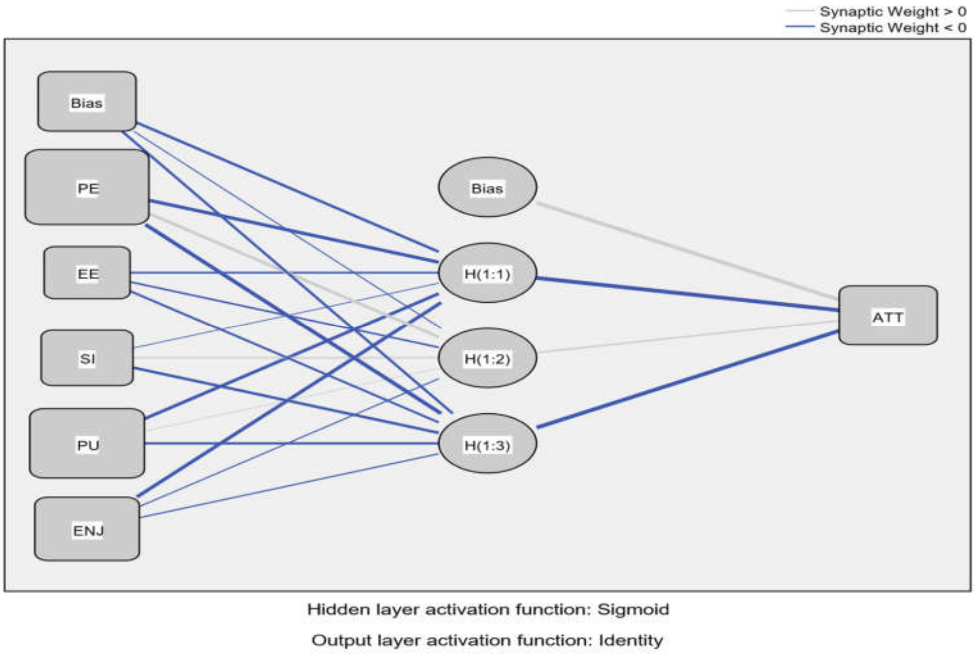

Figure 3: ANN Architecture for ATT

As presented in Table 8, the average RMSE values were 2.25 (training) and 0.43 (testing) for ATT, and 1.90 (training) and 0.53 (testing) for BI. These relatively low testing RMSE values indicate strong predictive accuracy and generalizability (Chong, 2013; Liébana-Cabanillas, Marinković, & Kalinić, 2017). These results highlight the robustness of the hybrid SEM–ANN approach for modeling students' attitudes and behavioral intentions toward VR-based virtual classrooms.

