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THE TECHNOLOGY ACCEPTANCE LEVEL OF VIRTUAL REALITY: HOW DO STUDENTS ADAPT TO VIRTUAL LEARNING?

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Abstract

This study investigates the acceptance of Virtual Reality (VR) technology in psychology education at Ciputra University. VR was introduced for phobia therapy learning, necessitating measurement of its acceptance among pioneering students. Understanding VR acceptance informs academic and operational strategies. Using the Technology Acceptance Model 3 (TAM3), factors like perceived usefulness, ease of use, subjective norm, enjoyment, attitude, and behavioral intention are explored. A survey involving 60 bachelor's students in psychology at Ciputra University will be analyzed using the Structural Equation Model Partial Least Squares (SEM-PLS) to identify significant factors affecting VR acceptance. Insights into barriers and motivators for VR adoption aim to enhance learning experiences and promote innovative teaching methods. The study reveals that subjective norms enhance perceived usefulness, while perceived enjoyment influences ease of use perception. Ease of use impacts perceived usefulness and learning effectiveness. Although ease of use doesn't directly affect attitude toward use, attitude positively influences behavioral intention. Social influence, user experience, and attitude are pivotal in shaping intentions to use VR for learning, suggesting a broader research scope for understanding successful VR-based learning across disciplines.

Keywords: Technology Acceptance Model, Virtual Reality, Structural Equation Model.

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A. INTRODUCTION

The application of the Technology Acceptance Model (TAM) within public administration remains highly pertinent for evaluating the adoption of IT-based innovations in public service delivery (Warsono et al., 2022). This relevance extends to the field of education, which has been revolutionized by rapid technological evolution. Among these advancements, Virtual Reality (VR) has emerged as a transformative pedagogical tool. Conceptually, VR is characterized as an immersive, computer-simulated environment that facilitates real-time interaction (Morimoto et al., 2022). While some scholars define it as a computer-generated environmental simulation (Bec et al., 2020), others emphasize its nature as an interactive 3D system integrating multi-sensory feedback, including auditory, visual, and haptic inputs (Tuena et al., 2020). Despite varying terminological nuances, a consensus exists that the core architecture of VR consists of computer-generated digital environments, high levels of user immersion, and complex Human-Computer Interaction (HCI) (Avilés-Castillo et al., 2025). Its immersive and interactive nature has the potential to revolutionize traditional pedagogical approaches, offering students unparalleled opportunities for engagement and understanding. In the realm of academia, Ciputra University's Faculty of Psychology has embraced this technological advancement by introducing VR into its curriculum, particularly in the field of mental health education. With the assistance of VR technology, users can experience exposure therapy more effectively, making it highly suitable for use in mental health courses. In the academic year 2023/2024, the faculty embarked on a groundbreaking journey by integrating VR technology into courses related to mental health, therapy, counseling for anxiety, and treatment for individual phobias.

As an emerging and versatile technological paradigm, Virtual Reality (VR) has garnered significant attention within the scientific community, particularly concerning the optimization of user experience (UX) (Avilés-Castillo et al., 2025). While the potential for pedagogical integration is substantial, the ultimate efficacy of such innovation is contingent upon user acceptance and actual system utilization. Consequently, identifying the determinants of VR adoption among psychology students at Ciputra University has become an empirical imperative. This study addresses this focal issue by providing a comprehensive exploration of technology acceptance within the specialized context of psychology education. Utilizing the Technology Acceptance Model 3 (TAM3) as its primary theoretical framework, the research aims to elucidate the complexities of user adoption through a systematic analysis of attitudes and behavioral intentions. By building upon the foundational literature and prior research findings, this study leverages the TAM3 architecture to examine multifaceted variables, including perceived usefulness (PU), perceived ease of use (PEOU), subjective norms (SN), and perceived enjoyment (ENJY). Through this rigorous approach, the research seeks to determine how these constructs collectively shape the attitude toward use (ATU) and the subsequent behavioral intention (BI) to adopt VR technology as a transformative learning medium.

The methodology employed in this study revolves around a survey-based approach, involving psychology students at Ciputra University. Through carefully crafted questionnaires, data will be collected to gauge students' perceptions and attitudes regarding VR technology. The survey for this research was conducted on the entire population and not through sampling methods. The collected data will undergo rigorous analysis using the Structural Equation Model Partial

Least Square (SEM-PLS) approach, a robust statistical technique suited for exploring complex relationships among variables. SEM-PLS has also been used in all previous studies referenced in this research. The significance of this research extends beyond academia. Its findings hold implications for educational institutions, faculty members, and curriculum developers, offering helpful perspectives on strategies for integrating VR into psychology education effectively. By identifying key factors influencing VR acceptance, this study aims to pave the way for the development of tailored interventions and pedagogical approaches that maximize the benefits of VR technology in enhancing learning outcomes. Furthermore, the research seeks to contribute to the broader discourse on technology adoption in academic settings. It enhances our comprehension of how educational contexts embrace and utilize emerging technologies by illuminating the complexities of VR acceptance. This knowledge, in turn, can inform future initiatives aimed at fostering innovation and enhancing teaching practices in higher education.

The primary objectives of this research are structured to provide a comprehensive understanding of technology adoption within a specialized academic environment. First, the study seeks to identify the critical determinants influencing the acceptance levels of Virtual Reality (VR) technology at the Faculty of Psychology, Ciputra University, thereby elucidating the underlying drivers of student adoption or resistance. Second, the research performs a structural path analysis to evaluate the interrelationships between these latent variables, offering an empirical mapping of how specific factors modulate student attitudes and behavioral intentions. Ultimately, the study translates these empirical findings into actionable strategic recommendations for faculty management, aimed at optimizing the pedagogical integration of VR technology to ensure a high-utility learning experience for both students and educators.

The synthesis of the research findings reveals a complex interplay between Subjective Norms (SN), Perceived Enjoyment (ENJY), Perceived Ease of Use (PEOU), Perceived Usefulness (PU), and Attitude Toward Use (ATU) in shaping Behavioral Intention (BI). Specifically, the positive impact of SN on PU suggests that social influence significantly bolsters the perceived functional value of VR. Similarly, the relationship between ENJY and PEOU indicates that the hedonic quality of the user experience directly reduces the perceived cognitive effort required to operate the system. While PEOU was found to enhance PU—thereby increasing perceived learning efficiency—it notably failed to serve as a significant predictor of ATU, suggesting that user-friendliness alone does not inherently foster a positive disposition without an accompanying perception of substantive value. Nevertheless, ATU remains a critical antecedent to BI, where a motivated psychological stance directly translates into a sustained commitment to VR utilization and peer recommendation. These results underscore the necessity of a holistic approach to technology adoption, suggesting that future inquiries should expand the sampling frame to cross-disciplinary cohorts and incorporate broader environmental variables to further refine the success factors of immersive learning.

B. LITERATURE REVIEW

Virtual Reality (VR) is conceptualized as a specialized domain of computing dedicated to the synthesis of digital environments that facilitate profound immersion and real-time user interaction. By leveraging sophisticated hardware to simulate sensory stimuli and provide haptic feedback, VR seeks to achieve a high degree of experiential authenticity (Gonçalves & Boas, 2012). Historically, the impetus for predicting technological adoption emerged in the 1970s, as organizations frequently encountered systemic failures in user integration. Early inquiries into this phenomenon lacked robust metrics for explaining the dichotomy of system acceptance and rejection. Addressing this gap, Fred Davis introduced the Technology Acceptance Model (TAM), positing that system utilization is a behavioral outcome driven by user motivation, which is intrinsically linked to external stimuli, namely the technical attributes and functional capabilities of the system (Chuttur, 2009). Grounded in Fishbein and Ajzen's (1975) Theory of Reasoned Action (TRA), Davis's refined conceptual model identified Perceived Ease of Use (PEOU), Perceived Usefulness (PU), and Attitude Toward Use (ATU) as the primary psychological determinants of technology adoption.

The theoretical architecture of TAM suggests that user attitude is a critical mediator influenced by two core beliefs: PU and PEOU, with the latter exerting a direct influence on the former. Recent literature emphasizes that online acceptance remains a vital component in bolstering the Behavioral Intention (BI) toward advanced technological artifacts (Abuhassna et al., 2023). Subsequent iterations of the model integrated BI as a distinct variable directly susceptible to a system's perceived utility (Davis et al., 1989; Granić & Marangunić, 2019). Recognizing that the original TAM had limited explanatory power regarding the specific antecedents of PU, Venkatesh and Davis (2000) introduced TAM2, which incorporates social influence and cognitive instrumental processes (Venkatesh & Bala, 2008). Within TAM2, social influence is operationalized through Subjective Norms and Image, grounded in the social influence theories of Kelman (1958) and the power dynamics of French and Raven (1959). These processes are governed by three mechanisms: compliance, involving behavior driven by reward or punishment; identification, where usage enhances social status within a reference group; and internalization, the cognitive integration of a referent's beliefs into the user's own belief structure.

The development of TAM3 represents a sophisticated theoretical synthesis, integrating TAM2 with the specific determinants of Perceived Ease of Use (PEOU) to form a comprehensive model of technology acceptance. This integrated framework offers a holistic set of factors that govern how individuals adopt and utilize technological innovations. As articulated by Venkatesh and Bala (2008), TAM3 introduces three distinct theoretical extensions that transcend the previous boundaries of TAM2 and earlier PEOU models. However, despite these advancements, establishing a universal research instrument for digital resources remains a methodological challenge, particularly when attempting to ascertain learner preferences within blended learning environments (Lazar et al., 2020).