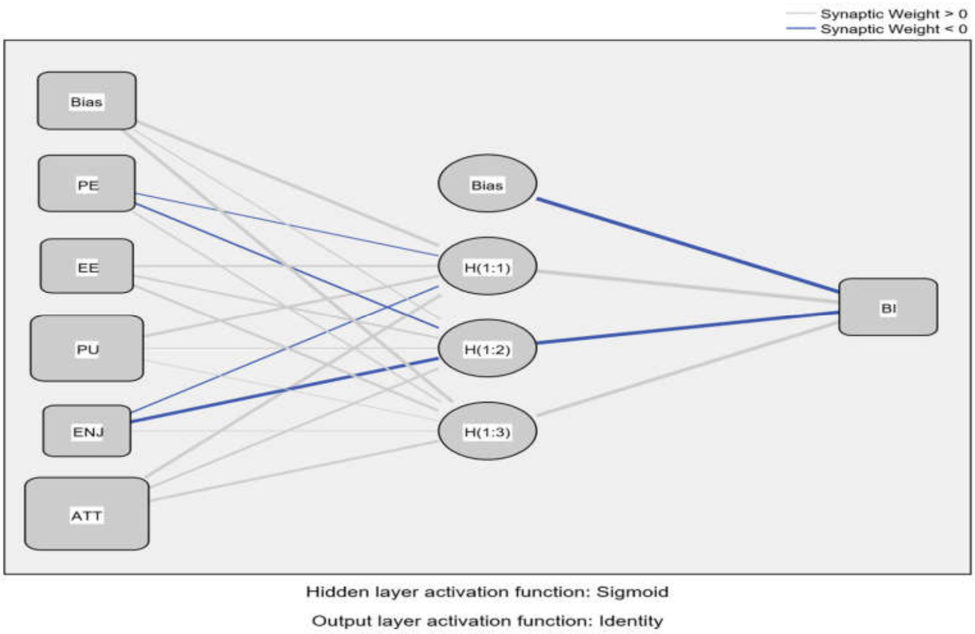

Figure 4: ANN Architecture for BI

Predictor importance analysis (Table 9) revealed that performance expectancy (PE, 100%), perceived usefulness (PU, 86%), and perceived enjoyment (ENJ, 65%) were the strongest determinants of ATT, with SI also showing moderate influence (40%). For BI, Attitude (100%) and PU (83%) dominated, followed by PE (53%), EE (45%), and ENJ (43%). These findings indicate that while cognitive evaluations (PE, PU) primarily drive students' perceptions of VR classrooms, intrinsic motivation (ENJ) and social considerations (SI) also contribute meaningfully. For behavioral intention, the overwhelming influence of ATT underscores the mediating role of students' overall attitude in translating perceptions into intention. This combined perspective from SEM and ANN emphasizes that both direct and indirect factors must be considered to fully understand adoption behavior in VR-based educational settings.

Table 8: RMSE Values for Neural Network

ANN	RMSE for Training		RMSE for Testing		Total Sample
	ATT	BI	ATT	BI	
1	2.1181	1.9417	0.4000	0.5897	373
2	2.1143	1.9280	0.4214	0.5108	373
3	2.0089	1.9600	0.4280	0.5142	373
4	2.2726	1.7990	0.4504	0.5071	373
5	2.2428	1.9855	0.4107	0.6359	373
6	2.4266	1.8866	0.4210	0.4521	373
7	2.3403	1.9313	0.4116	0.4635	373
8	2.2950	1.8175	0.3552	0.6294	373
9	2.3068	1.8835	0.4946	0.5178	373
10	2.4110	1.8801	0.4607	0.5002	373
Mean	2.2536	1.9013	0.4254	0.5321	-
SD	0.1284	0.0568	0.0356	0.0611	-

A sensitivity analysis confirmed the robustness of these findings, as small variations in input values did not significantly affect prediction accuracy. These results show that while SEM identifies linear significance, ANN highlights the relative, non-linear importance of predictors, strengthening the explanatory and predictive power of the study (Raut et al., 2018; Sternad Zabukovšek et al., 2019).

Table 9: Sensitivity Analysis

Constructs	ATT		BI	
	Average Importance	Normalize Importance	Average Importance	Normalize Importance
PE	0.96	100%	0.51	53%
EE	0.26	27%	0.44	45%
SI	0.38	40%	-	-
PU	0.83	86%	0.81	83%
ENJ	0.63	65%	0.42	43%
ATT	-	-	0.98	100%

5. Discussion

5.1. Overview of Findings

The present study set out to investigate the determinants of students' attitude (ATT) and behavioral intention (BI) to adopt VR-based virtual classrooms across universities in Pakistan. Drawing upon technology adoption models like UTAUT, TAM, and hedonic motivation theory, six independent variables performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), perceived enjoyment (ENJ), and perceived usefulness (PU) were examined for their influence on ATT and BI, with ATT further hypothesized to predict BI. Structural equation modeling (SEM) was first employed to test the hypothesized paths, followed by artificial neural network (ANN) analysis to assess non-linear effects and validate predictive robustness. Additional validation was carried out using PLS-predict, which confirmed the out-of-sample predictive power of the proposed model.

The findings of hybrid SEM-ANN analysis reveal that PE, PU, and ENJ emerged as the most influential predictors of both ATT and BI. Specifically, PU and ENJ demonstrated strong effects across both SEM and ANN analyses, underscoring the dual importance of extrinsic motivation (usefulness and performance benefits) and intrinsic motivation (enjoyment) in shaping students' acceptance of VR classrooms. These results are consistent with prior e-learning and technology adoption studies such as metaverse adoption in medical education (Almarzouqi et al., 2022), and Muslim students intention to accept metaverse (Azhar et al., 2024), suggesting that VR-based learning environments must simultaneously deliver functional value and enjoyable experiences to gain student acceptance. Attitude itself exerted a significant positive influence on BI, reinforcing its mediating role in technology adoption models such as TAM (Davis, 1989), and theory of planned behavior TPB (Ajzen, 1991). This finding confirms that students' favorable perceptions toward VR classrooms translate directly into stronger intentions to adopt them in their academic practices.

Interestingly, effort expectancy (EE) showed only a marginal effect on ATT and BI. This limited influence can be explained as users may prioritize other factors such as perceived usefulness of virtual reality over ease of use. Similarly (Nguyen et al., 2024) argue that if students perceive that virtual reality technology enhance their learning and engagement these benefits might outweigh concerns about the effort required to use that technology. This observation also aligns with Kalınkara and Özdemir (2024), who found effort expectancy to be insignificant to predict behavioral intentions to adopt virtual reality in education..