In the context of this study, the identification of research needs—as illustrated in Figure 1—is a fundamental step in analyzing the acceptance of Virtual Reality (VR) technology within the Faculty of Psychology. The primary objective is to evaluate the degree of technological acceptance and the multifaceted perceptions of students regarding VR-mediated instruction. This process necessitates a granular analysis of the perceived enhancement of the pedagogical experience, the level of user comfort during technological interaction, and the underlying sociocognitive factors that influence the student's intention to adopt VR within the learning process.

- Within the TAM3 architecture, Subjective Norm (SN) is defined as the degree to which an individual perceives that significant social referents expect them to perform a specific behavior—in this instance, the adoption of Virtual Reality (VR) technology. In a pedagogical context, these referents typically include academic instructors and peer groups whose expectations shape the student's normative beliefs. Subjective Norm is operationalized by evaluating the respondent's internal perception of social approval or pressure; for example, assessing whether a student believes their lecturers or peers would view the utilization of VR as a beneficial or prestigious academic pursuit. Because SN serves as a critical driver of acceptance for nascent or disruptive technologies, it remains a fundamental variable for institutions to consider when navigating the strategic implementation of innovative digital tools.

- Parallel to social influence, Perceived Enjoyment (ENJY) represents a significant hedonic determinant, defined as the extent to which the activity of using VR technology is perceived as inherently enjoyable, separate from any performance consequences. This intrinsic motivation is a powerful predictor of technology adoption; students who experience high levels of pleasure and satisfaction during their interaction with the VR interface are significantly more likely to exhibit sustained usage and long-term commitment. Conversely, a lack of hedonic value often results in diminished motivation and a higher probability of discontinuing the technology. To measure this construct, the research instrument employs targeted items focusing on the frequency of user satisfaction and the qualitative pleasure derived from the immersive experience. Given that enjoyment directly mitigates the perceived complexity of unfamiliar systems, it is an essential factor for educational stakeholders to optimize when integrating VR into a specialized curriculum.

- Perceived Usefulness (PU) is established as a fundamental determinant of technology acceptance, defined as the degree to which a student believes that utilizing Virtual Reality (VR) will augment their academic performance within the Mental Health course. In this context, PU represents a utilitarian evaluation of the technology's functional value in achieving specific learning outcomes. It is operationalized by gauging respondents' perceptions of the technology's efficacy, specifically regarding its ability to enhance learning efficiency and provide substantive assistance in mastering complex course material. Because PU directly influences a user's motivation to adopt a system, it remains a critical metric for educational institutions when justifying the integration of nascent digital tools into the curriculum.

- Perceived Ease of Use (PEOU) serves as a secondary but essential belief, defined as the extent to which a student anticipates that the interaction with VR technology will be devoid of significant physical or mental effort. Within the TAM framework, PEOU emphasizes the perceived accessibility and learnability of the system. This construct is measured by assessing the user's confidence in their ability to master the interface quickly and navigate its features with minimal cognitive load. Theoretically, PEOU acts as a prerequisite for adoption; if a technology is perceived as intuitive, the barrier to entry is lowered, thereby facilitating a more seamless transition into the learning process.

- Attitude Toward Use (ATU) represents the affective and evaluative dimension of technology acceptance, reflecting the student's overall positive or negative predisposition toward interacting with the VR platform. This construct captures the internal psychological response—ranging from satisfaction to apprehension—elicited by the technology. Measuring ATU involves an assessment of the user's happiness, satisfaction, and general sentiment during usage. As an emotional mediator, ATU is a pivotal factor in determining whether a user will embrace or resist a new system, making it an indispensable consideration for designers of immersive educational experiences.

- Finally, Behavioral Intention (BI) is conceptualized as the cognitive component of the model, defined as the student's conscious plan or desire to utilize VR technology for future learning activities. It serves as the most immediate predictor of actual system usage. BI is measured by evaluating the likelihood of a student's future engagement with the technology, including the frequency and duration of their planned usage. For unfamiliar or emerging technologies, a strong behavioral intention is the ultimate indicator of successful pedagogical integration, as it signifies the student's readiness to incorporate the digital medium into their long-term academic routine.