The roles of Social Influence (SI) and Facilitating Conditions (FC) were less straightforward. In the SEM analysis, SI influenced ATT but not BI, these findings align with (Hu, Xing, & Xin, 2024) in which SI found least predictor of virtual reality adoption intention in cultural education. Another study by (Ahmad Samed Al-Adwan & Al-Debei, 2024) found SI not significant for virtual reality adoption decisions in higher education. Also, as the concept of virtual reality is still in its initial stage so the lack of information among peoples about this technology could also be reason for this behavior. Further FC was also found insignificant for both ATT and BI in SEM outcomes. This show that students are not satisfied with relevant environment and infrastructure provided by their universities to support the use of this technology. Similar results are also found in case of cloud computing adoption in Pakistan (Bibi et al., 2025). Another study found that FC are not significant relevant to student behavioral intention to use metaverse for educational purpose (Kalınkara & Özdemir, 2024). However, due to insignificance effect of SI on BI, and FC on both ATT, and BI in SEM we did not include these constructs further for ANN analysis following (Sternad Zabukovšek et al., 2019).

Finally, the integration of SEM and ANN provided a more holistic understanding of adoption dynamics. While SEM validated the theoretical pathways and R^2 values, ANN highlighted predictor rankings and confirmed model robustness with low RMSE values. Sensitivity analysis further verified stability, with PE, PU, and ENJ consistently ranked as top predictors. This methodological triangulation strengthens both the explanatory and predictive validity of the study, aligning with (Raut et al., 2018; Sternad Zabukovšek et al., 2019) for combining linear and non-linear approaches in IS research. Overall, these findings demonstrate that the successful adoption of VR-based classrooms in Pakistani universities depends less on infrastructural readiness and social endorsement, and more on students' perceptions of usefulness, performance benefits, and enjoyment.

5.2. Theoretical Implications

The findings of this study contribute meaningfully to the theoretical discourse on technology adoption in higher education by reaffirming and extending key arguments of TAM and UTAUT. The strong effects of

PE and PU on both attitude and behavioral intention emphasize that students' acceptance of VR classrooms is driven by their expectations of improved learning outcomes and functional value. This validates the robustness of utilitarian constructs across digital learning contexts. At the same time, the significant role of ENJ underscores the importance of hedonic motivation, extending TAM and UTAUT by showing that intrinsic enjoyment is equally crucial for adoption in immersive VR environments. By integrating utilitarian and hedonic perspectives, this study provides a more holistic framework for explaining students' adoption of VR classrooms, consistent with (Van der Heijden, 2004) and recent VR learning research (Alalwan et al., 2019; Teo & Noyes, 2011). The mediating role of attitude further strengthens TAM's propositions, confirming that positive evaluations translate cognitive and affective perceptions into behavioral outcomes.

Equally important are the contextual refinements revealed by the weaker predictors. EE had only a marginal effect, suggesting that in digitally literate populations such students, ease of use becomes less relevant compared to perceived benefits. This highlights the need for adoption models to account for user expertise as a moderating factor, rather than assuming uniform importance across populations. Similarly, the weak or insignificant roles of SI and FC add nuance to UTAUT. While UTAUT emphasizes SI as a strong determinant in collectivist cultures, our results indicate that disciplinary culture and academic independence may diminish its effect, as students prioritize personal evaluations of usefulness and enjoyment. FC insignificance reflects infrastructural gaps in Pakistani universities, pointing to the importance of contextual readiness in shaping adoption.

Finally, the use of a hybrid SEM–ANN approach contributes methodologically by combining theory-driven validation with non-linear predictive insights, showing that while SEM confirmed the theoretical pathways and explained variance, ANN captured hidden complexities and ranked predictor importance more effectively. Together, these contributions enrich technology adoption theory by validating established constructs, extending them with hedonic and contextual insights, and demonstrating the value of integrating linear and non-linear methods.

5.3. Practical Implications

The findings of this study provide several practical insights for educational institutes, policymakers, and technology providers seeking to implement VR-based virtual classrooms in higher education. First, the strong influence of PU and PE highlights that students are more likely to adopt VR classrooms when they clearly see academic value and performance benefits. This suggests that institutions should carefully design VR-based learning environments to enhance tangible learning outcomes such as knowledge retention, practical skills, and problem-solving capabilities. At the same time, the significant role of ENJ shows that learning environments must be engaging and immersive rather than merely functional. Gamification elements, interactive simulations, and immersive scenarios can make VR classrooms enjoyable, thereby increasing both acceptance and long-term usage. Together, these results suggest that successful adoption depends on delivering both functional value and positive user experiences.

Second, the relatively weaker effects of EE, SI, and FC also carry important practical implications. Since university students already possess strong digital skills, ease of use was less critical indicating that institutions can focus more on content quality and infrastructure rather than basic training. However, the insignificance of SI and FC highlights gaps in institutional readiness. Universities should therefore invest in VR infrastructure, technical support, and faculty training to ensure sustainable implementation. Furthermore, awareness campaigns, pilot projects, and peer-led demonstrations could strengthen social acceptance by making students more familiar with VR's potential. Stakeholders should also highlight the practical benefits and educational value of VR technologies through communication and marketing strategies as recommended (Awan & Awais, 2023). At the policy level, government and educational authorities could encourage adoption through funding schemes, strategic partnerships with VR vendors, and integration into curricula. Finally, the methodological insights from combining SEM and ANN also hold practical value, while SEM can guide policymakers in understanding linear cause effect relationships, ANN can help predict which factors are most critical for student adoption in specific contexts. Educational institutes can use this insight to develop balanced strategies investing in both content quality and support systems to maximize adoption.

5.4. Limitations and Future Research Directions

Despite its contributions, this study has several limitations that should be considered when interpreting the findings. First, the cross-sectional survey design limits causal inferences, while SEM establishes statistical relationships and ANN validates predictive power, longitudinal data would provide deeper insights into how students' attitudes and intentions evolve with prolonged exposure to VR classrooms. Second, although the study targeted a broad range of university students across disciplines in Pakistan, variations in digital literacy and prior exposure to VR may influence the generalizability of the results. Students from non-technical fields may perceive constructs such as EE or SI differently, potentially leading to different adoption patterns. Third, reliance on self-reported measures may introduce biases, such as social desirability or common method variance, despite Harman's single-factor test and VIF checks indicating minimal impact. Fourth, the study examined six established predictors PE, EE, SI, FC, ENJ, and PU but other relevant factors such as self-efficacy, perceived cost, accessibility, and technology anxiety were not included. Finally, contextual factors specific to Pakistani higher education, including infrastructural constraints and cultural norms, may limit the applicability of findings to other countries or more technologically advanced educational environments.

Building on these limitations, several avenues for future research are suggested. First, longitudinal studies could track changes in attitudes and behavioral intentions over time, revealing patterns that cross-sectional surveys cannot capture. Second, future research should investigate adoption across a wider variety of disciplines to examine whether predictors such as EE, SI, or FC play different roles in less tech-savvy populations. Third, integrating survey data with behavioral metrics, such as actual usage logs or learning performance outcomes, would provide a more objective understanding of VR classroom adoption. Fourth, the adoption model can be extended by including additional constructs such as perceived cost, accessibility, learning styles, self-efficacy, and technology anxiety, particularly relevant in developing countries. Fifth, cross-cultural studies could explore whether factors like SI and FC behave differently in other contexts, helping to determine whether findings are specific to Pakistani students or reflect broader generational and cultural shifts. Finally, continued use of hybrid analytical approaches such as SEM–ANN or other machine learning methods (e.g., random forests, support vector machines) could uncover non-linear and interaction effects that traditional SEM alone might miss, further enhancing both theoretical and practical understanding of VR technology adoption in higher education.

Further, it is recommended that future researchers should conduct studies based on real-life scenarios or active users of VR technology to assess the actual satisfaction levels of students in the educational domain. This is important because student satisfaction is a key factor for educational institutes to ensure long-term adoption, retention, and effective utilization of emerging learning technologies. In developing countries like Pakistan, VR technologies are not yet actively integrated into educational institutes due to high costs and lack of infrastructure. However, researchers can conduct experimental or pilot studies to simulate classroom environments, which will provide valuable insights into potential benefits, challenges, and strategies for successful implementation in resource-constrained contexts.

In addition, future researchers should consider conducting meta-analyses, as determinants of VR adoption often show mixed effects across studies. For example, factors such as social influence, effort expectancy or facilitating conditions have been found to exert strong, weak, or even insignificant effects in different contexts. A systematic meta-analysis would help consolidate these findings, resolve inconsistencies, and offer a clearer understanding of the boundary conditions under which certain predictors are more or less influential. From a methodological perspective, previous studies have predominantly relied on traditional SEM approaches. While SEM is valuable for theory testing, it is recommended that researchers complement it with advanced analytical techniques such as ANN, or even modern machine learning methods (e.g., random forests, support vector machines). These techniques can capture non-linear patterns, enhance predictive accuracy, and uncover complex interactions that linear models alone may overlook.