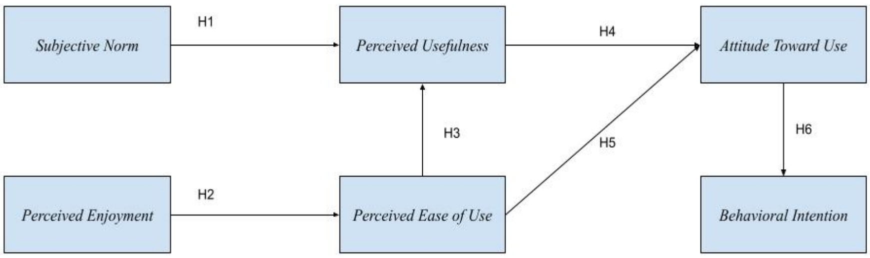

Figure 1 Analysis Model

This study adopts the TAM 3 model as shown in Table 1, which is an extension of the TAM and TAM 2 models. This model expands the understanding of variables influencing perceived usefulness, perceived ease of use, perceived enjoyment, and subjective norm by considering more detailed factors. The development of this research model is based on the adoption of previous research findings that measured the acceptance of VR technology using the same methodology, namely TAM (Technology Acceptance Model). However, not all variables from the previous research model are utilized in this study. Instead, a specific selection process has been conducted to choose certain variables as the main focus of this research.

Table 1 The Relationship Between TAM Variable

Hypothesis	Relationship Between Variable	References
H1	The Impact of Subjective Norm on Perceived Usefulness	(Vandendungan, 2023)

H2	The Impact Perceive Enjoyment on Perceived Ease of Use	(Vandendungan, 2023)
H3	The Impact Perceived Ease of Use on Perceived Usefulness	(Sagnier et al., 2020)
H4	The Impact Perceived Usefulness on Attitude Toward Use	(Jang et al., 2021)
H5	The Impact Perceived Ease of Use on Attitude Toward Use	(Jang et al., 2021)
H6	The Impact Intention to Use on Behavioural Intention	(Jang et al., 2021)

C. RESEARCH METHODS

To operationalize the research variables, a structured survey instrument was developed, as detailed in Table 2. This questionnaire was systematically aligned with the Technology Acceptance Model (TAM) framework to empirically evaluate the acceptance levels of virtual reality (VR) technology among the student population. The development process focused on formulating high-precision, measurable items and selecting robust analytical frameworks to identify significant patterns within the primary data. The study population comprised 65 students from the Psychology Department at Ciputra University Surabaya, specifically from the 2021/2022 academic cohort. This purposive sample consisted of fourth-semester students who had utilized VR technology as a pedagogical tool within their mental health coursework. Data collection was conducted digitally via Google Forms, distributed through the mental health class communication network. The final instrument consisted of 23 items: three demographic identifiers and 20 targeted questions designed to assess student perceptions regarding the integration of VR in mental health education.

Table 2 TAM Variable

Variable	Code	Assessment	Reference
Perceived Usefulness	PU1	Using VR technology will enhance my learning speed	(Khosasih, 2022)
	PU2	Using VR technology enhances the effectiveness of my learning	
	PU3	I find VR technology very beneficial	
Perceived Easy of Use	PEOU1	Learning to use Virtual Reality will be easier for me.	(Khosasih, 2022)
	PEOU2	I find it easier to engage in Mental Health learning with VR technology.	
	PEOU3	I find it easier to visualize cases of phobia sufferers with VR technology.	
	PEOU4	I am able to set up and use the Oculus Quest VR device.	
Perceived Enjoyment	ENJY1	I find that using VR technology provides a more enjoyable experience.	(Khosasih, 2022)
	ENJY2	The features of VR technology make it comfortable to study the Mental Health course.	
	ENJY3	I am delighted to use the features of VR technology in Mental Health learning.	
	ENJY4	The performance of VR technology makes me comfortable (quick response/no errors).	
Subjective Norm	SN1	If many other people use VR technology, I will also use it.	(Khosasih, 2022)
	SN2	I will use VR technology if many other people say that VR technology is very helpful.	
	SN3	I will use VR technology if many other people force me to use VR.	

Behavioural Intention	BI1	Before using it, I had a desire to use VR technology as my learning medium.	(Irhas, 2023)
	BI2	I plan to use this VR technology in the upcoming months for my learning.	
	BI3	I will recommend VR technology to others for learning purposes.	
Attitudes Toward Use	ATU1	Every time I use VR technology, I feel happier because I can engage well in Mental Health learning.	(Irhas, 2023)
	ATU2	I am always interested in exploring VR technology features that support Mental Health learning.	
	ATU3	I feel that my Mental Health learning is more effective when using VR technology.	