Also, it is observed that research on VR gained significant attention after the COVID-19 pandemic, but the majority of existing studies have focused on applications of metaverse adoption across different sectors, including higher education. It is therefore recommended that future researchers explore the broader potential of VR as an independent technology across diverse domains, thereby offering a more holistic understanding of its societal role and implications. Moreover, most existing work emphasizes the positive aspects of VR technology such as its usefulness, enjoyment, and adoption drivers, which is useful because it can guide stakeholders in developing strategies to promote VR adoption. But future research should also address potential drawbacks, including health concerns, social isolation, ethical challenges, and over-reliance. Such a balanced approach would enrich the understanding of VR's role not only in higher education but also in shaping broader societal outcomes.

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References:

Abbad, M. M. (2021). Using the UTAUT model to understand students' usage of e-learning systems in developing countries. *Education and information technologies, 26*(6), 7205-7224. doi:https://doi.org/10.1007/s10639-021-10573-5

Abdulmuhsin, A. A., Owain, H. O., & Alkhwaldi, A. F. (2024). Understanding the academic use of KM-driven Metaverse technology: insights from medical colleges. *Journal of Science and Technology Policy Management*. doi:https://doi.org/10.1108/JSTPM-12-2023-0229

Abdulmuhsin, A. A., Owain, H. O., Dbesan, A. H., Alkhwaldi, A. F., & Tarhini, A. (2025). Knowledge management in metaverse: does knowledge storage matter as a factor affecting adoption and acceptance? *International Journal of Organizational Analysis*. doi:https://doi.org/10.1108/IJOA-02-2024-4287

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes, 50*(2), 179-211. doi:https://doi.org/10.1016/0749-5978(91)90020-T

Akour, I. A., Al-Maroof, R. S., Alfaisal, R., & Salloum, S. A. (2022). A conceptual framework for determining metaverse adoption in higher institutions of gulf area: An empirical study using hybrid SEM-ANN approach. *Computers and Education: Artificial Intelligence, 3*, 100052. doi:https://doi.org/10.1016/j.caeai.2022.100052

Akram, H., Aslam, S., Saleem, A., & Parveen, K. (2021). The challenges of online teaching in COVID-19 pandemic: A case study of public universities in Karachi, Pakistan. *Journal of Information Technology Education: Research, 20*, 263-282. doi:https://doi.org/10.28945/4784

Al-Adwan, A. S., & Al-Debei, M. M. (2024). The determinants of Gen Z's metaverse adoption decisions in higher education: Integrating UTAUT2 with personal innovativeness in IT. *EDUCATION AND INFORMATION TECHNOLOGIES, 29*(6), 7413-7445. doi:https://doi.org/10.1007/s10639-023-12080-1

Al-Adwan, A. S., Al-Madadha, A., & Zvirzdinaite, Z. (2018). Modeling students' readiness to adopt mobile learning in higher education: An empirical study. *International Review of Research in Open and Distributed Learning, 19*(1). doi:https://doi.org/10.19173/irrodl.v19i1.3256

Al-Adwan, A. S., Alsoud, M., Li, N., Majali, T., Smedley, J., & Habibi, A. (2024). Unlocking future learning: Exploring higher education students' intention to adopt meta-education. *HELIYON, 10*(9). doi:https://doi.org/10.1016/j.heliyon.2025.e43226

Al-Samarraie, H., Teng, B. K., Alzahrani, A. I., & Alalwan, N. (2018). E-learning continuance satisfaction in higher education: a unified perspective from instructors and students. *Studies in higher education, 43*(11), 2003-2019.

Alalwan, N., Al-Rahmi, W. M., Alfarraj, O., Alzahrani, A., Yahaya, N., & Al-Rahmi, A. M. (2019). Integrated three theories to develop a model of factors affecting students' academic performance in higher education. *Ieee Access, 7*, 98725-98742.

Ali, R. A., Soliman, M., Weahama, M. R., Assalihee, M., & Mahmud, I. (2025). Investigating continuous intention to use metaverse in higher education institutions: a dual-staged structural equation modeling-artificial neural network approach. *Smart Learning Environments, 12*(1). doi:https://doi.org/10.1186/s40561-024-00357-y

Almarzouqi, A., Aburayya, A., & Salloum, S. A. (2022). Prediction of User's Intention to Use Metaverse System in Medical Education: A Hybrid SEM-ML Learning Approach. *IEEE ACCESS, 10*, 43421-43434. doi:https://doi.org/10.1109/ACCESS.2022.3169285

Aman, S., Aziz, N., & Abbas, M. (2023). Student satisfaction in higher education: A systematic review examining its impact on institutional growth and comparative dimensions. *Journal of AppliedMath, 1*(3).

Awais, M., Fatima, T., & Awan, T. M. (2022). Assessing behavioral intentions of solar energy usage through value-belief-norm theory. *Management of Environmental Quality: An International Journal, 33*(6), 1329-1343. doi:https://doi.org/10.1108/MEQ-09-2021-0227

Awan, T. M., & Awais, M. (2023). Post-Pandemic Business Scenario: Outlining HR Challenges in the Tourism Sector. In *Human Resource Management in a Post-Epidemic Global Environment* (pp. 331-355): Apple Academic Press.

Azhar, M., Ali, R., Naz, A., & Sujood, S. (2024). Faith in metaverse: understanding adoption intentions of metaverse amongst the Muslim students. *Journal of Islamic Marketing*. doi:https://doi.org/10.1108/JIMA-01-2024-0051

Bibi, N., Seher, P., & Aslam, A. (2025). Cloud computing adoption among small and medium enterprises: An SEM-based empirical study in Multan, Pakistan. *Journal of Management Science (JMAS), 8*(3), 584-593. doi:https://doi.org/10.35335/jmas.v8i3.711

Bower, M., DeWitt, D., & Lai, J. W. (2020). Reasons associated with preservice teachers' intention to use immersive virtual reality in education. *British Journal of Educational Technology, 51*(6), 2215-2233. doi:https://doi.org/10.1111/bjet.13009

Burdea, G. C., & Coiffet, P. (2003). *Virtual reality technology*: John Wiley & Sons.

Chong, A. Y.-L. (2013). Predicting m-commerce adoption determinants: A neural network approach. *Expert systems with applications, 40*(2), 523-530. doi:https://doi.org/10.1016/j.eswa.2012.07.068

Conrad, M., Kablitz, D., & Schumann, S. (2024). Learning effectiveness of immersive virtual reality in education and training: A systematic review of findings. *Computers & Education: X Reality, 4*, 100053. doi:https://doi.org/10.1016/j.cexr.2025.100097

Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches*: Sage publications.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340. doi:https://doi.org/10.2307/249008

Dhawan, S. (2020). Online learning: A panacea in the time of COVID-19 crisis. *Journal of educational technology systems, 49*(1), 5-22. doi:https://doi.org/10.1177/0047239520934018

Du, L., & Lv, B. (2024). Factors influencing students' acceptance and use generative artificial intelligence in elementary education: An expansion of the UTAUT model. *Education and information technologies, 29*(18), 24715-24734.

Dunmoye, I. D., Rukangu, A., May, D., & Das, R. P. (2024). An exploratory study of social presence and cognitive engagement association in a collaborative virtual reality learning environment. *Computers & Education: X Reality, 4*, 100054. doi:https://doi.org/10.1016/j.cexr.2024.100054

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research, 18*(1), 39-50. doi:https://doi.org/10.1177/002224378101800104

Guo, Y., & Barnes, S. (2011). Purchase behavior in virtual worlds: An empirical investigation in Second Life. *Information & Management, 48*(7), 303-312. doi:https://doi.org/10.1016/j.im.2011.07.004

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European business review, 31*(1), 2-24. doi:https://doi.org/10.1108/EBR-11-2018-0203

Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*: Springer Nature.

HEC. (2025). HEC focuses on digitising higher education in Pakistan. *DAWN*. Retrieved from https://www.dawn.com/news/1925618/hec-focuses-on-digitising-higher-education-in-pakistan?utm_source

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science, 43*(1), 115-135. doi:https://doi.org/10.1108/EBR-11-2018-0203

Hodge, E. M., Tabrizi, M., Farwell, M. A., & Wuensch, K. L. (2008). Virtual reality classrooms: Strategies for creating a social presence. *International Journal of Social Sciences, 2*(2), 105-109.

Hu, S., Xing, G., & Xin, J. (2024). Impacting elements of metaverse platforms' intentional use in cultural education: Empirical data drawn from UTAUT, TTF, and flow theory. *Applied Sciences, 14*(21), 9984. doi:https://doi.org/10.3390/app14219984

Hulland, J. (1999). Use of partial least squares (PLS) in strategic management research: A review of four recent studies. *Strategic management journal, 20*(2), 195-204. doi:https://doi.org/10.1002/(SICI)1097-0266(199902)20:2%3C195::AID-SMJ13%3E3.0.CO;2-7

İbili, E., Ölmez, M., Cihan, A., Bilal, F., İbili, A. B., Okumus, N., & Billinghurst, M. (2024). Investigation of learners' behavioral intentions to use metaverse learning environment in higher education: a virtual computer laboratory. *INTERACTIVE LEARNING ENVIRONMENTS, 32*(10), 5893-5918. doi:https://doi.org/10.1080/10494820.2023.2240860