For the analytical phase of this research, Structural Equation Modeling (SEM) was employed to process the primary data. Historically, Bentler (1980) identified SEM as a transformative approach with the potential to significantly advance psychological science—a prediction validated by extensive theoretical and practical developments over the subsequent decades. This evolution led to what Muthen (2001) categorized as the "second generation" of structural equation modeling, offering a robust framework for examining complex interrelationships among multiple variables (Donaldson, 1999). Specifically, this study implemented Partial Least Squares (PLS-SEM) utilizing Smart-PLS 4.0 software. The selection of the PLS method was predicated on its efficacy in elucidating the paths between latent variables and providing empirical confirmation for the proposed theoretical framework. Unlike covariance-based methods, PLS-SEM utilizes a linear combination of indicators to estimate latent constructs, operating under the assumption that all measured variance is explained as shared variance. This variance-based approach is particularly well-suited for predictive modeling and theory development within the behavioral sciences.

D. RESULT

Empirical evaluation of the measurement model was performed by examining the factor loadings derived from the SEM-PLS analysis, as illustrated in Figure 2. According to the criteria established by Hair et al. (2010), a factor loading should ideally exceed the 0.7 threshold to ensure the indicator effectively represents its underlying construct.

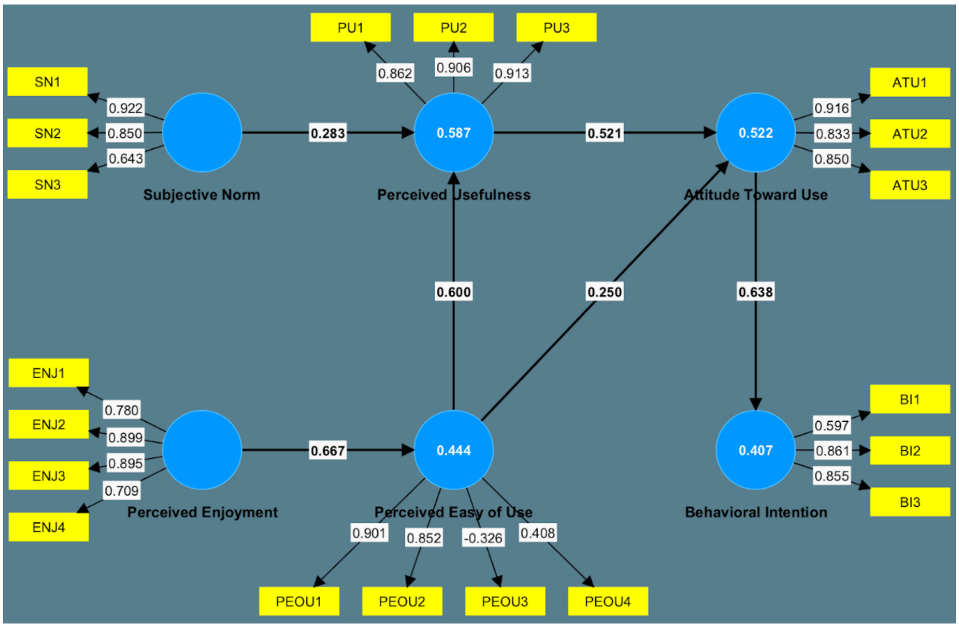

Figure 2 Smart-PLS Calculation

However, as indicated in Table 3, several latent variables exhibited loadings below this benchmark. Consequently, the Average Variance Extracted (AVE) was further scrutinized to assess convergent validity. This secondary analysis serves as a diagnostic tool to determine whether specific indicators should be eliminated to optimize the structural integrity of the model, with the corresponding AVE results detailed in Table 3.

Table 3 Loading Factors and AVE

Code	Loading Factors	AVE
SN1	0.922	0.662
SN2	0.850	
SN3	0.643	
ENJY1	0.780	0.680
ENJY2	0.899	
ENJY3	0.895	
ENJY4	0.709	
PU1	0.862	0.799
PU2	0.906	
PU3	0.913	
PEOU1	0.901	0.453
PEOU2	0.852	
PEOU3	-0.326	
PEOU4	0.408	
ATU1	0.916	0.752
ATU2	0.833	
ATU3	0.850	
BI1	0.597	0.610
BI2	0.861	
BI3	0.855	

According to the criteria established by Hair et al. (2010), a minimum Average Variance Extracted (AVE) threshold of 0.5 is required to establish sufficient convergent validity. As illustrated in Table 3, the initial assessment revealed that the Perceived Ease of Use (PEOU) construct failed to meet this benchmark, yielding an AVE value of 0.453. Consequently, to enhance the measurement model's precision and ensure the construct met the 0.5 requirement, an iterative refinement process was conducted. This involved the systematic elimination of the PEOU3 indicator, which exhibited the lowest factor loading (< 0.7). Following this adjustment, the model was recalculated using SEM-PLS, with the revised factor loadings and improved AVE values subsequently detailed in Table 4.