Jensen, L., & Konradsen, F. (2018). A review of the use of virtual reality head-mounted displays in education and training. *Education and information technologies, 23*(4), 1515-1529. doi:https://doi.org/10.1007/s10639-017-9676-0

Jo, H., & Park, D.-H. (2023). Affordance, usefulness, enjoyment, and aesthetics in sustaining virtual reality engagement. *Scientific Reports, 13*(1), 15097. doi:https://doi.org/10.1038/s41598-023-42113-1

Kalınkara, Y., & Özdemir, O. (2024). Anatomy in the metaverse: Exploring student technology acceptance through the UTAUT2 model. *Anatomical Sciences Education, 17*(2), 319-336. doi:https://doi.org/10.1002/ase.2353

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration (ijec), 11*(4), 1-10. doi:https://doi.org/10.4018/ijec.2015100101

Koteczki, R., & Balassa, B. E. (2025). Exploring Generation Z's Acceptance of Artificial Intelligence in Higher Education: A TAM and UTAUT-Based PLS-SEM and Cluster Analysis. *Education Sciences, 15*(8), 1044. doi:https://doi.org/10.3390/educsci15081044

Liébana-Cabanillas, F., Marinković, V., & Kalinić, Z. (2017). A SEM-neural network approach for predicting antecedents of m-commerce acceptance. *INTERNATIONAL JOURNAL OF INFORMATION MANAGEMENT, 37*(2), 14-24. doi:https://doi.org/10.1016/j.ijinfomgt.2016.10.008

Liu, C., Meng, S., Zheng, W., & Zhou, Z. (2025). Research on the impact of immersive virtual reality classroom on student experience and concentration. *VIRTUAL REALITY, 29*(2), 82. doi:https://doi.org/10.1007/s10055-025-01153-w

Mailizar, M., Burg, D., & Maulina, S. (2021). Examining university students' behavioural intention to use e-learning during the COVID-19 pandemic: An extended TAM model. *Education and information technologies, 26*(6), 7057-7077. doi:https://doi.org/10.1007/s10639-021-10557-5

Mehta, K., Nayak, K. M., Qureshi, R. A., Abhishek, N., & Parveen, S. (2025). Technology acceptance and SAMR in metaverse education: professors' willingness to engage in immersive classes in higher education. *Journal of Applied Research in Higher Education*. doi:https://doi.org/10.1108/JARHE-08-2024-0430

Naseer, M. A., Saeed, S., Afzal, A., Ali, S., & Malik, M. G. R. (2025). Navigating the integration of artificial intelligence in the medical education curriculum: a mixed-methods study exploring the perspectives of medical students and faculty in Pakistan. *BMC MEDICAL EDUCATION, 25*(1), 273. doi:https://doi.org/10.1186/s12909-024-06552-2

Naveeda, & Wajahat, S. (2024). E-learning experiences of students in Pakistan during COVID-19: Barriers and perceptions. *E-Learning and Digital Media, 21*(1), 1-23.

Nguyen, A. H. D., Le, T. T., Dang, T. Q., & Nguyen, L. T. (2024). Understanding metaverse adoption in education: The extended UTAUMT model. *HELIYON, 10*(19). doi:https://doi.org/10.1016/j.heliyon.2024.e38741

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of applied psychology, 88*(5), 879. doi:https://psycnet.apa.org/doi/10.1037/0021-9010.88.5.879

Pokhrel, S., & Chhetri, R. (2021). A literature review on impact of COVID-19 pandemic on teaching and learning. *Higher education for the future, 8*(1), 133-141. doi:https://doi.org/10.1177/2347631120983481

Radianti, J., Majchrzak, T. A., Fromm, J., & Wohlgenannt, I. (2020). A systematic review of immersive virtual reality applications for higher education: Design elements, lessons learned, and research agenda. *Computers & education, 147*, 103778. doi:https://doi.org/10.1016/j.compedu.2019.103778

Rashid, S. (2025). Habit Predicting Higher Education EFL Students' Intention and Use of AI: A Nexus of UTAUT-2 Model and Metacognition Theory. *Education Sciences, 15*(6), 756. doi:https://doi.org/10.3390/educsci15060756

Raut, R. D., Priyadarshinee, P., Gardas, B. B., & Jha, M. K. (2018). Analyzing the factors influencing cloud computing adoption using three stage hybrid SEM-ANN-ISM (SEANIS) approach. *TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE, 134*, 98-123. doi:https://doi.org/10.1016/j.techfore.2018.05.020

Riaz, N., & Awais, M. (2024). Assessing Pro-Environmental Behaviour toward Solar Energy using Norm Activation Model and Social Influence. *Educational Research (IJMCER), 6*(6), 253-262.