Table 4 The Second Iteration, Loading Factors and AVE

Code	Loading Factors	AVE
SN1	0.922	0.662
SN2	0.850	
SN3	0.643	
ENJY1	0.780	0.680
ENJY2	0.899	
ENJY3	0.895	
ENJY4	0.709	
PU1	0.862	0.799
PU2	0.906	
PU3	0.913	
PEOU1	0.901	0.572
PEOU2	0.852	
PEOU4	0.408	
ATU1	0.916	0.752
ATU2	0.833	
ATU3	0.850	
BI1	0.597	0.610
BI2	0.861	
BI3	0.855	

In Table 4, there are several latent variables with loading factors less than 0.7; however, in terms of the AVE value, each measured variable already meets the reference threshold of >0.5 (Chin & Todd, 1995). Therefore, the test results have fulfilled convergent validity, and the next step is to observe the results of the Fornell-Larcker discriminant validity test. The results of the Fornell-Larcker discriminant validity test can be seen in Table 5.

Table 5 Fornel Larcker Criterion

Variables	ATU	BI	PEOU	ENJY	PU	SN
ATU	0.867					
BI	0.638	0.781				
PEOU	0.645	0.643	0.756			
ENJY	0.647	0.467	0.663	0.825		
PU	0.702	0.564	0.731	0.746	0.894	
SN	0.569	0.314	0.425	0.572	0.541	0.814

To establish the discriminant validity of the research instrument, the Fornell-Larcker criterion was rigorously applied. This methodological standard necessitates that the square root of the Average Variance Extracted (AVE) for each latent construct remains higher than any of its inter-construct correlations, thereby confirming the empirical divergence and uniqueness of each variable within the structural framework. Once this divergence was verified, the evaluation transitioned to assessing internal consistency via Composite Reliability (CR). In accordance with the recommendations of Chin (1998), CR was prioritized over Cronbach's alpha due to its superior ability to provide a robust estimation of reliability by accounting for varying indicator loadings, thus mitigating potential underestimation biases common in PLS-SEM models. The reliability analysis, as detailed in Table 6, confirms that all constructs successfully exceeded the required 0.70 threshold, demonstrating high internal consistency across the measurement model. The successful fulfillment of these stringent validity and reliability benchmarks signifies that the outer model possesses sufficient psychometric integrity. Consequently, the measurement model was deemed fit, facilitating the progression of the analysis to the evaluation of the structural model (inner model) and the testing of the proposed hypotheses.

Table 6 Composite Reliability

Variable	Composite Reliability
ATU	0.901
BI	0.820
PEOU	0.785
ENJY	0.894
PU	0.922
SN	0.852

R-squared is used to measure how well the model can explain the variation in the dependent or endogenous variables, as shown in Table 7. The R-square index indicates the extent to which the variation in the endogenous variable can be explained by the combination of exogenous variables on a scale from 0 to 1. When the R-squared value approaches 1, it indicates a strong influence of the exogenous variables on the endogenous variable, and the higher the R-squared value, the better the regression model formed. R-squared values above 0.67 are considered indicators of strength (strong influence), above 0.3 as indicators of adequacy (moderate influence), and above 0.19 as indicators of weakness in the resulting model (Chin, 1998).

Table 7 R-Square

Variable	R-Square
ATU	0.530
BI	0.407
PEOU	0.440
PU	0.559

Evaluating effect size using the F-Square value involves the use of specific criteria as shown in Table 8. An F-Square value exceeding 0.35 indicates a strong effect, while values above 0.15 denote a moderate effect, and values above 0.02 indicate a weak effect. Based on the test results, listed in Table 8, the F-square values for each variable can be found.

Table 8 F-Square

Variable	F-Square
ATU → BI	0.687 (strong effect)
PEOU → ATU	0.080 (weak effect)
PEOU → PU	0.762 (strong effect)
ENJY → PEOU	0.785 (strong effect)
PU → ATU	0.242 (moderate effect)
SN → PU	0.162 (moderate effect)

Following the evaluation of effect sizes (f-square), a bootstrapping procedure was executed with 5,000 subsamples at a 5% significance level (alpha = 0.05), as detailed in Table 9. This resampling method provides the necessary inferential statistics to evaluate the proposed research hypotheses. The structural model's path significance was determined by examining the T-statistics and P-values. In accordance with standard statistical conventions, a hypothesis is considered supported (statistically significant) if the P-value is less than 0.05 and the T-statistic exceeds the critical value of 1.96. Conversely, if the P-value exceeds 0.05 or the T-statistic falls below 1.96, the null hypothesis cannot be rejected, indicating a lack of significant relationship. The comprehensive results of these significance tests are presented in Table 9.

Table 9 Path Coefficient

Hypotheses	Path Coefficient	P-Values	T-Statistics	Status
H1	SN → PU	0.001	3.471	Accept
H2	ENJY → PEOU	0.000	10.110	Accept
H3	PEOU → PU	0.000	7.682	Accept
H4	PEOU → ATU	0.055	1.922	Reject
H5	PU → ATU	0.000	3.676	Accept
H6	ATU → BI	0.000	10.870	Accept

Meanwhile, the results of the total effect test are as follows, as shown in Table 10. The total effect analysis indicates significant relationships among the variables: Attitude Toward Use (ATU) shows a substantial impact on Behavioral Intention (BI), with a T-statistic value of 10.870 and a P-value of 0.000, suggesting that higher ATU values correspond to higher BI values.

Table 10 Total Effect

Total Effect	P-Values	T-Statistics
ATU → BI	0.000	10.870
ENJY → ATU	0.000	4.770
ENJY → BI	0.000	3.957
ENJY → PEOU	0.000	10.110
ENJY → PU	0.000	5.284
PEOU → ATU	0.000	6.515
PEOU → BI	0.000	5.046
PEOU → PU	0.000	7.682
PU → ATU	0.000	3.676
PU → BI	0.001	3.288
SN → ATU	0.020	2.330

SN → BI	0.029	2.190
SN → PU	0.001	3.471

Perceived Enjoyment (ENJY) also influences ATU significantly, with a T-statistic value of 4.770 and a P-value of 0.000. Higher levels of Perceived Enjoyment (ENJY) correlate with higher levels of ATU. Furthermore, ENJY has a notable effect on BI, with a T-statistic value of 3.957 and a P-value of 0.000. Increased ENJY values are associated with higher BI values. Additionally, ENJY influences Perceived Ease of Use (PEOU) significantly, with a T-statistic value of 10.110 and a P-value of 0.000, as well as Perceived Usefulness (PU), with a T-statistic value of 5.284 and a P-value of 0.000. Higher levels of ENJY correspond to higher levels of PEOU and PU. PEOU significantly impacts ATU, BI, and PU, with T-statistic values of 6.515, 5.046, and 7.682, respectively, all with P-values of 0.000. Higher PEOU values are linked to higher ATU, BI, and PU values.

Moreover, PU influences ATU and BI, with T-statistic values of 3.676 and 3.288, respectively, both with P-values of 0.0001. Higher PU values correlate with higher ATU and BI values. Finally, Subjective Norm (SN) has a meaningful effect on ATU, BI, and PU, with T-statistic values of 2.330, 2.190, and 3.471, respectively, all with P-values below 0.05. Increased SN values correspond to higher ATU, BI, and PU values. These findings highlight the intricate connections among the variables, shedding light on the factors influencing users' attitudes and intentions regarding VR technology adoption.

The results of this investigation support the theories put forward in earlier studies. In particular, the variables subjective norm influencing perceived usefulness, perceived enjoyment influencing perceived ease of use, perceived ease of use influencing perceived usefulness, attitude toward use influencing behavioral intention, and perceived usefulness influencing attitude toward use are all consistent with earlier research. The theories developed in this study, however, differ from those of earlier studies. Perceived ease of use has no effect on attitude toward it in this study. Rather, in this research environment, students' attitudes toward use are more impacted by perceived utility, whereby they believe that their learning process will benefit more.

E. DISCUSSION

The Subjective Norm (SN) variable influences the Perceived Usefulness (PU) variable. This could mean that the influence of others' opinions, which is important, can enhance students' perceived benefits in the process of learning using VR technology. The greater the encouragement from others to use VR technology, the higher the perceived effectiveness of students in using VR technology.

The Perceived Enjoyment (ENJY) variable influences the Perceived Ease of Use (PEOU) variable. This means that an individual's level of comfort and enjoyment when using a technology platform will also affect their perception of its ease of use. The more comfortable a student is in using VR technology, the higher their perception of the ease of use of the VR technology device.

The Perceived Ease of Use (PEOU) variable influences the Perceived Usefulness (PU) variable. This means that a student's perception of the ease of use of VR technology devices will affect how effectively they learn. The easier the VR device is to use, the better the learning effectiveness. Additionally, the speed of learning is also something that can be achieved when VR technology is easier to use, as students can focus more on the content rather than struggling with the technology itself.