Rosli, M. S., & Saleh, N. S. (2024). Predicting the acceptance of metaverse for educational purposes in universities: A structural equation model and mediation analysis of the extended technology acceptance model. *SN Computer Science, 5*(6), 688. doi:https://doi.org/10.1007/s42979-024-03015-9

Seher, P., Tofique, S., & Afzal, S. (2025). Determinants of Solar Energy Adoption Intention: A Meta-Analysis. *International Journal of Research Publication and Reviews, 6*(9), 2503-2512.

Shair, W., Waheed, A., Kamran, M. M., & Kubra, N. (2022). Digital divide in Pakistan: barriers to ICT usage among the individuals of Pakistan. *Journal of Economic Impact, 4*(3), 196-204. doi:https://doi.org/10.52223/jei4032206

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. *European journal of marketing, 53*(11), 2322-2347. doi:https://doi.org/10.1108/EJM-02-2019-0189

Sternad Zabukovšek, S., Kalinic, Z., Bobek, S., & Tominc, P. (2019). SEM–ANN based research of factors' impact on extended use of ERP systems. *Central European Journal of Operations Research, 27*(3), 703-735. doi:https://doi.org/10.1007/s10100-018-0592-1

Šumak, B., Heričko, M., & Pušnik, M. (2011). A meta-analysis of e-learning technology acceptance: The role of user types and e-learning technology types. *Computers in human behavior, 27*(6), 2067-2077. doi:https://doi.org/10.1016/j.chb.2011.08.005

Sun, Y., Liu, L., Peng, X., Dong, Y., & Barnes, S. J. (2014). Understanding Chinese users' continuance intention toward online social networks: An integrative theoretical model. *Electronic Markets, 24*(1), 57-66. doi:https://doi.org/10.1007/s12525-013-0131-9

Tabassum, F., Akram, N., & Moazzam, M. (2022). Online learning system in higher education institutions in Pakistan: Investigating problems faced by students during the COVID-19 pandemic. *International Journal of Web-Based Learning and Teaching Technologies (IJWLTT), 17*(2), 1-15. doi:https://doi.org/10.4018/IJWLTT.20220301.oa1

Teo, T., & Noyes, J. (2011). An assessment of the influence of perceived enjoyment and attitude on the intention to use technology among pre-service teachers: A structural equation modeling approach. *Computers & education, 57*(2), 1645-1653. doi:https://doi.org/10.1016/j.compedu.2011.03.002

Van der Heijden, H. (2004). User acceptance of hedonic information systems. *MIS quarterly*, 695-704. doi:https://doi.org/10.2307/25148660

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425-478. doi:https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS quarterly*, 157-178. doi:https://doi.org/10.2307/41410412

Villena-Taranilla, R., Tirado-Olivares, S., Cózar-Gutiérrez, R., & González-Calero, J. A. (2022). Effects of virtual reality on learning outcomes in K-6 education: A meta-analysis. *Educational Research Review, 35*, 100434. doi:https://doi.org/10.1016/j.edurev.2022.100434

Wiangkham, A., & Vongvit, R. (2024). Exploring the Drivers for the Adoption of Metaverse Technology in Engineering Education using PLS-SEM and ANFIS. *EDUCATION AND INFORMATION TECHNOLOGIES, 29*(6), 7385-7412. doi:https://doi.org/10.1007/s10639-023-12127-3

Wohlgenannt, I., Simons, A., & Stieglitz, S. (2020). Virtual reality. *Business & Information Systems Engineering, 62*(5), 455-461. doi:https://doi.org/10.1007/s12599-020-00658-9

Yakubu, M. N., Dasuki, S. I., Abubakar, A. M., & Kah, M. M. (2020). Determinants of learning management systems adoption in Nigeria: A hybrid SEM and artificial neural network approach. *EDUCATION AND INFORMATION TECHNOLOGIES, 25*(5), 3515-3539. doi:https://doi.org/10.1007/s10639-020-10110-w

Yang, F., Ren, L., & Gu, C. (2022). A study of college students' intention to use metaverse technology for basketball learning based on UTAUT2. *HELIYON, 8*(9). doi:https://doi.org/10.1016/j.heliyon.2022.e10562

Zeewaqar, M. (2024). Barriers to Digital Learning: Challenges in Online Education in Pakistan. doi:https://www.preprints.org/manuscript/202409.1489/v1