The empirical results indicate that Perceived Ease of Use (PEOU) does not significantly influence the Attitude Toward Use (ATU) within this specific cohort. This suggests that the technical simplicity of the virtual reality (VR) interface is not a primary determinant of a student's motivation or disposition toward exploring the platform's features. Instead, an individual's attitude appears to be more heavily moderated by perceived usefulness (PU) and the perceived acceleration of the learning process. Theoretically, this lack of significant correlation implies that ease of use alone is insufficient to cultivate a positive attitude if the technology is perceived as lacking functional value or substantive benefits. Furthermore, ATU is a complex, multi-dimensional construct influenced by factors such as Perceived Enjoyment (ENJY) and Subjective Norms (SN); thus, even an intuitive system may elicit a neutral or negative attitude if it fails to align with the user's pedagogical goals or intrinsic interests. This discrepancy may also be attributed to individual differences, such as cognitive biases or prior negative predispositions toward immersive technology, which can shape user attitudes independently of the system's usability. For VR to be accepted in a psychological learning environment, the emphasis must shift from mere user-friendliness to the congruence between technological attributes and concrete educational results.

The Attitude Toward Use (ATU) variable influences the Behavioral Intention (BI) variable. This means that an individual's interest or motivation in exploring VR technology features will influence their intention to use VR technology as a learning medium, both now and in the future. The influence of ATU can also prompt someone to recommend VR technology to others in their learning process.

This study also found that all tested variables, including the influence of others' views on the importance of using VR technology, the level of comfort in using VR technology for learning, the ease of use of VR technology, the perceived benefits of using VR technology, and an individual's motivation or interest in exploring VR technology features, can affect their intention or desire to use VR technology as a learning medium both now and in the future, as well as enhance their ability to recommend VR technology for learning.

To enhance the generalizability and robustness of these findings, future research should expand the sampling frame through longitudinal analyses and cross-disciplinary cohorts. By conducting this study across various faculties—such as medicine, dentistry, and visual arts—researchers can obtain more comprehensive insights and discern distinctive adoption trends across different academic fields. Furthermore, the current model can be extended by incorporating additional moderating variables, such as computer self-efficacy or technostress, to uncover further determinants that influence the success of VR-integrated learning environments, which may include factors like student engagement and instructional design effectiveness. From a managerial perspective, the empirical insights derived from this study offer a strategic foundation for academic administrators to refine the integration of virtual reality within the psychology curriculum. Educational institutions should leverage these findings to develop targeted pedagogical frameworks and capacity-building programs that align VR technology with specific learning objectives. Furthermore, these implications underscore the necessity for proactive policy shifts and strategic resource allocation, including the provision of faculty incentives and comprehensive technical training. By fostering a supportive institutional culture and addressing both psychological and technical barriers, universities can optimize the implementation of VR technology to significantly enhance pedagogical efficacy and the overall quality of the student learning experience.

F. CONCLUSION

In summary, this research provides empirical evidence regarding the multifaceted determinants that influence the adoption and integration of virtual reality (VR) within a pedagogical context. The findings demonstrate that Subjective Norms (SN) significantly enhance Perceived Usefulness (PU), suggesting that social influence and the endorsement of academic peers are instrumental in shaping a student's perception of the technology's functional value. Furthermore, the significant impact of Perceived Enjoyment (ENJY) on Perceived Ease of Use (PEOU) underscores the importance of the user's hedonic experience; students who find the immersive environment engaging tend to perceive the interface as more intuitive. While PEOU was found to be a critical antecedent to both PU and overall learning effectiveness, it notably failed to serve as a direct predictor of Attitude Toward Use (ATU). This indicates that technical simplicity alone is insufficient to cultivate a positive disposition if the tool does not align with the user's broader educational objectives or intrinsic motivations.

Nevertheless, ATU remains a powerful driver of behavioral intention (BI), where a positive psychological stance directly dictates a student's commitment to long-term usage and their likelihood of serving as proponents of the technology. Collectively, these results highlight a complex interplay between social influence, comfort, and utility in determining the success of VR-based instruction. To advance the current understanding of immersive learning, future research should expand the sampling frame to include longitudinal data and cross-disciplinary cohorts, such as those in medicine or visual design. Moreover, integrating additional variables—including instructional design quality, user engagement metrics, and technological accessibility—will provide more granular insights into the structural factors that optimize the efficacy of VR as a transformative educational medium.

G. LIMITATION

This research has several limitations that need to be noted. First, the institutional scope is limited to the Faculty of Psychology at Ciputra University, so the research findings may not be directly applicable to various geographical contexts or other educational institutions. Second, the availability of resources such as access to VR technology devices like Oculus Quest 2 and applications such as Psytech VR may limit the level of implementation of this technology in an academic environment. Third, the research subjects consist of students from the Faculty of Psychology at Ciputra University who have taken the Mental Health course in the academic year 2023/2024, with a limited number of students totaling 60. Factors influencing VR acceptance by other parties, such as administrative staff or external stakeholders, will not be discussed in this research. Fourth, the theoretical framework used primarily focuses on TAM and SEM-PLS, so other factors that may affect VR acceptance will not be discussed in depth. Finally, this research will limit data collection to a specific period of time, so the dynamics of longer-term changes in VR technology adoption may not be fully covered.

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